Efficiency or statistical illusion? The case for the Japanese Stock Market

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By

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Thesis submitted for the degree of PhD in Finance

April 2005

For my father Nicholas

and

grandparents Angelos and Sofia

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Abstract

The recent proliferation of hedge funds suggests that capital markets present windows of opportunity to realise substantial arbitrage profits thus violating the 'no arbitrage' condition of efficient markets. This thesis examines several observed return patterns that have raised questions about the efficiency of capital markets and/or the validity of the asset pricing models used to analyse them. The study focuses on the Japanese stock market which is under-analysed despite being the second largest in the world. We first look at three stock attributes that can arguably differentiate between future winners and losers. These are size, price and book value to market. In contrast to older studies, we find no significant evidence of a size effect. The price and book value to market effects however are statistically significant although both appear to be cyclical in nature suggesting that they are at least partially driven by macroeconomic risk factors and so are not pure anomalies. The short term reversal of stock returns is investigated next. Unlike previous studies, a strategy that utilises optimal investment portfolios is simulated. By avoiding previously documented methodological problems, it is shown that contrarian profits are statistically and economically significant and that they are overwhelmingly attributed to investor over-reaction to firm-specific events, implying that significant short term inefficiencies occur in the Japanese stock market. Finally the effectiveness of the law of one price and its implications for the relative pricing of assets is examined. It is shown that the returns of securities with similar systematic risk are highly correlated and their relative prices oscillate around an equilibrium value. Large deviations from that value can be exploited by a trading strategy known as pairs trading. Simulations of several strategy variants generate statistically and economically significant profits which are not attributable to systematic risk. It is concluded that relative stock prices are not always efficient in the short term. Such inefficiencies can be profitably exploited as prices are eventually driven to equilibrium.

ACKNOWLEDGEMENTS

I am eternally grateful to my supervisor Professor Tony Antoniou for being both a great friend and mentor and without whom this thesis would not have been possible. I thank him for his continued encouragement, occasional prodding, comments and guidance. Our discussions about market efficiency and other ephemeral matters while walking on the hills overlooking Durham are memorable.

I would also like to thank Advanced Portfolio Technologies and specifically Jon Javidson for providing me their factor model data. Special thanks to Dr. Ramses Abulnaga for his friendship and our numerous discussions about life and what is important. Many thanks to good friends Dr. Yiannis Doumenis and Dr. Emilios Galariotis for all their help.

I am indebted to my loving wife Stella for her support and understanding and to my son Nicholas for being a constant source of happiness despite the hard work. Thank you to my in-laws for providing a happy family environment and nourishment during the last year. Thank you to my mother for urging me to 'get an education' for as long as I can remember.

Chapter 3

THESIS INTRODUCTION

During the 52 weeks between January 2004 and January 2005, The Economist, a weekly politics, business and finance magazine, published no less than 78 articles relating to hedge funds. That's an average of 1.5 articles per issue. During the same period 684 articles with the phrase 'hedge fund(s)' in their title appeared in the Financial Times a daily business newspaper. That's more than 2 articles per day. What a few years ago appeared to be an exclusive area of finance reserved for a few very wealthy individuals and financial institutions has now become mainstream. Initially hedge funds were being set up by investment banks as a way of investing their own money in financial markets as part of their overall investment portfolio. Banks paid handsome rewards to bright and talented individuals with postgraduate degrees in engineering and mathematics mainly, to apply the analytical tools of their chosen discipline on financial assets in order to identify investment opportunities. Some of these individuals were later able to set up their own hedge funds and offer their services to other wealthy individuals and institutions. The recent lackluster performance of developed stock markets around the world and the promise of high returns (many times higher than the average straight investment fund) resulted in a proliferation of such funds. However the term 'hedge fund' has changed over the years. It used to be that hedge funds engaged mainly in arbitrage, buying undervalued assets and selling short over valued assets believing that market forces will eventually drive asset prices closer to their fair value thus leaving the fund with an almost risk-less arbitrage profit. Nowadays, managers engaging in a spot of short selling call themselves hedge-fund managers and command high premiums for their services. In all cases the main motivating force of these funds is the belief that financial assets are not valued fairly and the extent of the miss-pricing is such that allows for transaction cost to be covered and a profit to be made by taking the appropriate positions. This runs contrary to one of modern finance theory's most contested assertions, the efficient market hypothesis (EMH).

The concept of market efficiency in modern finance was introduced by Fama (1970) and is inextricably linked to the advent of asset pricing models. Asset pricing models revolutionized the way we look at financial markets by formalizing the relation between risk and return. The first such model was the Capital Asset Pricing Model (CAPM). The CAPM was developed by Sharpe (1964), Lintner (1965) and Mossin

(1966) and stipulates that the market is the only priced risk factor and that asset returns are linear functions of their co-variability with the market return. The main criticism of the CAPM (Roll, 1977) is that it is not feasible to test its empirical validity since it is impossible to identify the composition of the true market portfolio, as specified in the theoretical form of the model, and calculate the market return. The Arbitrage Pricing Theory (APT) emerged as a result of an attempt by Ross (1976) to develop an asset pricing model that relies on weaker assumptions than the CAPM. The APT improved on the CAPM by suggesting that there are more than one factors affecting asset returns. However it failed to specify how many and which these factors are. Asset pricing models attracted a lot of interest from researchers. A large number of empirical versions of both types of models have appeared through the years but all have failed to explain the cross-sectional and temporal variation of asset returns adequately. Researchers started observing patterns in asset prices that could not be explained by the available asset pricing models. One of the first to be identified and probably the most frequently reported anomalous pricing pattern is the size effect (Banz 1981) i.e. the consistent out-performance of large by small capitalization stocks. Other effects identified early on relate to variables such as dividend yield (Litzenberger and Ramaswamy, 1979), price/earning ratios (Basu 1977, Reinganumn, 1981) and price (Blume and Husic, 1973). More recently, De Bondt and Thaler (1985 and 1987) showed that past loser stocks tend to outperform past winners and Fama and French, (1992) identified the book value to market equity ratio as another characteristic that differentiates stock returns strongly.

The two main explanations for the observed patterns are that either the asset pricing model is miss-specified or the market does not price assets efficiently. Early on, pricing anomalies were usually attributed to the inadequacy of the asset pricing model. The identified anomalies were believed to be proxies for risk factors absent from the model so the model was extended to include portfolios mimicking the pricing anomalies as explanatory variables. However even these extended models failed to explain all the pricing irregularities thus raising questions about market efficiency. The degree to which a market is efficient measures its ability to allocate resources efficiently and maximize wealth. Hence testing for market efficiency has attracted a vast amount of academic interest. There are two alternative definitions of efficient markets reflected in the strong and weak formulations of the EMH respectively. The strong form (Fama, 1991) states that in efficient markets, prices reflect instantly all publicly and privately held information thus making it impossible to predict their future course based on this information. The weak form of the EMH (Jensen, 1978, Ross, 1987) is more amenable to testing and states that efficient markets are characterized by the absence of arbitrage opportunities, implying that economic profits from trading, net of all costs are zero. The main difficulty associated with EMH testing is the 'joint hypothesis problem'. Hakkio & Rush (1989) note that the EMH is a joint hypothesis that (a) investors are risk neutral and (b) they make rational use of all available information so that speculators have a zero expected return. Violation of either hypothesis will lead to rejection of the joint hypothesis but does not mean that the market is inefficient. Furthermore, EMH tests require the use of an asset pricing model to generate equilibrium prices against which actual prices are compared and judged to be efficient or not. As Fama (1991) points out, the EMH may be rejected because the asset pricing model used is miss-specified, the market is not efficient or both. This joint hypothesis problem makes the interpretation of the test results very difficult and is echoed in the alternative explanations given for the observed pricing anomalies. Nevertheless it is not entirely impossible to determine whether a market is efficient or not. Absence of efficiently performing markets has very serious, directly observable consequences for society. For example, the astronomical valuations of telecommunications and internet related firms in recent years were believed to reflect the very favorable growth prospects of these industries in the coming years and so were believed to be efficient. However a closer look would reveal that the stock prices were discounting unrealistic growth rates in perpetuity. The subsequent collapse of the stock prices, failure of many businesses and reporting of huge losses by others resulted in massive wealth destruction and thus failure of the market to allocate resources efficiently. By the same token, the creation of an entire industry whose purpose is the profitable exploitation of market inefficiencies should point to the fact that such inefficiencies do probably exist.

It is the weak form of the EMH that we think is being continually disproved by the survival of hedge funds and the preeminence they have attained over the years. The impression one gets from reading newspaper articles on the subject is that hedge funds have the mystical ability to generate very large returns with very little risk. With the exception of the spectacular failure of the Long Term Capital Management fund of Professors Myron Scholes and Robert Merton there are mainly success stories reported. Then again, the success of hedge funds is disputed in a recent Financial

Times article by Prof. Malkiel ('The return of the blindfolded monkey', FT, 1 Feb 2005). He argues that these returns are nothing but a self-promoting fiction advertised by the industry itself and cites the CSFB/Tremont hedge fund index which has under-performed the S&P 500 over the last two years. However there are quite a few caveats in his argument. The CSFB index is by no means conclusive in that many funds are not reported. Funds that are closed to new money for instance do not have the need to advertise their performance. Furthermore many funds are set up internally by investment banks and are not reported separately. Other funds, as mentioned before, are only hedge funds in name. Nevertheless Prof. Malkiel makes the point that hedge funds are probably becoming the victims of their own success. The fact that too many funds are chasing a fixed number of opportunities makes the market more efficient thus hampering their performance. If the higher returns are accompanied by ever higher risk, one should expect more frequent failures which will eventually mitigate investor interest. The proliferation of such funds and their ability to generate large returns has therefore serious implications about the efficiency of the markets in which they operate.

The aim of this thesis is to examine various aspects of efficiency of the Japanese stock market. This is done examining whether the Japanese market is also susceptible to some of the pricing anomalies identified in the US market and by simulating some of the trading strategies popular with hedge funds over the years. The main contribution of the thesis is threefold. First, we bring to the fore the Japanese stock market which despite being the second largest developed market in the world, has largely been neglected by the academic community. Instead the vast majority of the efficiency literature is concentrated on the US market. The thesis therefore helps us assess the efficiency of the Japanese market per se and relative to the US market. Second we use a simulation design that is more akin to a practitioner's point of view and hence closer to real trading conditions thus minimizing the probability that our results are driven by methodological flaws. Finally we systematically examine a trading strategy, namely statistical pairs trading, which has not appeared in the academic literature before but has been popular with proprietary trading desks around the world for a long time.

Many results in the efficiency literature can be attributed to methodological flaws. One very important issue that emerges throughout the thesis is the measurement of the performance of the simulated trading strategies. The way portfolio returns are calculated for example can often make the difference between statistical significance and insignificance and hence between market efficiency and inefficiency. Great care is therefore taken to avoid introducing positive biases in performance measures. The performance of the trading strategies is evaluated by examining both the return of the strategy and the risk associated with it. A lot of emphasis is put on examining and comparing the Sharpe ratios of the respective profit and loss streams as they measure the reward received for each unit of risk borne by the strategy. The breakdown of the total risk into a systematic and a residual risk component is also examined. However, constructing the risk profile of a particular profit and loss streams is particularly difficult because it involves the use of an asset pricing model implying that the systematic risk measures are encumbered by the 'joint hypothesis problem' mentioned before. For this reason we avoid making conclusive remarks on whether a market is efficient or not. In any case, this would be self-contradictory since two of the trading strategies tested herein rely on the market being 'ultimately' efficient for the prices to converge to their 'fair' model value. A more productive use of the efficiency tests, as suggested by Campbell, Lo and MacKinlay (1997) is to assess the relative efficiency of a market. Markets can be more or less efficient but not perfectly efficient. Perfect efficiency in finance is a rather idealistic concept and would be equivalent to frictionless motion in engineering, thus improbable. This is the approach adopted in this thesis when interpreting the various test results. The magnitude of the miss-pricing and the speed of the correction can be indicative of the extent to which the market is efficient. The smaller the miss-pricing and the speedier the correction the more efficient the market is. The speed of the correction is reflected in the strategy's turnover, i.e. the number of positions opened and closed during the simulation period. The magnitude of the perceived miss-pricing is reflected in the magnitude of the profits themselves. In order to alleviate the join hypothesis problem further, we report risk measures that are independent of any asset pricing model, such as descriptive statistics of the distribution of the strategy's return, historical VAR and total variance measures.

The thesis comprises three empirical chapters in total. The first chapter is devoted to examining the size, price and book-value-to-market effects in Japan. All three effects have been analyzed in the US market and have been characterized as pricing anomalies. The chapter is divided in four parts. The first part examines all three effects separately and attempts to establish whether each effect is observed in the sample under investigation. The effect of the portfolio weighting scheme and transactions costs on the portfolio premiums is also examined. We present evidence that points to a weak size effect but very strong price and book value to market effects. A closer look at the annualized standard deviations of the relevant portfolios reveals that the weak statistical significance of the small size premium is due to the excess volatility of the small size portfolio compared to the large size portfolio. Since the evidence on the size effect is not strong the rest of the chapter concentrates on the price and book value to market effects. The second part investigates whether the effects exist independently of one another. This is done by double-sorting price portfolios on book value to market and vice versa using two alternative methodologies. We show that the conditional price effect is weaker but still significant. In contrast the book value to market effect remains unaffected when conditioned on price. The third part examines the correlation of the effects to the macro-economy. The magnitude of the correlation between a given effect and various macro-economic scenarios would reveal the extent to which the effect is driven by risk factors underlying the economy. It is shown that both the price and book value to market effects are stronger when certain macroeconomic conditions occur so they cannot be entirely characterized as anomalous. The final part of the chapter examines the existence of seasonal patterns in the effects under examination. A large volume of literature in the US shows that the size effect is seasonal in nature and is stronger on January (e.g. Keim, 1983). This coincides with the financial year end which for most US companies occurs in December and so prompted researchers to offer explanations for the phenomenon that relate to investor behavior during the end of the year. These are formally known as the Tax Loss Selling Hypothesis (Dyl, Branch, 1977), the Risk Measurement Hypothesis (Rogalski and Tinic, 1986) and the Portfolio Rebalancing Hypothesis (Hausen and Lakonishok, 1987). The financial year end for most companies in Japan falls in March and April. We show that the effects under investigation are positive and statistically significant during the first half of the year and become insignificant thereafter.

The second chapter examines a trading strategy popular with hedge funds known as return or residual reversal. The strategy is based on the observed negative serial correlation exhibited by stock returns which has been a well-documented phenomenon since the 1960's. The presence of serial correlation in stock returns directly contradicts the efficient market hypothesis- according to which all past information is already reflected in current stock prices and cannot be a guide for future performance. The basic form of the strategy calls for selling short stocks that performed extremely well in the past and buying stocks that did poorly. As such the strategy is characterized as contrarian because it takes action that is contrary to that followed by 'naïve' investors. Academic interest in contrarian strategies mushroomed since the publication of a very influential article by De Bondt and Thaler, (1985) who linked contrarian profits to the over-reaction hypothesis. The over-reaction hypothesis states that investors tend to over-react to good news and bad news about a firm thus driving its stock price away from its fundamental value. Therefore a central assumption of the EMH, namely that investors are rational, is violated. Many empirical estimates since suggest that contrarian strategies can consistently yield substantial profits with serious implications about the weak form of the efficient market hypothesis. In addition to the over-reaction hypothesis, the other main explanation is that the contrarian profits are justified by their accompanying systematic risk. This again reflects the joint hypothesis problem as in the case of the anomalies literature.

This chapter contributes to the debate in a variety of ways. We examine optimal investment portfolios that have zero (or near zero) exposure to systematic risk factors. To this end we use a commercially available, APT type multifactor model. This will help alleviate any concerns about the risk associated with the simulated profits. In contrast all empirical studies so far adopt portfolio weighting schemes that do not optimize portfolio performance. The implication is that the portfolios under consideration are not on the efficient frontier and so are inconsequential. It is shown that contrarian profits are very sensitive to the asset-pricing model used to estimate risk-adjusted returns and the systematic covariance matrix of the investment universe. Liquidity is shown to be another factor affecting the magnitude of contrarian profits. The simulated strategy is subject to realistic trading costs. Trading costs have largely been ignored in the extant literature despite the fact that they simulate very high turnover strategies whose performance is naturally very sensitive to transaction costs. Portfolio returns are calculated using prices that are readily and cheaply delivered by Japanese stock brokers and so portfolio returns are more realistic. Finally the strategy is simulated entirely out of sample meaning that no information is assumed known until after it becomes available. This is in stark contrast to many empirical studies so far whose portfolio returns invariably suffer from in-sample bias. The main finding of the chapter is that the simulated strategy generates significant profits subject to negligible systematic risk. This lends support to the over-reaction hypothesis and raises questions regarding the short-term efficiency of the Japanese stock market.

The final chapter of the thesis explores the law of one price. This is done by simulating a trading strategy called pairs trading. The law of one price is yet another aspect of market efficiency and states that equivalent future payoffs with identical risk profiles should carry the same price. Otherwise a risk-less profit could be made by selling short the relatively expensive and using part of the proceeds to buy the relatively cheap payoff. Pairs-trading is a trading strategy that is based on the law of one price and exploits perceived pricing anomalies between pairs of highly correlated securities. It calls for selling the relatively expensive and buying the relatively cheap one of a pair of highly correlated securities whose relative price appears to diverge from the perceived equilibrium level in the belief that the law of one price will eventually drive the two prices back to a level justified by their risk profiles. We differentiate between two types of pairs, statistical and fundamental pairs. Statistical pairs are those whose high correlation is induced by an indirect relationship between the paired assets such as membership of the same industry group for example. The correlation of fundamental pairs on the other hand is due to a more direct link between the paired assets. Different classes of shares of the same company, dual listings and shares of companies with large cross-ownership interests are all examples of fundamental pairs. The chapter concentrates on the systematic examination of statistical pairs. The existence of statistically significant profits from the strategy violates the 'no-arbitrage' definition of the efficient market hypothesis and so has very serious implications for the efficiency of relative asset pricing in particular and for market efficiency in general. We examine two versions of the strategy based on the method used to assess the stability of the relative price of the pair over time. Relative share prices are analyzed using two alternative cointegration techniques namely the Johansen procedure and the augmented dickey-Fuller test. The two procedures differ mainly in terms of the restrictions imposed on the cointegrating relationship. We present evidence that shows that both versions of the strategy generate profits that are statistically and economically significant. The results of the two procedures are not substantially different. This implies that economically significant violations of the 'no arbitrage' condition do occur in the short-term. Such violations eventually are corrected by the market and can be profitably exploited.

The chapter contributes to the extant literature by examining a profitable trading strategy which is popular with investment professionals but has attracted little attention from the academic community. It provides a generalized framework for identifying and analyzing pairs of highly correlated stocks which can be applied to any developed stock market. As such it highlights another aspect of efficient markets which may have been ignored by academics.

CHAPTER 1

Size, Price and Book Value to Market: Anomalies or priced risk factors?

Introduction

The advent of the Capital Asset Pricing Model (CAPM) has fundamentally changed our understanding of capital markets. It has helped investors develop a more structured approach to making investment decisions and has attracted the interest of a countless number of empirical researchers and academics. The CAPM stipulates that market risk is the only priced risk factor and that asset returns are linear functions of their covariability with the market return otherwise known as Beta. The main criticism of the CAPM came from Roll (1977) who argued that the portfolios used in empirical tests of the model are not good proxies of the portfolio of all risky assets (market portfolio) specified by the theoretical form of the model. In fact it is impossible to identify the composition and calculate the return of the true market portfolio.

The Arbitrage Pricing Theory developed by Roll and Ross took the CAPM one step further by suggesting that the market is not the only priced risk factor. There are economic state variables that drive returns and a methodology was developed to identify those variables. The APT though fails to suggest how many and which these variables are. Empirical forms of all available asset pricing models have failed to give an adequate explanation of the cross-sectional and temporal variation of asset returns. This prompted researchers to look for 'regularities' or 'anomalies' in the behaviour of the capital markets. The presence of empirical anomalies in asset returns suggests that empirical forms of asset pricing models are miss-specified and/or that capital markets are not efficient. One of the most frequently reported anomalies in the empirical finance literature is the so called size effect. Firms with a small market capitalisation are noted to have both higher risk adjusted and unadjusted returns than firms with a large market capitalisation. There is a vast volume of literature, the majority of which is concentrated on the US market, documenting the effect and offering competing explanations. Notwithstanding the methodological issues, there are two main rationalisations on offer for the observed size anomaly. The first argues that the CAPM betas are not estimated correctly thus leading to spurious estimates of excess returns e.g. Roll (1981). The second argues that risk is in fact multidimensional and therefore the CAPM does not explain the cross-variation of stock returns adequately (e.g. Chen 1981, 1983). Fama and French (1992) argue that size alongside with other observed anomalies like E/P, leverage and Book to Market Equity (BE/ME) proxy for underlying macro-economic risk factors not captured by the CAPM. Others like Kross

(1985) and Bhardwaj and Brooks (1992) argue that the size effect is really a price effect. Finally a number of studies (e.g. Keim, 1983) have linked the size effect with the January effect noticing that most of the small size premium is realised in January and therefore the anomaly is seasonal and not constant throughout the year.

The aim of this study is to examine the existence and viability of the size, price as well as the BE/ME anomalies in the Japanese stock market using a broad sample of stocks from Jan 1985 until Aug 2003. The paper proceeds as follows: Section 1.1 reviews the relevant literature, Section 1.2 describes the methodology and the data set used, Section 1.3 describes the portfolio formation procedure in detail, Section 1.4 presents results on the unconditional percentile portfolios, Section 1.5 presents the results on the conditional percentile portfolios, Section 1.6 examines the correlation between the effects under investigation and several macro-economic scenarios and finally Section 1.7 examines the existence of seasonal patterns in the studied effects.

1.1 Literature Review

1.1.1 The Size Effect

The size effect was first reported by Banz (1981) who examined the relationship between the return and the market value of NYSE common stocks. He found that smaller firms had larger risk adjusted returns than larger firms for more than forty years. The persistence of the size effect manifests misspecification of the CAPM rather than lack of market efficiency. Banz also found that the relationship between the size effect and market value is not linear. There is little difference between the return of medium sized and large firms, the main effect occurring for very small firms. Finally, he suggested that size may be a proxy for one or more true but unknown risk factors correlated with size. By examining both NYSE and AMEX securities, Reinganumn (1981) also found evidence in support of the size effect. In addition, he found that portfolios consisting of securities with high earnings/price (E/P) ratios had systematically larger returns than portfolios of low E/P securities. This effect though vanished once security returns were controlled for the size effect. The abnormal returns of portfolios formed on size or E/P persisted for longer than two years, in support of the hypothesis that the CAPM is miss-specified. Roll (1981), argued that the abnormal risk adjusted returns associated with size might be due to miss-estimated betas caused by infrequent trading. Reinganumn (1982) responded that the size effect could not be accounted for even when betas estimated with methods designed to correct for non-synchronous and infrequent trading were used. Blume and Stambaugh (1983) show that the portfolio formation technique used by Reinganumn i.e. daily portfolio rebalancing so that security weights are kept equal, may induce a positive bias to the portfolio returns. This bias is inversely related to firm size and when avoided, they find that the difference between small and large firm portfolio returns is halved.

In a very extensive study of the size effect, Keim (1983) used daily returns of NYSE and AMEX common stocks for the period 1963-1979. He examined the distributions of the abnormal returns of portfolios formed on size, for each month separately. Keim found that the return distributions in January had larger means than those for the remaining months. Abnormal returns were always inversely related to firm size but even more so in January. This was true even in years when large firms had higher risk adjusted returns than small firms. Keim showed that nearly fifty percent of the small cap premium was due to January abnormal returns and that more than fifty percent of the January premium occurred during the first week of trading, particularly on the first day. A January seasonal in stock returns was first reported by Officer (1974) and Rozeff and Kinney (1976) but Keim was the first author to link the January effect with the size effect. In an attempt to explain the January effect, Dyl (1977) and Branch (1977) developed the Tax Loss selling Hypothesis (TLSH). According to the TLSH, investors will engage in selling of shares that have declined in value in the previous year in order to realise losses before the new tax year and thus postpone taxes on the realised capital gains. This will initiate a downward pressure on the price of these stocks near the end of the year. The pressure dissipates at the beginning of the new tax year and the price rebounds. The possible association between the January-size effect and the TLSH was investigated by Reinganumn (1983) whose results corroborate those of Keim. Although the abnormally high returns in January seemed to be consistent with tax-loss-selling, Reinganumn argued that the TLSH cannot explain the entire January effect. Brown, Keim, Kleidon and Marsh (1983) argued that since Australia has similar tax laws to the USA but a July-June tax year, there should be a small firm July premium in stock returns according to the TLSH. Nevertheless Australian data showed a pronounced December-January and July-August seasonal and a premium for small firms of about four percent for all months. They concluded that the relation between the US tax year end and the January effect could be more correlation than causation. Cook and Rozeff (1984) investigated January and all other months separately for the period 1968-1981 and found that there was both a size and an E/P effect. Both effects were significant in all months with no effect dominating the other. Nevertheless Banz and Breen (1986) and Rogers (1988) suggested that both effects are present but size dominates E/P.

Chen (1981,1983) argued that the size effect is captured by the factor loadings of an Arbitrage Pricing Model and so the risk adjusted returns of portfolios of different size firms are not significantly different. These results are consistent with the Efficient Markets Hypothesis and lend support to the hypothesis that the CAPM is miss-specified. Chan, Chen and Hsieh (1985) also used identifiable economic factors in a pricing equation and their results indicated that a measure of the changing risk premium explained much of the size effect. Rogalski and Tinic (1986) argued that there is nothing in asset pricing theory that requires stock risk to remain constant over time, as assumed in most of the previous studies of the size effect. If the risk of small firm stocks increases at the beginning of the year, their required rates of return should also increase. This became known as the Risk Measurement Hypothesis (RMH). They found that small firm stocks had higher returns and significantly higher risk in January compared to other months. Ritter and Chopra (1989) found that even in Januaries with a negative market return, small firm portfolio returns were positive and the magnitude of the return was directly related to the portfolio beta. More specifically they showed that high-beta small stocks had higher excess returns in January than low-beta small stocks. They found that both the TLSH and the RMH were unable to explain their results which were more consistent with the Portfolio Rebalancing Hypothesis (PRH) developed by Hausen and Lakonishok (1987). According to the PRH, institutional investors engage in 'window dressing' by rebalancing their portfolios prior to year end to remove securities which might be embarrassing if they appeared in the year-end balance sheets. As soon as December 31 is over they rebalance their portfolios investing in more speculative securities including high risk small firm stocks. Jegadeesh (1992) evaluated the claim in some papers that betas that were precisely estimated could explain the cross-sectional differences in expected returns of portfolios formed on size. He argued that the correlation between betas and firm size across the test portfolios in these studies was close to one, leading to potentially spurious inferences. He went on to show that when the test portfolios were constructed so that the correlation between beta and size was small, the betas explained almost none of cross-sectional variation in returns.

Fama and French (1992) tried to capture the cross-sectional variation of NYSE, AMEX and NASDAQ stock returns by combining market beta, size, E/P, leverage and Book to Market Equity (BE/ME) in a multivariate framework. They found that beta did not seem to help explain the cross-section of average stock returns. The unconditional relations between average returns and each of the variables were strong; however size and BE/ME seemed to absorb the effect of E/P and leverage and BE/ME had a considerably stronger effect than size. He and Ng (1994) investigated whether size and BE/ME are proxies for macroeconomic risks found in Chen, Roll and Ross's (1986) (CRR) multifactor model or are measures of the stocks' exposure to relative distress. They found that the effect of size overwhelmed that of the risk exposures associated with the CRR factors and that the CRR model could not explain the BE/ME effect. They also found that size, BE/ME and relative distress are interrelated and that relative distress could explain the size effect but only partially the BE/ME effect. Berk (1995) pointed out that the type of risk that size will proxy for is entirely determined by the asset pricing model that is being tested: if two different pricing models miss different factors in the risk premium, then size will proxy for different factors in the two tests. Fama and French (1993, 1995) demonstrated that size and BE/ME can proxy for risk factors that capture strong common variation in stock returns. They also showed that the two variables help explain the cross section of average returns since they are related to profitability. Their research was so influential that exposure to book-value-to-market was used to distinguish between value and growth investing styles. However, the Fama/French results were contested by Daniel and Titman (1997) who provide evidence suggesting that the Fama/French factors rather than explaining the cross sectional variation of stock returns by being proxies for underlying risk factors, are directly related to these returns for reasons relating to market structure and investor behaviour. By examining Compustat data from 1976 to 1995, Kim and Burnie (2002) show that the size effect is affected by the economic cycle with the small cap premium being significant during expansionary periods of the economy but not during recessions. Wang (2000) examined the same data and concluded that the size and book value-to-market effects are spurious statistical artefacts resulting from the fact that small companies are more likely to drop out of the sample by failing to meet the stock exchanges listing criteria thus inducing survivorship bias in the sample.

Finally, Chan and Lakonishok (2004) provide an excellent up to date survey of empirical academic research on value and growth investing. Furthermore they update the existing research by examining datasets from various developed economies that span time periods ending as recently as 2001. They show that despite recent experience in the 90's value investing still outperforms growth investing with small capitalisation value stocks outperforming their large cap peers.

1.1.2 The size effect in Japan and the rest of the World

The size and the January effects have also been documented by a number of studies for markets other than the US. In Japan, Kato and Schallheim (1985) report a significant January-size effect using data on Tokyo common stocks. Rao, Aggarwal and Hiraki (1992) confirm the existence of significant size and seasonal anomalies in the Tokyo Stock Exchange. In addition they report a significant dividend yield effect which persists even after controlling for size. Daniel et al. (2001) examine a sample of companies listed on the Tokyo stock exchange to test whether the higher returns associated with small size and high book-to-market stocks arise because these attributes are proxies for risk factors. Their evidence suggests that, for reasons such as behavioural biases or liquidity, the superior returns are directly related to the stocks' attributes rather than the covariance structure of the returns. Their results corroborate those of previous studies using US data. Chiao and Hueng (2004) challenge the validity of Daniel's (2001) findings by showing that the returns of zero investment portfolios that sell short past winners and buy past losers cannot be fully attributed to their size and book-to-market characteristics. They analyse monthly data of companies listed on the Tokyo Stock Exchange from 1975 to 1999 to show that in addition to size and book-to-market yet another effect should be taken into consideration in order to explain the cross-sectional variation of returns namely the overreaction effect. They find that the expanded Fama/French model is better at explaining stock returns both in Japan and the US.

In the UK, Levis (1985) reported that the size effect in the London Stock Exchange was not significant. Banz (1985) though contradicts that claim by examining 29 years of monthly returns arranged in ten value weighted portfolios. Fraser (1995) found that the size effect is present prior to mid 1989 but vanishes thereafter. Examples of other international studies are Berges et. al. (1984) for Canada, Herrera and Lockwood (1994) for Mexico, Wong and Lye (1990) for Singapore, Brown et al. (1983) and Gaunt (2004) for Australia, Ma and Chow (1990) for Taiwan, Rubio (1988) for Spain, Hawawini (1988) for Belgium, Walilros and Berglund (1986) for Finland and finally Stehle (1990) for Germany.

1.1.3. The price-effect

Some studies have presented evidence of a relationship between share price and future stock returns. For example, by regressing market model residuals on share prices, Blume and Husic (1973) found that current share prices are inversely related to future stock returns. They argued that the reason for this association is either transaction costs, or the possibility that the share price is a surrogate for the underlying *ex ante* beta. Using NYSE and AMEX stocks, Kross (1985), deconstructed the measurements of market value and earnings yield into separate components, and presented evidence that approximately three fourths of the relationship between stock returns and size, and stock returns and earnings yield, is represented by share price. Bhardwaj and Brooks (1992) also demonstrate that the January effect is primarily a low-share price effect and less so a market value effect. More specifically, they show that low-share-price stocks earn abnormal returns in January, before transaction costs, and in addition this 'low-price-effect' seems to be stable over time and to subsume the size effect. However, once transaction costs and the bid-ask bias in computed returns are taken into account, no positive abnormal returns are found. Bhardwaj and Brooks (1992), also investigate whether excess returns on neglected stocks are a manifestation of a stock price effect, i.e. whether the neglected-firm effect is really a low-price effect. The neglected-firm effect states that firms which are not regularly followed by financial analysts and which are not widely held by institutional investors tend to outperform firms which are scrutinised by analysts. Arbel, Carvell and Strebel (1983) have argued that the size-effect is really a neglected-firm effect (since small firms are not frequently followed by a sufficiently large number of analysts, the size effect may simply reflect a premium to individuals who choose to obtain information about small firms). Although Bhardwaj and Brooks present material evidence supporting an independent neglected firm effect, the results are much weaker than in prior studies. Examining a large sample of New York Stock Exchange and American Stock Exchange stocks from 1977 to 1988, they found that both January and non-January months do not have a statistically significant neglect effect after controlling for a price effect.

1.2 Data and Methodology

The sample used in the analysis consists of all common stocks traded in both sections of the Tokyo Stock Exchange at any time between January 1985 and August 2003. There are 4215 such companies of which 1125 no longer exist due to cessation of trading or merger/takeover. Non-established companies with fewer than 12 monthly observations are excluded from the analysis. There are 54 such companies in total. Month end closing prices from the Datastream database were used for the calculation of stock returns and other variables involving prices. Total returns indices and balance sheet data were also extracted from the same database. In order to examine the size effect the companies are grouped into ten percentile portfolios based on market capitalisation which is calculated as the product of the month-end price and the total number of shares outstanding. The values used for the number of shares outstanding are those reported at the end of the test period (August 2003) as prices are adjusted for stock splits and therefore reflect all changes in the number of shares during this period. Portfolios are also formed on the stocks' month end price before the rebalance date in order to determine the possible existence of a price anomaly as suggested by some of the studies mentioned in the introduction. Any systematic difference in the mean and standard deviation of the monthly returns of the bottom and the top percentile portfolios will be indicative of the existence of a size or price effect. Throughout the analysis outlier portfolio returns are dealt with by truncating them to be equal in absolute value to the mean return plus three standard deviations. Portfolio premiums (which are defined as differences of portfolio returns) are calculated using the portfolio returns before truncation. Any outlying premiums observations are subsequently truncated in a similar manner. All portfolio returns as well as all premiums are tested for normality using the Berra-Jarcques statistic. The critical values for the 0.05 and 0.1 levels of significance are 5.99 and 4.6 respectively. Failure to accept the null hypothesis would not justify the use of regression based tests to examine different hypotheses. Two types of portfolios are examined: equally and capitalisation weighted. Once formed the portfolios are rebalanced every twelve months. The first portfolios are formed in January 1985 and rebalancing occurs on a regular basis thereafter in January of each year. This is done in order to determine whether the size effect is immune to the way portfolios are formed. A more detailed description of the portfolio formation procedure is given in the next section.

In order to establish the existence of any seasonal patterns in the portfolio returns as well as in the small size and price premiums, their means and annualised standard deviations are calculated separately for each of the twelve months in the year. To test the null hypothesis of equal expected portfolio returns for each month of the year, the following regression is used as in Keim (1983): $r_t = b_1 M_1 + \ldots + b_{12} M_{12} + u_t$ where r_t is the portfolio return and $M_i, i = 1 \ldots 12$ are dummies indicating the month in which each return is observed. The same regression is used to test the hypothesis that the premiums are spread equally over all months. In order to determine what macroeconomic variables, if any, affect the small-size and price premiums and in what way, the means and annualised standard deviations of the portfolio returns and the premiums are calculated conditional on various macroeconomic scenarios. For example average returns are compared when inflation is above or bellow its median over the entire analysis period.

Finally, once the existence of a size and a price effect has been established separately, it needs to be determined whether the two effects exist independently of each other and if not whether one effect dominates the other. The degree of independence between the two effects is examined by forming portfolios on either variable conditioned on the other. Conditional portfolios can be formed in either of two ways. In order to explain the two procedures, the example of forming size portfolios conditioned on price will be used. The first procedure used by Fama and French (1995) sorts all the stocks in the universe into P percentile price groups and S percentile size groups independently. The intersections of the P and the S groups are then used to define P*S conditional portfolios. This procedure reduces the differences in the average stock prices between the portfolios. The number of securities allocated in each portfolio though may be quite different thus making some portfolios more susceptible to idiosyncratic stock behaviour than others. The properties of the size-effect are subsequently analysed by examining the portfolio returns within each price group separately and by combining corresponding size portfolios across price groups into a new set of portfolios. The returns of the new portfolios are calculated by taking the average of the returns of their constituent portfolios. According to the second procedure, the universe of stocks is sorted by price into P percentile groups. Each of the P price groups is subsequently sorted by size into S percentile portfolios resulting in P*S portfolios in total. This procedure ensures that all P*S portfolios have the same number of constituent firms and exhibit therefore the same degree of diversification.

The procedure also mitigates the differences in the average price of each size portfolio within each price group thus alleviating to a certain extent the price effect. The price effect can be further neutralised by combining the corresponding size portfolios across all price groups into one size portfolio. This will result into S size portfolios with the same number of constituents and very similar average prices.

1.3 Portfolio Formation Procedure

Portfolios are formed at the beginning of the period under examination and are subsequently rebalanced when a time interval of fixed length has elapsed. Let's call the beginning of such a time interval, the rebalancing point. At each rebalancing point, N percentiles $p_1, p_2, \ldots, p_N$ are calculated for a specific security attribute (e.g. market capitalisation) and are ranked in ascending order of magnitude. The number of percentiles is fixed during the entire analysis period. These percentiles mark the boundaries of N+1 portfolios of securities. The value of the attribute for each of the securities in the first portfolio is less than or equal to p_1. For portfolio i, i=1,...,N the value of the attribute for each portfolio constituent is greater than p_{i-1} and less than or equal to p_i. Finally for portfolio N+1 the value of the attribute for each portfolio constituent is greater than p_N. Securities with no available attribute or price information at the rebalancing point are excluded from the analysis for the duration of the given time interval. The value of the portfolios thus formed can be calculated as the weighted sum of the values of the constituent securities. Portfolios can be either equally or capitalisation weighted. For equally weighted portfolios the weight of each security at the rebalancing point is $1/K_i$ where $i = 1, \ldots, N+1$ and K_i is the number of securities in portfolio i. The weights for capitalisation weighted portfolios are calculated as $mc_j / \sum_{j=1}^{K_i} mc_j$ where mc_j is the market capitalisation for security j and $\sum_{j=1}^{K_i} mc_j$ is the total market capitalisation of the constituents of portfolio i. The return for each portfolio over a given time interval is calculated as the weighted sum of the returns of the portfolio's constituents over the same period. This time interval can be the entire length of time between two consecutive rebalances. Alternatively the period between consecutive rebalances can be divided into shorter sub-periods of equal length. Portfolio returns are then calculated for each of these sub-periods. For example the returns on portfolios formed on size and rebalanced semi-annually can be calculated on a semi-annual basis where the return is calculated for the entire period intervening between two consecutive rebalances. Alternatively this period can be divided into 6 one-month-long intervals and portfolio returns can be calculated for each month. In the latter case the weight assigned to a specific security return on a given sub-period has to be adjusted to reflect the change in the relative portfolio value represented by the security. The adjustment is calculated as follows: let w_j be the weight of security j at the beginning of a sub-period and r_j , PR the return of the security and the portfolio respectively over the sub-period. The weight of the security at the end of the sub-period is calculated as $[(1+r_j)*w_j]/(1+PR)$. A time series of monthly portfolio returns spanning the entire period of interest can be subsequently calculated for all the portfolios.

1.4 Analysis of unconditional percentile portfolios

1.4.1 Equally weighted market capitalisation percentile portfolios

Table 1 shows the average monthly returns and the annualised standard deviations for the equally weighted portfolios formed on Market Capitalisation. Statistics for the market portfolio are also displayed. The small company portfolio is denoted P10 and comprises the bottom 10% of the companies when ranked in ascending order of market capitalisation. P100 is the portfolio consisting of the top 10% of the companies. The annually rebalanced P10 portfolio has an average monthly return which is 34 basis points larger than that of the P100 portfolio but P10 is clearly more risky than P100. A more informative measure of portfolio performance that takes into account both the risk and return measures is the risk/return trade-off as measured by the ratio of the average annualised return over the annualised standard deviation of the return. The risk/return trade-off shows the return received by investors for each unit of risk undertaken. The risk/return ratio for portfolio P10, P100 and the market are 0.44, 0.30 and 0.32 respectively. This may suggest that the Market portfolio is not on the efficient frontier and that company size is a market anomaly leading to higher returns without a commensurate increase in risk indicating the presence of the small size effect.

Table 1

Equally Weighted, Annually Rebalanced Unconditional Size Portfolios

Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
P10	0.008	0.219	0.773	0.281	0.319	3.886
P20	0.007	0.218	0.507	0.192	0.440	3.166
P30	0.005	0.217	0.030	0.104	0.474	2.482
P40	0.004	0.215	-0.128	0.090	0.584	3.468
P50	0.004	0.222	-0.272	0.177	0.657	5.175
P60	0.004	0.226	-0.222	0.120	0.655	4.517
P70	0.004	0.217	-0.343	0.047	0.610	3.543
P80	0.003	0.206	-0.730	-0.065	0.779	5.798
P90	0.004	0.192	-0.661	0.061	0.979	9.036
P100	0.005	0.186		0.076	0.660	4.259
Market	0.006	0.204		0.108	0.675	4.665

In order to test the hypothesis that average portfolio returns are significantly different from the average returns of portfolio P100, the following regression was used: $PR_{it} = \mu_{it} + u_{it}, i = 10,20,\ldots,90$ where PR_i is the premium for portfolio i. The premium is defined as $PR_{it} = r_{it} - r_{100t}$ where r_i, r_{100} are the monthly returns for portfolios Pi, i=10,...,90 and P100 respectively. T-statistics for μ_i are displayed in the column headed 'Premium T-stats'. The null hypothesis of a zero average premium is not rejected for the P10 portfolio both at the 10% and 5% levels of significance. Therefore although the P10 return is almost twice as large as that of P100, the difference in the returns does not appear to be statistically significant suggesting the absence of the size effect in the Japanese stock market over the specific period under investigation.

1.4.2 Equally weighted price percentile portfolios

Table 2 displays average returns and their annualised standard deviations for portfolios formed by sorting firms into 10 groups according to their month-end price prior to portfolio formation. Therefore portfolios formed in February 1985 are done so using month-end prices for January 1985. The results reveal a very strong small-price effect with small price firms (P10) on average over-performing large-price firms (P100) by 118 basis points. The return/risk ratios for the P10, P100 and the market portfolios are 0.47, -0.0935 and 0.32 respectively. The small-price portfolio outperforms both the market and the large-price portfolios. Most of the premiums of portfolios P10 to P90 with respect to portfolio P100 are statistically significant but declining suggesting the existence of a more linear structure in the small-price premium. This contrasts the behaviour of the small-size portfolio returns where none of the premiums is significant. Compared to the small-size premium, the small-price premium is almost three times larger and this can be mainly attributed to the significantly smaller average return for the P100 price portfolio when compared with the corresponding size portfolio. The average difference between the two portfolio returns is 61 basis points with a t-statistic of 2.02 and a critical value of 1.65. It is therefore significantly different from zero. The P10 size and price portfolios do not appear to have significantly different average returns. Their average return difference is 23 basis points with a t-statistic of 1.3. Figure 1 presents a plot of the small-price premium and the small-size premium over time. It is evident that the price premium is relatively stable over long periods of time and consistently positive with the only exception being the period between May 96 and February 2000.

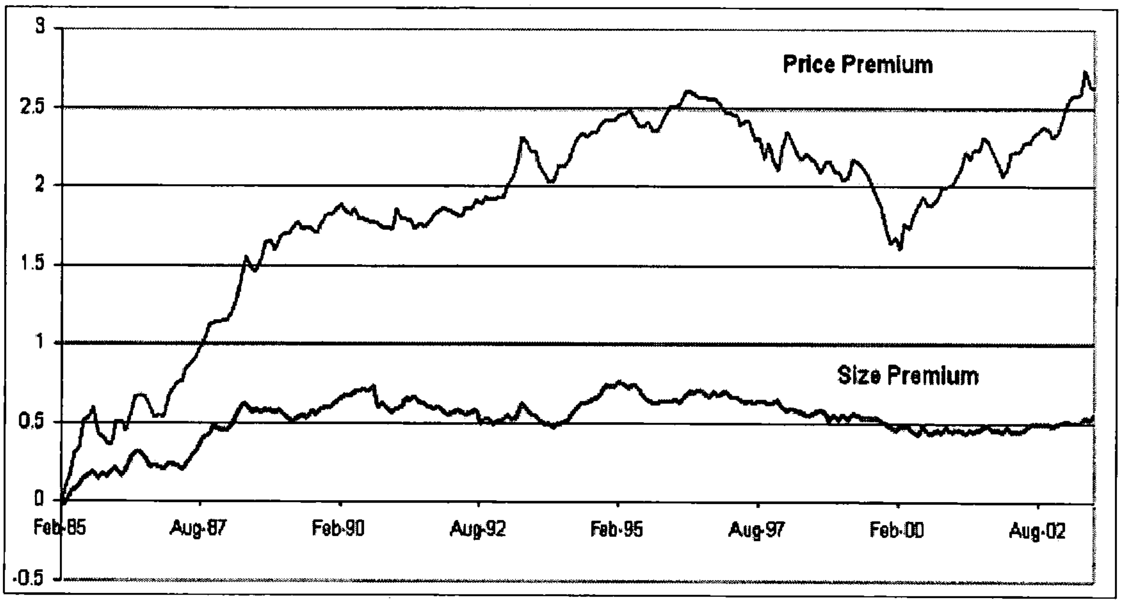
Table 2

Equally Weighted, Annually Rebalanced Unconditional Price Portfolios

Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
P10	0.010	0.261	2.561	0.222	0.017	1.831
P20	0.009	0.263	2.480	0.097	0.300	1.188
P30	0.006	0.237	2.049	0.111	0.638	4.238
P40	0.006	0.213	1.975	0.055	0.689	4.529
P50	0.005	0.201	1.957	0.047	0.730	5.034
P60	0.004	0.193	1.901	0.040	0.641	3.882
P70	0.004	0.188	2.017	-0.016	0.756	5.323
P80	0.002	0.184	1.551	0.087	0.882	7.508
P90	0.000	0.181	0.867	0.021	0.621	3.595
P100	-0.001	0.186		0.004	0.356	1.177
Market	0.006	0.204		0.108	0.675	4.665

Figure 1

Cumulative price and size premiums



The cumulative small size premium in contrast is rather flat and is characterised by long periods of negative values. The flatness of the curve is due to relatively small premium values that oscillate around zero. The higher peaks and deeper troughs of the cumulative price premium curve reflect the higher volatility of the large price portfolio (P100) compared to the large size portfolio. The existence of prolonged periods of negative values in both curves suggests that the effects may be cyclical in nature. It is therefore interesting to look at the relationship between macroeconomic scenarios and the return patterns under investigation.

1.4.3 Equally weighted market to book value percentile portfolios

Finally all the companies in our investment universe are sorted in ascending order of their Market-to-Book-Value ratio (henceforth MTBV) in the month prior to portfolio formation[1]. The return statistics for the percentile portfolios thus formed are presented in Table 3. It is evident that the small MTBV portfolio outperforms its large ratio counterpart significantly. The average premium of portfolio P10 over portfolio P100 is 108 basis points. This is very similar to the premium of the corresponding price portfolios and would imply that the two variables produce highly correlated rankings of the securities in our investment universe. In order to test whether this is true, the cross-sectional correlation coefficient of the rankings according to the two variables is calculated for each month. These coefficients are then averaged across all years thus ending up with 12 average ranking correlation coefficients. The values of these averages range from 18.76% to 23.48% indicating the absence of strong correlation in the rankings. In contrast the correlation coefficients of the rankings according to price and market capitalisation range from 42.16% to 44.54%.

Table 3

Equally Weighted, Annually Rebalanced Unconditional MTBV Portfolios

Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
P10	0.009	0.224	3.306	0.201	0.311	2.395
P20	0.008	0.220	3.249	0.144	0.706	5.400
P30	0.007	0.214	3.038	0.092	0.483	2.486
P40	0.007	0.212	2.982	0.114	0.672	4.680
P50	0.006	0.208	2.971	0.030	0.646	3.914
P60	0.004	0.199	2.301	0.052	0.629	3.777
P70	0.004	0.200	2.437	-0.019	0.606	3.425
P80	0.003	0.206	2.484	0.080	0.548	3.027
P90	0.002	0.207	2.025	-0.008	0.530	2.617
P100	-0.002	0.230		0.140	0.511	3.153
Market	0.006	0.204		0.108	0.675	4.665

[1] In line with Fama and French (1993, 1995) who demonstrate that size together with BE/ME can proxy for risk factors that capture strong common variation in stock returns, the thesis uses the Market-to-Book-Value ratio as a robustness test of the findings this far.

The return/risk ratios for the P10, P100 and the market portfolios are 0.47, -0.1 and 0.32 respectively. The small-ratio portfolio outperforms both the market and the large-ratio portfolios. In a similar manner to the price portfolios, all of the premiums of portfolios P10 to P90 with respect to portfolio P100 are statistically significant and declining in magnitude indicating the existence of a more linear structure in the small MTBV premium. Compared to market capitalization, sorting companies according to their MTBV ratio is more effective at picking out losers. Indeed the returns of the P10 size and MTBV portfolios are almost indistinguishable whereas the average returns of the corresponding P100 portfolios are different by 66 basis points. The MTBV portfolios also differ markedly from their price and size portfolios is that they all exhibit more or less the same volatility. In fact the volatilities of portfolios P10 and P100 are almost identical. This results in a very strongly significant premium for P10. These results are strikingly similar to the results obtained by Fama and French (1992). The authors report that 'The more striking evidence … is the strong positive relation between average return and book-to-market equity. Average returns rise from 0.30% for the lowest BE/ME portfolio to 1.83% for the highest, a difference of 1.53% per month. This spread is twice as large as the difference of 0.74% between the average monthly returns on the smallest and largest size portfolios in Table II. Note also that the strong relation between book-to-market equity and average return is unlikely to be a *beta* effect in disguise; Table IV shows that post-ranking market betas vary little across portfolios formed on ranked values of BE/ME.'. Bearing in mind that MTBV is the inverse of BE/ME, the above sentence describes perfectly the results obtained herein from the Japanese data. Furthermore the fact that the total risk, as measured by the standard deviation of the returns, does not vary much between the different MTBV portfolios contradicts the Fama and French hypothesis that the effect is really a proxy for some underlying risk factor and gives credence to the assertion that it is an anomaly.

So far the small price and MTBV portfolios appear to out-perform significantly their large value counterparts. The following section examines whether this superior performance persists when capitalisation weighted portfolios are formed and trading costs are accounted for.

1.4.3 The effect of capitalisation weights and trading costs

Tables 4, 5 and 6 present statistics for the capitalisation weighted returns of the market capitalisation, price and MTBV percentile portfolios. Portfolio weights are calculated at the end of the month prior to portfolio formation. All portfolios are balanced annually and returns are calculated at the end of each month. As is evident, the small size portfolio still has an average monthly return which is almost twice as large as that of the large size portfolio. However the small size portfolio return is also much more volatile than its large size counterpart thus resulting in the difference between the two portfolio returns not being statistically significant. None of the other size portfolios exhibits returns that are statistically distinguishable from the P100 portfolio return, which is in accordance with the equally weighted portfolio results. The small price portfolio, despite being much more volatile, still commands a sizeable and statistically significant premium over the large price portfolio. None of the other price portfolios has a statistically significant premium over the P100 portfolio, although they all outperform P100 in absolute return terms. It is noted that the P100 return is now positive and much larger than its equally weighted counterpart. In contrast almost all of the MTBV portfolios still outperform portfolio P100 significantly the only exception being portfolio P80. The portfolio volatilities are again very similar in magnitude and so their premiums over P100 are statistically significant.

In order to study the effect of trading costs the equally weighted portfolio returns are calculated again by imposing a cost of 30 basis point for buying shares and 70 basis point for selling shares. The selling cost is inclusive of taxes imposed on trading shares by the Japanese government during most of the period under investigation. Tables 7 and 8 present results for the price and MTBV portfolios. The results for the size portfolios are inconsequential and therefore not presented. As expected the imposition of trading costs results in lower portfolio returns across the board. Since the effect of trading costs is symmetric, the portfolio premiums and volatilities are not affected much. Therefore the patterns of out-performance remain unchanged for both the price and the MTBV portfolios.

Table 4 Capitalisation Weighted, Annually Rebalanced Unconditional Size Portfolios						
Portfolio	**Mean Return**	**Portfolio Risk**	**Premium T-Stat**	**Skewness**	**Kurtosis**	**Normality Test**
P10	0.008	0.231	0.709	0.285	0.245	3.584
P20	0.007	0.219	0.580	0.194	0.449	3.274
P30	0.005	0.217	0.140	0.099	0.471	2.423
P40	0.004	0.215	0.034	0.080	0.590	3.468
P50	0.004	0.222	-0.117	0.170	0.661	5.134
P60	0.004	0.226	-0.056	0.119	0.641	4.342
P70	0.004	0.217	-0.044	0.050	0.612	3.567
P80	0.003	0.205	-0.320	-0.064	0.797	6.056
P90	0.004	0.191	-0.095	0.065	0.978	9.040
P100	0.004	0.189		0.190	0.858	8.175
Market	0.004	0.179		0.105	0.842	6.993

Table 5 Capitalisation Weighted, Annually Rebalanced Unconditional Price Portfolios						
Portfolio	**Mean Return**	**Portfolio Risk**	**Premium T-Stat**	**Skewness**	**Kurtosis**	**Normality Test**
P10	0.013	0.283	2.104	0.131	0.210	1.046
P20	0.008	0.261	1.493	0.044	0.147	0.273
P30	0.007	0.238	1.304	0.008	0.463	1.997
P40	0.006	0.214	1.043	0.095	0.341	1.412
P50	0.005	0.200	1.033	0.076	0.597	3.527
P60	0.007	0.203	1.622	0.244	0.514	4.663
P70	0.005	0.203	1.219	0.056	0.658	4.143
P80	0.004	0.190	0.985	0.192	0.691	5.810
P90	0.004	0.186	1.415	0.020	1.177	12.888
P100	0.001	0.186		0.039	0.489	2.276
Market	0.004	0.179		0.105	0.842	6.993

Table 6 Capitalisation Weighted, Annually Rebalanced Unconditional MTBV Portfolios						
Portfolio	**Mean Return**	**Portfolio Risk**	**Premium T-Stat**	**Skewness**	**Kurtosis**	**Normality Test**
P10	0.007	0.231	1.995	0.316	0.659	7.762
P20	0.006	0.231	2.223	0.141	1.133	12.662
P30	0.009	0.210	2.812	0.009	0.519	2.501
P40	0.007	0.222	2.383	0.110	0.586	3.639
P50	0.009	0.206	4.010	0.120	0.521	3.056
P60	0.004	0.199	2.039	0.148	0.792	6.647
P70	0.006	0.193	2.501	0.151	0.481	2.998
P80	0.002	0.206	1.565	0.199	0.638	5.261
P90	0.002	0.218	1.929	0.195	1.306	17.274
P100	-0.002	0.234		0.140	0.384	2.105
Market	0.004	0.179		0.105	0.842	6.993

Table 7 Equally Weighted, Annually Rebalanced Unconditional Price Portfolios With Trading Costs						
Portfolio	**Mean Return**	**Portfolio Risk**	**Premium T-Stat**	**Skewness**	**Kurtosis**	**Normality Test**
P10	0.010	0.261	2.546	0.222	0.015	1.826
P20	0.009	0.262	2.422	0.096	0.291	1.126
P30	0.006	0.237	1.973	0.105	0.616	3.939
P40	0.005	0.212	1.888	0.046	0.669	4.231
P50	0.004	0.200	1.857	0.040	0.706	4.696
P60	0.004	0.192	1.797	0.034	0.630	3.725
P70	0.004	0.187	1.908	-0.025	0.735	5.041
P80	0.002	0.183	1.440	0.084	0.872	7.329
P90	-0.001	0.181	0.768	0.022	0.606	3.425
P100	-0.002	0.186		0.007	0.349	1.131
Market	0.006	0.204		0.108	0.675	4.665

Table 8 Equally Weighted, Annually Rebalanced Unconditional MTBV Portfolios With Trading Costs						
Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
P10	0.009	0.223	3.287	0.200	0.306	2.359
P20	0.007	0.219	3.168	0.142	0.683	5.083
P30	0.007	0.214	2.942	0.086	0.452	2.179
P40	0.006	0.211	2.874	0.108	0.646	4.307
P50	0.005	0.207	2.845	0.028	0.623	3.640
P60	0.003	0.198	2.183	0.049	0.611	3.554
P70	0.003	0.199	2.313	-0.030	0.572	3.074
P80	0.003	0.206	2.354	0.075	0.528	2.795
P90	0.002	0.206	1.927	-0.013	0.511	2.435
P100	-0.002	0.230		0.140	0.505	3.099
Market	0.006	0.204		0.108	0.675	4.665

1.4.5 Summary

In this section the stocks in the investment universe were ranked according to three attributes namely their price, their market capitalisation and their MTBV ratio. They were subsequently assigned to 10 equally weighted percentile portfolios which were rebalanced annually. By examining the returns of the extreme portfolios it emerged that the well documented size effect is not very strong in the Japanese stock market. However the small price and MTBV portfolios exhibit a sizeable and statistically significant premium over their larger value counterparts. In the case of the price portfolios, this premium is accompanied by a commensurate increase in risk as measured by the annualised standard deviation of the portfolio return. This is in stark contrast to the MTBV portfolios whose returns exhibit more or less the same volatility. It was also shown that the stock rankings produced by these two attributes are not highly correlated thus indicating that at first glance the two effects are independent of each other. The use of capitalisation rather than equal weights affects both the absolute as well as the relative portfolio returns. In the case of the price portfolios, the premium of P10 over P100 still persists, but all other premiums are now statistically insignificant. In contrast, the premiums of the MTBV portfolios P10 to P90 over portfolio P100 are all statistically significant and so the small MTBV premium is immune to the portfolio weighting scheme. Accounting for trading costs finally affects the nominal but not the relative values of the returns thus leaving the portfolio premiums and their related statistics unaffected.

1.5 Analysis of conditional percentile portfolios

Of the three variables tested so far, two, namely price and MTBV, seem to have a strong effect on the Japanese stock market. Both attributes generate small value percentile portfolios that out-perform significantly their large value counterparts. As mentioned in Section 4, both the price and MTBV P10 portfolios exhibit similar premiums over their corresponding P100 portfolios. However a preliminary examination shows that there is very little correlation between the two variables. The average correlation between the stock rankings produced by the two variables is 21%. Another way to examine whether the two effects exist independent of each other is to use the two procedures for forming conditional portfolios described in the methodology section. These procedures will be employed in this section to separate the MTBV and price effects. More particularly sub-section 1.5.1 examines the price portfolios when they are conditioned to have similar exposures to MTBV while sub-section 1.5.2 examines the MTBV portfolios when they are conditioned to have similar exposures to price.

1.5.1 Price conditioned on Market-to-Book-Value

Return statistics for the conditioned price portfolios are presented in Table 9 for the first conditioning procedure and Table 10 for the second one. According to the first procedure followed by Fama & French (1995) the universe of stocks is separated into two groups by the median MTBV and into five groups by the price quintile points. The intersection of the two sets of groups results into ten price/MTBV portfolios. The second procedure again separates the universe into two groups by the median MTBV and then each group into 5 sub-groups by its respective price quintile points. The first procedure results in the number of holdings in each portfolio being quite different from its peers while the second procedure ensures that all portfolios have the same number of holdings and hence the same degree of diversification. Table 9 shows that only the small price P20 portfolios within both MTBV groups have average returns that are significantly different from the average returns of their respective large price (P100) portfolios. In accordance with the unconditioned portfolio results in Section 1.4, the small price portfolios are substantially riskier than their large price counterparts.

Table 9 Equally Weighted, Annually Rebalanced Conditional Price Portfolios With Procedure 1						
SMALL MTBV PORTFOLIOS						
Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
P20	0.012	0.270	2.310	0.192	0.140	1.557
P40	0.007	0.224	1.302	0.074	0.666	4.327
P60	0.006	0.202	0.791	0.149	0.647	4.712
P80	0.006	0.192	1.117	0.129	1.089	11.647
P100	0.005	0.192		0.084	0.894	7.693
LARGE MTBV PORTFOLIOS						
Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
P20	0.008	0.291	1.931	0.116	0.143	0.689
P40	0.003	0.235	1.476	0.052	0.651	4.042
P60	0.003	0.203	1.658	-0.020	0.726	4.906
P80	0.002	0.185	1.489	0.044	0.515	2.535
P100	-0.002	0.184		0.038	0.354	1.218

Table 10 Equally Weighted, Annually Rebalanced Conditional Price Portfolios With Procedure 2						
SMALL MTBV PORTFOLIOS						
Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
P20	0.012	0.276	2.570	0.214	0.124	1.850
P40	0.007	0.232	1.687	0.153	0.535	3.523
P60	0.006	0.206	1.117	0.137	0.642	4.536
P80	0.006	0.195	1.694	0.082	0.791	6.069
P100	0.005	0.189		0.099	1.177	13.244
LARGE MTBV PORTFOLIOS						
Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
P20	0.007	0.281	1.847	0.091	0.290	1.091
P40	0.004	0.226	1.803	0.004	0.945	8.301
P60	0.001	0.200	1.326	0.031	0.681	4.341
P80	0.001	0.186	1.562	0.125	0.641	4.400
P100	-0.003	0.193		0.036	0.280	0.777

Table 11

Average Price and MTBV values for the Constituents of the Price Portfolios Conditioned on MTBV using Procedure 1

	Average Price					Average MTBV			
	P20SB	P100SB	P20LB	P100LB		P20SB	P100SB	P20LB	P100LB
1985	211	1212	221	1953		-243	159	413	668
1986	266	1571	273	1904		-620	185	476	505
1987	325	2198	318	2431		123	172	784	678
1988	477	2446	463	21194		72	228	819	667
1989	728	2964	717	16404		131	159	949	760
1990	937	4255	924	13566		270	299	961	1134
1991	479	3286	454	7351		110	169	596	483
1992	467	3440	444	7276		112	169	442	432
1993	332	2505	308	5326		87	122	475	296
1994	400	2938	377	14677		-39	151	538	369
1995	411	13636	394	13159		48	142	747	329
1996	421	11826	428	14170		-10	143	441	552
1997	327	9719	324	14874		2	116	343	358
1998	191	14059	186	13937		19	22	547	240
1999	141	10614	136	20697		-87	30	372	241
2000	141	26561	135	104017		1	34	137	278
2001	125	47854	124	60249		32	56	300	352
2002	98	67433	103	84805		20	51	218	331
2003	89	62323	93	68444		22	37	277	220
Total Avg	346	15307	338	25602		3	124	499	459

Table 12
Average Price and MTBV values for the Constituents of the Price Portfolios Conditioned on MTBV using Procedure 2

	Average Price					Average MTBV			
	P20SB	**P100SB**	**P20LB**	**P100LB**		**P20SB**	**P100SB**	**P20LB**	**P100LB**
1985	194	967	252	2375		-364	159	395	601
1986	265	1296	283	2242		-639	183	460	541
1987	307	1694	355	2930		108	192	706	744
1988	470	2116	479	28145		61	216	782	736
1989	766	2964	754	19227		154	159	899	780
1990	979	4015	929	14686		285	298	973	1180
1991	478	2344	455	8705		111	106	598	504
1992	458	2394	459	8147		108	165	443	436
1993	324	1769	321	6569		85	121	453	313
1994	403	2219	376	18404		-34	148	541	394
1995	416	8443	368	15057		53	123	864	340
1996	430	7351	408	17745		6	144	467	631
1997	325	6032	310	18959		1	115	352	389
1998	183	5105	209	22504		10	58	449	272
1999	127	3024	167	34673		-126	52	299	290
2000	126	3700	188	194918		13	31	127	429
2001	106	8291	170	108729		32	60	330	488
2002	78	11573	164	153070		16	55	228	365
2003	69	15158	152	119807		20	51	218	244
Total Avg	342	4761	358	41942		-4	123	486	505

Table 13 Consolidated Price Portfolios Net of the MTBV Effect						
Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
Procedure 1						
SMALL	0.010	0.279	2.137	0.146	0.134	0.956
LARGE	0.002	0.180		0.011	0.878	7.159
PREMIUM	0.008	0.187		0.283	0.192	3.313
Procedure 2						
SMALL	0.009	0.276	2.211	0.138	0.160	0.941
LARGE	0.001	0.182		0.028	0.859	6.888
PREMIUM	0.009	0.186		0.259	0.277	3.214

Table 14 Average Price and MTBV for Constituents of Consolidated Price Portfolios Net of MTBV Effect									
	Procedure 1					Procedure 2			
	SMALL	LARGE	SMALL	LARGE		SMALL	LARGE	SMALL	LARGE
1985	216	1582	85	414		223	1671	15	380
1986	270	1738	-72	345		274	1769	-89	362
1987	321	2315	454	425		331	2312	407	468
1988	470	11820	445	448		474	15131	422	476
1989	723	9684	540	459		760	11096	526	470
1990	930	8911	616	716		954	9351	629	739
1991	467	5318	353	326		467	5525	354	305
1992	455	5358	277	300		458	5270	275	301
1993	320	3915	281	209		322	4169	269	217
1994	389	8807	250	260		389	10312	254	271
1995	402	13398	397	236		392	11750	459	232
1996	424	12998	216	347		419	12548	237	388
1997	326	12297	172	237		317	12496	176	252
1998	189	13998	283	131		196	13805	230	165
1999	139	15656	142	135		147	18849	87	171
2000	138	65289	69	156		157	99309	70	230
2001	125	54051	166	204		138	58510	181	274
2002	100	76119	119	191		121	82322	122	210
2003	91	65383	150	128		111	67482	119	147
Total Avg	342	20455	251	291		350	23351	241	314

The second conditioning procedure generates similar although slightly stronger results. Now both portfolios P20 and P40 out-perform portfolio P100 for both MTBV groups. The price portfolios again become riskier as we move from P100 to P20. Tables 11 and 12 show the average MTBV and average price of the constituents of the P20SB (P20 Small MTBV), P100SB, P20LB (P20, Large MTBV) and P100LB portfolios for both conditioning procedures. The average Market-to-Book-Value spread between the P20 and P100 portfolios in the small MTBV group is clearly large enough to claim part of the return difference for both procedures. This is not true for the large MTBV price portfolios which have virtually the same exposure to MTBV. In order to mitigate the MTBV effect and assess the pure price effect we compare the returns of two new portfolios which are simply called SMALL PRICE and LARGE PRICE and their return statistics are displayed in Table 13 for both procedures. The SMALL PRICE portfolio is formed by taking the simple arithmetic average of the P20 portfolios across the two MTBV groups. Equivalently the LARGE PRICE portfolio return series is calculated as the arithmetic mean of the two P100 portfolios. Table 14 contains the average Market-to-Book-Value and the average stock price of the portfolio constituents. Apparently the SMALL PRICE portfolio premiums are positive and significant for both procedures. The Fama & French procedure average premium is 84 basis points, almost identical to the premium resulting from the second procedure which is 86 basis points. The return differential can only be attributed to the larger average price spread between the LARGE PRICE and the SMALL PRICE portfolios. The two portfolios have a small Market-to-Book-Value spread for both procedures, compared to the spread in exposure of the unconditioned MTBV portfolios P10 and P100 (40 and 73 versus 1116). It is therefore evident that the price effect persists even when exposure to Market-to-Book-Value is controlled for.

1.5.2 Market-to-Book-Value conditioned on Price

Results for the Market-to-Book-Value portfolios which are conditioned to have similar exposures to price are presented in Table 15 for the Fama-French procedure. All portfolios in both price groups outperform their respective P100 portfolio the only exception being the large price group P80 portfolio. Furthermore the P20 premium over portfolio P100 is almost exactly the same for both price groups (73 and 77 basis points respectively). At first glance this indicates that the Market-to-Book-Value effect continues to be very strong and exists independently from the price effect. The risk profiles of all portfolios within each group are very similar however the large price MTBV portfolios are less risky than the small price MTBV portfolios. This is due to the latter group's exposure to small prices and is in accordance with the unconditional price portfolio results where it was noted that the small price portfolios were much more volatile than their large price counterparts. The average price and Market-to-Book-Value exposures for all portfolios are presented in Table 16. It is noted that the average price spread of the constituents of the P20 and P100 MTBV portfolios is much larger in the large price group than in the small price group leaving open the possibility that results for the former group may be driven by both price and Market-to-Book-Value. However the price spread between the large price group P20 and P100 MTBV portfolios pales in comparison even to that of the unconditional P90 and P100 price portfolios (18,974 versus 53,725). It is therefore highly unlikely that exposure to price bears any effect to the performance differences of the large price group MTBV portfolios.

Table 15
Equally Weighted, Annually Rebalanced Conditional MTBV Portfolios With Procedure 1

Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
SMALL PRICE PORTFOLIOS						
P20	0.010	0.238	5.093	0.180	0.393	2.642
P40	0.008	0.234	4.615	0.128	0.442	2.423
P60	0.006	0.238	3.863	0.076	0.417	1.829
P80	0.006	0.248	4.275	0.067	0.438	1.950
P100	0.002	0.267		0.090	0.490	2.537
LARGE PRICE PORTFOLIOS						
Portfolio	**Mean Return**	**Portfolio Risk**	**Premium T-Stat**	**Skewness**	**Kurtosis**	**Normality Test**
P20	0.006	0.198	2.446	0.130	1.036	10.606
P40	0.005	0.193	2.366	0.041	0.962	8.661
P60	0.003	0.181	2.248	0.074	0.975	9.034
P80	0.001	0.183	1.464	0.028	0.492	2.278
P100	-0.001	0.190		-0.024	0.171	0.294

Table 16 Average Price and MTBV values for the Constituents of the MTBV Portfolios Conditioned on Price using Procedure 1									
	Average Price					Average MTBV			
	P20SP	P100SP	P20LP	P100LP		P20SP	P100SP	P20LP	P100LP
1985	295	312	757	1571		-268	638	117	861
1986	363	351	919	1644		-534	704	132	830
1987	435	413	1067	2058		63	1120	114	846
1988	609	606	1788	23903		26	1118	64	953
1989	877	834	2015	17565		82	1091	103	1085
1990	1134	1117	2713	3699		204	1524	235	1469
1991	606	562	1667	2436		80	818	47	634
1992	591	561	1557	2414		82	584	123	537
1993	431	409	1158	2663		59	573	87	429
1994	527	476	1548	13021		-29	1143	97	504
1995	535	464	2926	14528		24	1148	77	433
1996	559	515	2684	16503		-14	557	91	763
1997	436	398	1916	15516		3	460	48	462
1998	300	286	5600	14089		7	715	-13	302
1999	231	217	1274	22678		-85	517	15	350
2000	119	118	2556	59169		-11	817	9	661
2001	220	221	10472	59208		0	669	35	420
2002	185	207	16898	73203		11	446	31	392
2003	168	199	16351	52855		11	554	19	287
Total Avg	437	419	3921	22895		-15	800	75	643

Table 17 presents the return statistics for the MTBV portfolios that are controlled to have the same exposure to price using the second procedure. Again this procedure produces remarkably similar results to the Fama-French method and reaffirms the results presented in the previous paragraph. Finally an attempt is made to mitigate the price effect further by examining two new portfolios namely SMALL MTBV and LARGE MTBV. The SMALL MTBV (LARGE MTBV) portfolio returns are calculated by taking the simple arithmetic average of the returns of the two P20 (P100) BVALUE portfolios corresponding to the two price groups. This procedure reduces the price spread between the large and small MTBV portfolios even more thus minimising the impact that the price effect may have on the relative portfolio performances. Return statistics are presented in Table 19 for both procedures while Table 20 shows the average exposure of the two portfolios to the MTBV and price factors. As is evident, the SMALL MTBV portfolio out-performs the LARGE MTBV portfolio strongly. Notice how both portfolios have almost identical risk profiles now.

that their difference in exposure to price has been mitigated. The evidence therefore suggests that the Market-to-Book-Value effect persists and is quite strong even when the percentile portfolios are forced to have similar exposures to price.

Table17
Equally Weighted, Annually Rebalanced Conditional MTBV Portfolios With Procedure 2

SMALL PRICE PORTFOLIOS						
Portfolio	**Mean Return**	**Portfolio Risk**	**Premium T-Stat**	**Skewness**	**Kurtosis**	**Normality Test**
P20	0.010	0.241	4.395	0.188	0.340	2.382
P40	0.009	0.236	4.534	0.171	0.516	3.562
P60	0.007	0.239	3.686	0.073	0.503	2.551
P80	0.007	0.245	3.682	0.049	0.414	1.685
P100	0.003	0.265		0.069	0.540	2.893
LARGE PRICE PORTFOLIOS						
Portfolio	**Mean Return**	**Portfolio Risk**	**Premium T-Stat**	**Skewness**	**Kurtosis**	**Normality Test**
P20	0.006	0.195	2.390	0.082	0.995	9.461
P40	0.005	0.188	2.617	0.077	0.850	6.933
P60	0.002	0.177	1.486	0.006	0.725	4.891
P80	0.001	0.186	1.789	0.047	0.406	1.616
P100	-0.002	0.195		0.019	0.063	0.051

Table 18 Average Price and MTBV values for the Constituents of the MTBV Portfolios Conditioned on Price using Procedure 2								
	Average Price				Average MTBV			
	P20SP	P100SP	P20LP	P100LP	P20SP	P100SP	P20LP	P100LP
1985	285	308	748	1798	-417	522	129	1019
1986	363	352	883	1739	-728	640	140	913
1987	415	427	1048	2273	23	917	139	934
1988	600	598	1681	26036	-8	1033	93	997
1989	858	819	1957	16377	80	1119	104	1059
1990	1126	1101	2704	3535	210	1596	232	1407
1991	615	582	1718	2560	69	753	68	670
1992	596	580	1660	2550	70	559	131	559
1993	423	411	1208	1922	46	536	95	448
1994	519	480	1566	13913	-67	1086	107	519
1995	550	480	2878	14779	20	1126	82	429
1996	568	530	2641	16558	-19	560	94	755
1997	433	402	1820	16298	-18	448	60	475
1998	275	277	3049	15866	-21	541	28	339
1999	215	217	2617	24887	-167	350	38	420
2000	109	119	1677	88538	-49	438	43	898
2001	201	227	5735	70215	-27	377	48	539
2002	154	214	6580	96460	-9	255	46	508
2003	143	205	8325	62852	-5	326	40	354
Total Avg	428	422	2609	28385	-54	694	90	697

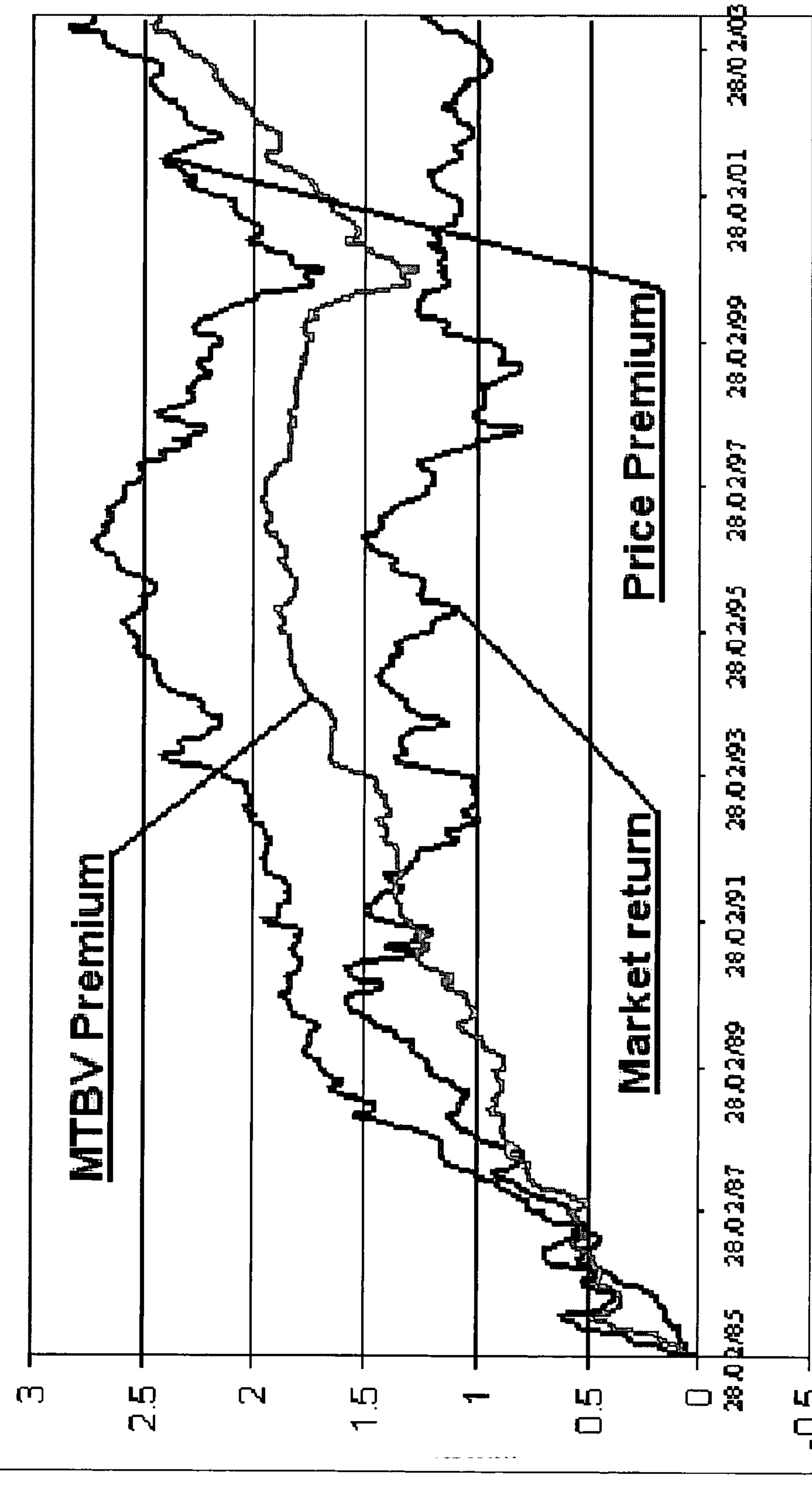
Table 19 Consolidated MTBV Portfolios Net of the Price Effect						
Portfolio	Mean Return	Portfolio Risk	Premium T-Stat	Skewness	Kurtosis	Normality Test
Procedure 1						
SMALL	0.008	0.214	3.583	0.133	0.611	4.127
LARGE	0.001	0.218		0.037	0.506	2.426
PREMIUM	0.007	0.090		-0.058	0.402	1.630
Procedure 2						
SMALL	0.008	0.213	3.368	0.116	0.544	3.252
LARGE	0.001	0.219		0.043	0.503	2.423
PREMIUM	0.007	0.092		-0.040	0.593	3.324

Table 20 Average Price and MTBV for Constituents of Consolidated MTBV Portfolios Net of Price Effect								
	Procedure 1				Procedure 2			
	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE
1985	-76	749	526	941	-144	770	516	1053
1986	-201	767	641	997	-294	776	623	1045
1987	88	983	751	1236	81	925	731	1350
1988	45	1036	1199	12255	42	1015	1141	13317
1989	93	1088	1446	9200	92	1089	1408	8598
1990	220	1497	1923	2408	221	1502	1915	2318
1991	63	726	1137	1499	68	711	1167	1571
1992	102	561	1074	1487	101	559	1128	1565
1993	73	501	794	1536	71	492	815	1167
1994	34	823	1038	6749	20	802	1043	7196
1995	50	791	1730	7496	51	777	1714	7630
1996	38	660	1622	8509	37	658	1604	8544
1997	25	461	1176	7957	21	461	1126	8350
1998	-3	508	2950	7188	4	440	1662	8072
1999	-35	433	753	11447	-64	385	1416	12552
2000	-1	739	1338	29644	-3	668	893	44329
2001	17	545	5346	29714	11	458	2968	35221
2002	21	419	8542	36705	18	382	3367	48337
2003	15	421	8260	26527	18	340	4234	31528
Total Avg	30	721	2179	11657	18	695	1518	14404

1.5.3 Summary

Two different procedures were used to mitigate the Market-to-Book-Value differences among the price portfolios and the price differences among the Market-to-Book-Value portfolios in order to disentangle the MTBV and the price effects. Both methods manage to mitigate these differences in exposure substantially although neither method eliminates them completely. This is because the two effects are weakly correlated. This obstacle is overcome, when necessary, by comparing the returns of the conditional portfolios with those of unconditional portfolios that have a similar exposure to the factor in question. The analysis of the returns of the conditional portfolios shows that both effects seem to exist independent of each other; however the evidence is overwhelmingly in favour of the MTBV effect. The price effect appears weakened when the average MTBV differences of the price portfolios are reduced but is still statistically significant. In contrast the MTBV effect still persists in the absence of large price differences in the constituents of the Market-to-Book-Value portfolios.

Figure 2
Cumulative portfolio premiums and market return



1.6 The effect of Macroeconomic scenarios on portfolio premiums

Inherent in the previous analysis is that the return differential between the extreme percentile portfolios for both factors is stable over time. There is evidence presented in some studies though that the premium changes in magnitude and some times even in sign over time. A closer look at the way the difference in the monthly returns of the P10 and the P100 portfolios, evolves over time is very revealing. Figure 2 plots the cumulative return differences between P10 and P100 over time, for both the MTBV and the price portfolios. It can be seen that the slope of both premiums is declining over certain periods of time meaning that the premiums are actually negative during these periods. This may suggest that the Market-to-Book-Value and the price premiums are cyclical in nature and are affected by the macro-economy. The relationship between the magnitude of the small Market-to-Book-Value and price premiums and certain macroeconomic variables (factors) is examined by analysing both premiums under four scenarios:

- The macro-economic factor value in the highest quartile of it's distribution (high growth in the factor)
- The macro-economic factor value in the lowest quartile of it's distribution (low growth in the factor)
- The macro-economic factor value above the median of it's distribution
- The macro-economic factor value below the median of it's distribution

The factors used to create the different scenarios are:

- Inflation defined as the percentage change in the Consumer Price Index
- Changes in the level of consumer confidence
- Percentage change in the Japanese Yen/US Dollar exchange rate
- Changes in the short term interest rate
- Changes in the long term interest rate
- The growth rate of industrial production
- The growth rate of the narrow money supply measure M1
- The growth rate of the broad money supply measure M4

Tables 21 and 22 contain results for the price and Market-to-Book-Value portfolios respectively. The first six columns in each table display the means and standard deviations of the monthly returns for the P10 and P100 portfolios as well as for the premium when each scenario is true. The columns headed P(Prem>0), P(Prem>mean+std) and P(Prem<mean-std) display the empirical probability that the premium is larger than zero, larger than the average premium plus one standard deviation and smaller than the average premium minus one standard deviation respectively. The empirical probability for a given event is calculated as the percentage of the total number of observations for which the event is true. The interpretation of the probabilities is straightforward: if the probability of the premium being greater (smaller) than zero is above 0.5, then portfolio P10 outperforms (underperforms) portfolio P100 under that scenario. The probability of the premium being greater than the mean plus one standard deviation indicates the chances for significant over performance whilst the probability that the premium is less than the mean minus one standard deviation gives a measure of the chances for significant underperformance.

Starting with the price portfolios, Table 21 shows that the average premium is larger and more likely to be positive when inflation is high. The average premium is higher by 120 basis points when inflation is either above its median value or at its highest quartile. However there is no indication that this is due to the premium attaining more extreme values during high inflation periods. The probability that the premium is further away than one standard deviation from its mean is roughly the same for both high and low inflation periods. Consumer confidence seems to have a very strong effect on the observed small-price premium. The average premium during periods of high consumer confidence is almost nine times higher than when consumer confidence is low. Over 70% of the observed monthly premiums are positive when consumer confidence changes are in the highest quartile. The premium seems to be symmetrically distributed around it's mean as shown by the percentage of values greater or smaller than the mean plus or minus one standard deviation respectively. Therefore the difference cannot be attributed to the effect of one off shocks. The premium also appears to be larger and more evenly distributed when the Yen/US Dollar exchange rate is less volatile. Using similar reasoning it can be deduced that the premium remains relatively unaffected by changes in the long term interest rates, the corporate bond yield and both money supply measures.

Table 21
Price Portfolio Returns and Macroeconomic Scenarios

Scenario		Premium	Small	Large	Pr > 0	Pr > m + std	Pr < m - std
Inflation	lowest 25%:	0.003 (0.059)	0.004 (0.067)	0.002 (0.052)	0.516	0.141	0.156
	highest 25%:	0.016 (0.071)	0.014 (0.087)	-0.001 (0.062)	0.587	0.13	0.196
	lowest 50%:	0.006 (0.059)	0.003 (0.072)	-0.003 (0.050)	0.521	0.145	0.137
	highest 50%:	0.019 (0.062)	0.019 (0.079)	0.001 (0.057)	0.632	0.151	0.16
Consumer Confidence	lowest 25%:	0.007 (0.060)	-0.002 (0.080)	-0.008 (0.049)	0.544	0.175	0.175
	highest 25%:	0.024 (0.066)	0.029 (0.065)	0.006 (0.054)	0.623	0.17	0.151
	lowest 50%:	0.004 (0.064)	0.005 (0.080)	0.000 (0.050)	0.505	0.153	0.162
	highest 50%:	0.022 (0.055)	0.016 (0.070)	-0.005 (0.056)	0.655	0.145	0.109
Changes in Consumer Conf.	lowest 25%:	0.004 (0.051)	-0.021 (0.066)	-0.023 (0.046)	0.583	0.15	0.133
	highest 25%:	0.030 (0.053)	0.050 (0.070)	0.020 (0.051)	0.704	0.13	0.111
	lowest 50%:	0.008 (0.056)	-0.006 (0.072)	-0.014 (0.050)	0.535	0.158	0.114
	highest 50%:	0.017 (0.064)	0.028 (0.077)	0.011 (0.054)	0.629	0.124	0.171
Changes in YEN/USD Rate	lowest 25%:	0.018 (0.057)	0.018 (0.088)	0.002 (0.064)	0.585	0.151	0.132
	highest 25%:	0.007 (0.052)	0.002 (0.072)	-0.005 (0.054)	0.538	0.173	0.173
	lowest 50%:	0.017 (0.057)	0.013 (0.078)	-0.003 (0.056)	0.619	0.143	0.133
	highest 50%:	0.004 (0.059)	0.004 (0.075)	-0.000 (0.052)	0.514	0.171	0.162
Short Term Rate	lowest 25%:	0.010 (0.067)	0.009 (0.075)	-0.001 (0.060)	0.585	0.151	0.17
	highest 25%:	0.012 (0.053)	0.006 (0.084)	-0.004 (0.066)	0.528	0.151	0.151
	lowest 50%:	0.003 (0.061)	0.001 (0.073)	-0.002 (0.051)	0.528	0.17	0.16
	highest 50%:	0.020 (0.055)	0.018 (0.079)	-0.001 (0.056)	0.613	0.17	0.132

Table 21 Continued

Scenario		Premium	Small	Large	Pr > 0	Pr > m + std	Pr < m - std
Changes in Short Term Rate	lowest 25%:	0.031 (0.060)	0.034 (0.074)	0.004 (0.045)	0.667	0.185	0.111
	highest 25%:	0.007 (0.053)	0.010 (0.079)	0.004 (0.058)	0.604	0.151	0.208
	lowest 50%:	0.019 (0.058)	0.018 (0.077)	-0.001 (0.053)	0.613	0.17	0.17
	highest 50%:	0.003 (0.058)	0.000 (0.076)	-0.002 (0.055)	0.524	0.143	0.171
Long Term Rate	lowest 25%:	0.009 (0.066)	0.007 (0.073)	-0.001 (0.056)	0.561	0.175	0.175
	highest 25%:	0.020 (0.060)	0.008 (0.079)	-0.011 (0.067)	0.589	0.143	0.125
	lowest 50%:	0.003 (0.060)	0.004 (0.077)	0.001 (0.052)	0.527	0.17	0.152
	highest 50%:	0.021 (0.060)	0.016 (0.074)	-0.004 (0.056)	0.622	0.162	0.126
Changes in Long Term Rate	lowest 25%:	0.010 (0.064)	0.009 (0.075)	-0.000 (0.052)	0.589	0.143	0.143
	highest 25%:	0.016 (0.061)	0.010 (0.073)	-0.005 (0.057)	0.536	0.214	0.107
	lowest 50%:	0.011 (0.060)	0.011 (0.076)	-0.000 (0.052)	0.598	0.161	0.143
	highest 50%:	0.013 (0.061)	0.010 (0.075)	-0.003 (0.056)	0.55	0.171	0.126
Corp. Bond Yield	lowest 25%:	-0.000 (0.070)	0.005 (0.083)	0.005 (0.058)	0.5	0.161	0.196
	highest 25%:	0.014 (0.062)	0.009 (0.080)	-0.003 (0.064)	0.554	0.143	0.107
	lowest 50%:	0.004 (0.061)	0.004 (0.076)	-0.000 (0.051)	0.536	0.17	0.161
	highest 50%:	0.021 (0.059)	0.017 (0.075)	-0.003 (0.056)	0.613	0.153	0.126
Changes in Corp. Bond Yld	lowest 25%:	0.005 (0.060)	0.004 (0.080)	-0.000 (0.060)	0.569	0.086	0.138
	highest 25%:	0.014 (0.053)	0.010 (0.074)	-0.003 (0.057)	0.482	0.214	0.161
	lowest 50%:	0.012 (0.062)	0.011 (0.078)	-0.001 (0.053)	0.609	0.148	0.148
	highest 50%:	0.012 (0.059)	0.010 (0.073)	-0.002 (0.055)	0.537	0.185	0.13

Table 21 Continued

Scenario		Premium	Small	Large	Pr > 0	Pr > m + std	Pr < m - std
Changes in Industrial Prod.	lowest 25%:	0.009 (0.061)	0.007 (0.083)	-0.001 (0.052)	0.517	0.172	0.138
	highest 25%:	0.027 (0.062)	0.025 (0.077)	-0.002 (0.057)	0.667	0.148	0.13
	lowest 50%:	0.008 (0.058)	0.004 (0.075)	-0.004 (0.053)	0.531	0.15	0.142
	highest 50%:	0.016 (0.064)	0.016 (0.075)	0.000 (0.054)	0.624	0.138	0.138
Changes in Money Supply M1	lowest 25%:	0.013 (0.063)	0.010 (0.080)	-0.003 (0.057)	0.618	0.127	0.145
	highest 25%:	0.020 (0.064)	0.019 (0.085)	0.001 (0.055)	0.618	0.182	0.127
	lowest 50%:	0.012 (0.063)	0.007 (0.074)	-0.005 (0.054)	0.568	0.162	0.153
	highest 50%:	0.013 (0.059)	0.013 (0.077)	0.001 (0.053)	0.591	0.173	0.127
Changes in Money Supply M4	lowest 25%:	0.009 (0.055)	0.003 (0.086)	-0.006 (0.058)	0.586	0.121	0.138
	highest 25%:	0.012 (0.056)	0.011 (0.077)	0.000 (0.057)	0.565	0.174	0.196
	lowest 50%:	0.017 (0.062)	0.012 (0.079)	-0.005 (0.054)	0.605	0.147	0.14
	highest 50%:	0.006 (0.059)	0.007 (0.070)	0.001 (0.052)	0.543	0.174	0.174

Table 22
MTBV Portfolio Returns and Macroeconomic Scenarios

Scenario		Premium	Small	Large	Pr > 0	Pr > m + std	Pr < m - std
Inflation	lowest 25%:	0.011 (0.040)	0.009 (0.059)	-0.001 (0.063)	0.672	0.141	0.156
	highest 25%:	0.010 (0.043)	0.012 (0.079)	0.000 (0.079)	0.587	0.174	0.109
	lowest 50%:	0.012 (0.036)	0.005 (0.060)	-0.007 (0.061)	0.667	0.137	0.12
	highest 50%:	0.009 (0.038)	0.014 (0.069)	0.004 (0.071)	0.594	0.142	0.17
Consumer Confidence	lowest 25%:	0.014 (0.028)	-0.000 (0.066)	-0.014 (0.060)	0.632	0.14	0.088
	highest 25%:	0.017 (0.040)	0.022 (0.057)	0.005 (0.062)	0.66	0.132	0.132
	lowest 50%:	0.006 (0.038)	0.005 (0.067)	-0.000 (0.066)	0.577	0.135	0.144
	highest 50%:	0.017 (0.036)	0.013 (0.062)	-0.004 (0.068)	0.7	0.155	0.136
Changes in Consumer Conf.	lowest 25%:	0.010 (0.027)	-0.019 (0.057)	-0.030 (0.060)	0.667	0.15	0.15
	highest 25%:	0.017 (0.034)	0.044 (0.064)	0.028 (0.060)	0.704	0.204	0.167
	lowest 50%:	0.010 (0.030)	-0.007 (0.060)	-0.017 (0.064)	0.605	0.167	0.132
	highest 50%:	0.012 (0.044)	0.026 (0.066)	0.013 (0.066)	0.676	0.133	0.152
Changes in YEN/USD Rate	lowest 25%:	0.014 (0.038)	0.016 (0.080)	0.002 (0.079)	0.698	0.132	0.189
	highest 25%:	0.010 (0.034)	0.005 (0.063)	-0.005 (0.069)	0.692	0.173	0.173
	lowest 50%:	0.010 (0.038)	0.009 (0.068)	-0.001 (0.068)	0.619	0.124	0.162
	highest 50%:	0.009 (0.033)	0.006 (0.063)	-0.004 (0.068)	0.638	0.181	0.152
Short Term Rate	lowest 25%:	0.015 (0.046)	0.011 (0.059)	-0.003 (0.064)	0.717	0.113	0.151
	highest 25%:	0.012 (0.033)	0.003 (0.074)	-0.008 (0.085)	0.642	0.132	0.189
	lowest 50%:	0.006 (0.038)	0.001 (0.059)	-0.004 (0.063)	0.585	0.132	0.132
	highest 50%:	0.014 (0.032)	0.015 (0.071)	0.001 (0.072)	0.679	0.17	0.142

Table 22 Continued

Scenario		Premium	Small	Large	Pr > 0	Pr > m + std	Pr < m - std
Changes in Short Term Rate	lowest 25%:	0.010 (0.032)	0.025 (0.063)	0.016 (0.062)	0.574	0.167	0.185
	highest 25%:	0.010 (0.036)	0.012 (0.071)	0.002 (0.074)	0.642	0.113	0.17
	lowest 50%:	0.011 (0.033)	0.015 (0.065)	0.004 (0.067)	0.632	0.16	0.16
	highest 50%:	0.009 (0.038)	0.001 (0.065)	-0.008 (0.068)	0.629	0.114	0.152
Long Term Rate	lowest 25%:	0.013 (0.046)	0.009 (0.056)	-0.004 (0.059)	0.667	0.123	0.14
	highest 25%:	0.016 (0.039)	0.003 (0.073)	-0.014 (0.080)	0.661	0.107	0.143
	lowest 50%:	0.008 (0.040)	0.006 (0.065)	-0.002 (0.065)	0.589	0.134	0.134
	highest 50%:	0.014 (0.034)	0.012 (0.064)	-0.002 (0.068)	0.676	0.153	0.135
Changes in Long Term Rate	lowest 25%:	0.010 (0.043)	0.008 (0.068)	-0.002 (0.064)	0.589	0.161	0.125
	highest 25%:	0.007 (0.039)	0.005 (0.063)	-0.002 (0.068)	0.571	0.161	0.161
	lowest 50%:	0.012 (0.037)	0.009 (0.066)	-0.003 (0.065)	0.652	0.152	0.134
	highest 50%:	0.009 (0.037)	0.008 (0.063)	-0.001 (0.068)	0.613	0.135	0.162
Corp. Bond Yield	lowest 25%:	0.006 (0.045)	0.007 (0.065)	0.002 (0.067)	0.607	0.143	0.161
	highest 25%:	0.013 (0.040)	0.007 (0.070)	-0.007 (0.079)	0.625	0.107	0.143
	lowest 50%:	0.008 (0.039)	0.005 (0.063)	-0.002 (0.064)	0.607	0.125	0.143
	highest 50%:	0.014 (0.035)	0.013 (0.066)	-0.001 (0.069)	0.658	0.153	0.144
Changes in Corp. Bond Yld	lowest 25%:	0.011 (0.041)	0.007 (0.075)	-0.004 (0.074)	0.603	0.138	0.138
	highest 25%:	0.009 (0.034)	0.010 (0.065)	0.001 (0.072)	0.589	0.179	0.161
	lowest 50%:	0.012 (0.037)	0.010 (0.068)	-0.003 (0.066)	0.661	0.13	0.139
	highest 50%:	0.009 (0.038)	0.008 (0.061)	-0.001 (0.067)	0.602	0.157	0.157

Table 22 Continued

Scenario		Premium	Small	Large	Pr > 0	Pr > m + std	Pr < m - std
Changes in Industrial Prod.	lowest 25%:	0.011 (0.032)	0.008 (0.070)	-0.002 (0.068)	0.655	0.138	0.138
	highest 25%:	0.019 (0.042)	0.021 (0.069)	0.002 (0.071)	0.667	0.093	0.148
	lowest 50%:	0.008 (0.035)	0.003 (0.065)	-0.005 (0.065)	0.593	0.15	0.15
	highest 50%:	0.014 (0.039)	0.014 (0.064)	0.001 (0.068)	0.679	0.138	0.147
Changes in Money Supply M1	lowest 25%:	0.009 (0.043)	0.007 (0.068)	-0.001 (0.075)	0.655	0.109	0.145
	highest 25%:	0.015 (0.032)	0.014 (0.069)	-0.001 (0.067)	0.691	0.145	0.164
	lowest 50%:	0.009 (0.038)	0.006 (0.063)	-0.003 (0.068)	0.64	0.099	0.162
	highest 50%:	0.013 (0.036)	0.012 (0.066)	-0.001 (0.065)	0.636	0.182	0.164
Changes in Money Supply M4	lowest 25%:	0.015 (0.037)	0.007 (0.078)	-0.007 (0.079)	0.69	0.155	0.121
	highest 25%:	0.013 (0.037)	0.010 (0.066)	-0.003 (0.067)	0.63	0.152	0.13
	lowest 50%:	0.015 (0.036)	0.011 (0.068)	-0.004 (0.069)	0.667	0.155	0.132
	highest 50%:	0.005 (0.038)	0.005 (0.060)	0.000 (0.062)	0.598	0.13	0.13

Large changes in the short term interest rates seem to have an adverse effect on the small-price premium. This may be due to the fact that declining short term rates benefit small companies more since a larger proportion of their debt portfolio consists of short term liabilities as opposed to large companies that have easier access to long term capital. However, as the next few rows in Table 21 indicate, periods of low short term interest rate levels tend to be associated with a smaller average premium. This is due to the fact that when interest rates are already low they are more likely to go up than down. Extreme changes in industrial production (values in the top quartile) have a positive effect on the premium but that effect dissipates when looking at the two halves of the distribution (above and below median). The above analysis when applied to the Market-to-Book-Value percentile portfolios does not yield the same conclusions. The difference between the returns of small Market-to-Book-Value P10 portfolio and the large MTBV P100 portfolio seems to be fairly stable and largely unaffected by the different macroeconomic scenarios. The only exceptions seem to be periods of large positive and large negative changes in consumer confidence and periods of high versus low corporate bond yields. High consumer confidence and high bond yields benefit the difference between the returns of the P10 and P100 MTBV portfolios.

Overall, there seems to be evidence in the data that the small price premium is strongly affected by macroeconomic conditions. The premium of the small MTBV portfolio however remains relatively stable when different macroeconomic scenarios are applied. A related question that has drawn the attention of many researchers is whether portfolio returns and their related premiums exhibit any seasonal patterns. This is the subject of the next section.

Table 23
Seasonalities in the Price portfolio Returns

		P10	P20	P30	P40	P50	P60	P70	P80	P90	P100	Market	Premium
R-Sq		0.141	0.133	0.114	0.107	0.093	0.096	0.101	0.085	0.073	0.033	0.110	0.115
Jan	Mean	0.040	0.040	0.029	0.028	0.023	0.021	0.024	0.019	0.009	0.004	0.029	0.036
	STD	0.076	0.088	0.081	0.072	0.063	0.063	0.060	0.053	0.048	0.044	0.068	0.051
	T-Stat	2.363	2.042	1.584	1.710	1.567	1.466	1.763	1.556	0.795	0.417	1.891	3.187
Feb	Mean	0.033	0.034	0.025	0.022	0.020	0.017	0.016	0.010	0.008	-0.003	0.018	0.038
	STD	0.069	0.068	0.061	0.056	0.055	0.052	0.051	0.052	0.050	0.043	0.053	0.065
	T-Stat	2.129	2.252	1.888	1.792	1.640	1.481	1.444	0.840	0.762	-0.290	1.558	2.639
Mar	Mean	0.029	0.025	0.020	0.021	0.018	0.015	0.014	0.016	0.009	0.008	0.018	0.021
	STD	0.068	0.069	0.059	0.058	0.057	0.056	0.055	0.058	0.058	0.060	0.057	0.051
	T-Stat	1.918	1.661	1.547	1.619	1.467	1.251	1.172	1.235	0.762	0.605	1.443	1.842
Apr	Mean	0.039	0.032	0.026	0.019	0.018	0.020	0.022	0.018	0.017	0.014	0.023	0.024
	STD	0.077	0.072	0.067	0.060	0.057	0.054	0.051	0.045	0.043	0.040	0.053	0.060
	T-Stat	2.320	2.046	1.783	1.425	1.489	1.743	1.959	1.907	1.871	1.653	2.043	1.845
May	Mean	0.054	0.056	0.048	0.041	0.035	0.034	0.031	0.026	0.020	0.010	0.038	0.044
	STD	0.077	0.069	0.064	0.054	0.048	0.047	0.039	0.042	0.039	0.044	0.049	0.067
	T-Stat	3.053	3.587	3.288	3.411	3.232	3.220	3.580	2.779	2.332	0.958	3.423	2.908
Jun	Mean	0.024	0.018	0.017	0.012	0.011	0.014	0.011	0.011	0.011	0.006	0.013	0.018
	STD	0.082	0.074	0.064	0.057	0.054	0.053	0.053	0.053	0.051	0.053	0.054	0.064
	T-Stat	1.317	1.048	1.185	0.942	0.879	1.119	0.933	0.947	0.976	0.469	1.089	1.237
Jul	Mean	-0.011	-0.010	-0.010	-0.005	-0.002	-0.002	-0.001	-0.006	-0.009	-0.007	-0.007	-0.004
	STD	0.054	0.058	0.045	0.042	0.041	0.044	0.041	0.041	0.048	0.059	0.043	0.065
	T-Stat	-0.925	-0.815	-1.061	-0.527	-0.193	-0.194	-0.166	-0.665	-0.867	-0.528	-0.733	-0.297
Aug	Mean	-0.002	-0.006	-0.005	-0.010	-0.009	-0.010	-0.009	-0.006	-0.011	-0.006	-0.007	0.004
	STD	0.073	0.075	0.077	0.063	0.065	0.056	0.063	0.059	0.061	0.069	0.065	0.040
	T-Stat	-0.148	-0.330	-0.270	-0.719	-0.583	-0.752	-0.601	-0.485	-0.819	-0.405	-0.473	0.415

Table 23 Continued

		P10	P20	P30	P40	P50	P60	P70	P80	P90	P100	Market	Premium
Sep	**Mean**	-0.037	-0.035	-0.026	-0.025	-0.021	-0.019	-0.021	-0.019	-0.017	-0.018	-0.026	-0.016
	STD	0.075	0.075	0.068	0.063	0.060	0.059	0.056	0.054	0.056	0.056	0.059	0.061
	T-Stat	-2.194	-2.130	-1.751	-1.783	-1.623	-1.494	-1.727	-1.609	-1.422	-1.442	-1.994	-1.163
Oct	**Mean**	-0.011	-0.008	-0.012	-0.009	-0.015	-0.018	-0.016	-0.018	-0.022	-0.016	-0.011	0.006
	STD	0.062	0.064	0.065	0.057	0.059	0.056	0.053	0.061	0.059	0.069	0.058	0.070
	T-Stat	-0.743	-0.528	-0.812	-0.689	-1.087	-1.402	-1.287	-1.288	-1.608	-1.038	-0.847	0.357
Nov	**Mean**	-0.019	-0.022	-0.023	-0.017	-0.017	-0.016	-0.020	-0.017	-0.018	-0.010	-0.018	-0.009
	STD	0.082	0.089	0.082	0.077	0.071	0.067	0.063	0.062	0.062	0.064	0.072	0.055
	T-Stat	-1.034	-1.107	-1.216	-0.971	-1.027	-1.010	-1.375	-1.188	-1.248	-0.663	-1.078	-0.751
Dec	**Mean**	-0.019	-0.018	-0.015	-0.013	-0.007	-0.007	-0.004	-0.007	-0.001	-0.001	-0.008	-0.018
	STD	0.058	0.063	0.054	0.047	0.043	0.040	0.043	0.036	0.039	0.034	0.045	0.045
	T-Stat	-1.382	-1.180	-1.206	-1.152	-0.725	-0.738	-0.355	-0.784	-0.155	-0.085	-0.734	-1.777

1.7 Seasonalities in the portfolio premiums

Table 23 displays average monthly returns for the price portfolios and their standard deviations for each month of the year. All the portfolio returns exhibit an interesting decaying pattern. They remain positive during the first half of the year (January to June) and achieve their highest value in May. Subsequently the portfolio returns become negative in July and stay so until December. The high value of all portfolio returns in May confirms the "January" effect documented in many similar studies whereby exceptionally high returns are observed in the month following the financial year end. However most Japanese companies have their financial year end in April and hence the large returns in May. A similar pattern is followed by the small price portfolio premium, although it assumes its largest value in July. The premium attains large positive values between February and July and subsequently it becomes small and oscillates around zero. It is interesting to note that the market return is also consistently negative between July and December which corroborates the evidence in the previous section that the small price premium is affected by the macro economy. The aforementioned seasonal patterns in the mean returns tend to be confirmed by the respective t-statistics which result from the regressions of the portfolio returns and the premium on 12 monthly dummy variables. The coefficients for the small price premium are positive and statistically significant between January and May. During the rest of the year they oscillate around zero and bear no statistical significance.

The same seasonal pattern is exhibited by the Market-to-Book-Value portfolios. Table 24 shows the average portfolio returns and the regression results of the portfolio returns on the 12 monthly dummy variables. The portfolio returns are consistently negative during the second half of the year and positive during the first half. The premium of portfolio P10 over P100 is mostly positive and like the small price premium, attains its largest value in July. The only three negative average premium values occur in the second half of the year.

To summarize therefore, both groups of portfolios exhibit the same seasonal pattern whereby returns are negative between July and December and positive during the rest of the year. Interestingly the same pattern is identified in the market return. This suggests that the observed seasonalities are pervasive and not specific to either group of portfolio returns. In a similar manner the premium of portfolio P10 over P100 does not persist across all months of the year but is strongest during the first half, for both groups of portfolios.

Table 24
Seasonalities in the MTBV portfolio Returns

		P10	P20	P30	P40	P50	P60	P70	P80	P90	P100	Market	Premium
R-Sq		0.140	0.122	0.113	0.099	0.096	0.086	0.095	0.082	0.078	0.075	0.110	0.126
Jan	Mean	0.029	0.023	0.030	0.024	0.022	0.015	0.024	0.022	0.022	0.020	0.029	0.008
	STD	0.067	0.068	0.069	0.068	0.060	0.060	0.063	0.065	0.066	0.072	0.068	0.027
	T-Stat	1.907	1.515	1.896	1.566	1.631	1.130	1.690	1.491	1.429	1.241	1.891	1.297
Feb	Mean	0.028	0.024	0.023	0.021	0.018	0.018	0.018	0.015	0.017	0.008	0.018	0.022
	STD	0.059	0.058	0.057	0.058	0.057	0.054	0.054	0.055	0.053	0.055	0.053	0.037
	T-Stat	2.160	1.855	1.866	1.645	1.454	1.475	1.505	1.264	1.438	0.650	1.558	2.638
Mar	Mean	0.026	0.022	0.021	0.023	0.022	0.019	0.016	0.014	0.012	0.007	0.018	0.019
	STD	0.063	0.059	0.059	0.061	0.060	0.061	0.056	0.059	0.062	0.068	0.057	0.037
	T-Stat	1.886	1.711	1.627	1.723	1.664	1.436	1.293	1.104	0.921	0.465	1.443	2.316
Apr	Mean	0.032	0.028	0.024	0.023	0.022	0.023	0.019	0.022	0.016	0.019	0.023	0.013
	STD	0.066	0.066	0.058	0.058	0.054	0.051	0.051	0.053	0.051	0.060	0.053	0.032
	T-Stat	2.239	1.983	1.904	1.826	1.882	2.055	1.744	1.872	1.442	1.450	2.043	1.777
May	Mean	0.045	0.045	0.039	0.038	0.037	0.031	0.034	0.031	0.031	0.023	0.038	0.022
	STD	0.057	0.057	0.053	0.051	0.050	0.052	0.048	0.054	0.049	0.057	0.049	0.038
	T-Stat	3.524	3.483	3.280	3.309	3.256	2.702	3.125	2.554	2.793	1.839	3.423	2.676
Jun	Mean	0.023	0.027	0.022	0.018	0.015	0.009	0.010	0.006	0.003	-0.001	0.013	0.025
	STD	0.065	0.065	0.062	0.059	0.060	0.053	0.052	0.053	0.053	0.068	0.054	0.036
	T-Stat	1.600	1.851	1.577	1.326	1.126	0.778	0.810	0.531	0.229	-0.083	1.089	3.030
Jul	Mean	0.006	0.000	-0.002	0.000	-0.005	-0.005	-0.006	-0.010	-0.012	-0.023	-0.007	0.025
	STD	0.049	0.042	0.043	0.041	0.043	0.042	0.046	0.049	0.050	0.059	0.043	0.043
	T-Stat	0.547	0.043	-0.180	-0.024	-0.572	-0.559	-0.584	-0.969	-1.124	-1.745	-0.733	2.659
Aug	Mean	0.007	-0.009	-0.008	-0.008	-0.003	-0.007	-0.004	-0.004	-0.007	-0.007	-0.007	0.000
	STD	0.064	0.065	0.065	0.065	0.067	0.066	0.068	0.068	0.073	0.075	0.065	0.038
	T-Stat	-0.523	-0.605	-0.569	-0.567	-0.170	-0.497	-0.260	-0.251	-0.414	-0.439	-0.473	-0.014

Table 24 Continued

		P10	P20	P30	P40	P50	P60	P70	P80	P90	P100	Market	Premium
Sep	**Mean**	0.029	-0.024	-0.020	-0.018	-0.022	-0.019	-0.026	-0.025	-0.026	-0.038	-0.026	0.008
	STD	0.065	0.066	0.066	0.065	0.059	0.060	0.060	0.064	0.062	0.066	0.059	0.032
	T-Stat	-2.022	-1.662	-1.334	-1.223	-1.699	-1.412	-1.943	-1.768	-1.898	-2.615	-1.994	1.077
Oct	**Mean**	0.024	-0.019	-0.016	-0.017	-0.015	-0.010	-0.012	-0.010	-0.012	-0.001	-0.011	-0.022
	STD	0.053	0.057	0.056	0.065	0.062	0.059	0.061	0.063	0.061	0.070	0.058	0.037
	T-Stat	-1.929	-1.406	-1.253	-1.159	-1.045	-0.730	-0.862	-0.657	-0.844	-0.050	-0.847	-2.584
Nov	**Mean**	0.021	-0.020	-0.023	-0.018	-0.018	-0.019	-0.016	-0.014	-0.012	-0.017	-0.018	-0.002
	STD	0.072	0.074	0.074	0.072	0.074	0.068	0.069	0.070	0.074	0.080	0.072	0.035
	T-Stat	-1.287	-1.205	-1.335	-1.079	-1.030	-1.198	-1.029	-0.874	-0.678	-0.900	-1.078	-0.302
Dec	**Mean**	0.006	-0.006	-0.008	-0.009	-0.009	-0.013	-0.011	-0.014	-0.010	-0.016	-0.008	0.010
	STD	0.052	0.050	0.048	0.044	0.049	0.045	0.043	0.043	0.043	0.050	0.045	0.033
	T-Stat	-0.487	-0.485	-0.704	-0.868	-0.775	-1.259	-1.131	-1.331	-1.011	-1.397	-0.734	1.402

Conclusion

The existence of the so called size effect in stock returns is investigated for the Japanese stock market. If the size effect is present, stocks of small companies should command a premium, that is earn a higher return than the stock of large companies. This is known as the small cap premium. The stocks comprising the investment universe are sorted in ascending order of their market capitalisation and are subsequently allocated into ten percentile portfolios whose returns are examined to establish the existence of the small cap premium. Likewise two other attributes namely price and Market-to-Book-Value, are also used to form percentile portfolios and examine the existence of other related potential sources of pricing anomalies. Analysis of the returns of these portfolios lends very weak support to the hypothesis that the size effect is present in the Japanese market. In contrast the small price and Market-to-Book-Value portfolios appear to outperform their large value counterparts significantly. Since there is little evidence in support of the size effect in Japan, the subsequent analysis concentrates on the price and Market-to-Book-Value portfolios. Both the Market-to-Book-Value and price premiums as well as most of the portfolio returns show a seasonal pattern in that they tend to be positive during the first half of the year (more so in April and May) and negative thereafter. This phenomenon is termed the "January" effect and has been identified by a multitude of studies in the US and European markets where most companies have their financial year end in December. In the case of Japan most companies report year end results in March and April and so the effect is observed in April/May.

When conditioned on macroeconomic variables, it is clear that the price premium and to a lesser extent the Market-to-Book-Value premium are associated with the state of the underlying economy. Scenarios that are representative of upswings in the business cycle such as high inflation, strong currency relative to the US Dollar, strong consumer confidence, monetary and fiscal stability are linked with positive premiums.

The existence of moderate correlation between price and Market-to-Book-Value implies that the respective portfolio returns are also correlated. An attempt to disentangle the two effects is made by examining the returns of Market-to-Book-Value and price portfolios that are price and Market-to-Book-Value neutral respectively. The price effect appears weaker but still statistically significant in the absence of large differences in the average Market-to-Book-Value value between the price portfolios. In contrast the premium of the small Market-to-Book-Value appears unaffected by the elimination of large price differences in the constituents of the Market-to-Book-Value portfolios.

The debate surrounding market anomalies has recently focused on the validity of the CAPM as an asset pricing model. The argument is that observed market anomalies are due to the influence of risk factors unaccounted for by the simple structure of the CAPM. The higher observed returns for small-size or price portfolios are therefore due to the higher exposure of these portfolios to certain risk factors. An insight into verity of this hypothesis can be gained by looking at a measure of total risk for the portfolios analysed in this chapter. The measure of risk used is the annualised standard deviation of the returns. At first glance the small price and small market capitalisation portfolios appear to be much riskier than their 'large' value counterparts. Since all portfolios have the same number of constituent securities, it is fair to assume that the differences in total risk tend to reflect differences in systematic rather than residual risk. However, according to modern portfolio theory the efficient investment frontier is concave when drawn in the risk/return space. This implies that the slope of the curve is diminishing as we move towards larger risk numbers, implying that each additional unit of risk undertaken is rewarded with an ever decreasing return. Therefore the return/risk ratio of securities becomes smaller as both risk and return increase. As shown in the tables displaying statistics for the portfolio returns, the 'small' portfolios have a larger rather than smaller return/risk ratio than the 'large' ones or the market. This implies that either the market portfolio in not on the efficient frontier or that the total risk of the small portfolios cannot account for the whole of the return and that part of the return must be due to pricing errors captured by size and/or price. This analysis is irrelevant for the Market-to-Book-Value portfolios, where the P100 portfolio not only has a negative return on average but also appears to be slightly riskier than the P10 portfolio thereby negating the claim that return differences are accounted for by risk differences.

CHAPTER 2

A critical evaluation of short-term contrarian profits in Japan

Introduction

The negative serial correlation exhibited by stock returns has been a well-documented phenomenon since the 1960's (Fama, (1965)). This observation casts doubt on the validity of the strong form of the efficient market hypothesis. Moreover, a multitude of studies over the last 20 years, indicate that this phenomenon can be exploited economically (e.g. De Bondt & Thaler (1987), Lakonishok et al (1994), Bacmann & Dubois (1998)). Empirical estimates suggest that contrarian strategies can consistently yield substantial profits with serious implications about the weak form of the efficient market hypothesis. A contrarian strategy calls for action that is contrary to that followed by 'naïve' investors. Examples of 'naïve' investment behaviour range from assuming a trend in stock prices to extrapolating past earnings growth too far into the future, to overreacting to good or bad news or to equating a good investment with a well-run company irrespective of price.

Contrarian strategies can be grouped in two categories according to their investment horizon (the length of the period for which an investment is held before it is liquidated): short-term and long-term strategies. Typical short-term strategies hold investment for up to a month. Long-term strategies hold investments for a year or longer. There is a large body of evidence showing that both long and short term contrarian strategies are significantly profitable (e.g. De Bondt & Thaler (1985, 1987), Jegadeesh & Titman (1995)). However, empirical studies of both types of contrarian strategy are susceptible to methodological pitfalls which are explained in the literature review. The academic community developed two competing explanations for contrarian profits. The first argues that contrarian strategies bear higher fundamental risk than naïve strategies and so are rewarded by higher returns (e.g. Chan (1988), Ball & Kothari (1989)) An alternative explanation (e.g. De Bondt & Thaler (1985, 1987), Lakonishok et al (1994), Daniel et al (1998)) is that investors become overly enthusiastic about stocks that performed well in the past and buy them up. The result is that these stocks become overpriced. In a similar manner, they overreact to stocks that had a poor performance in the past and these stocks become under-priced. Contrarian investors bet against this behaviour by selling the 'overpriced' stocks and buying the under-priced ones. More recent articles (e.g. Jegadeesh & Titman (1995)) suggest that return reversals may not be the only source of contrarian profits. Such profits can also arise when some firms react faster to information than others.

Much of the criticism directed to the contrarian literature stems from problems with the applied methodology that may lead to spurious results. For example portfolio returns are commonly susceptible to bid-ask bias and other measurement errors and so over-estimate contrarian returns (Ball et al (1995)). This study contributes to the debate by seeking to address these issues and extend the analysis as follows:

a) The Japanese stock market is tested for the existence of contrarian profits. The academic community has relatively neglected this market and most of the research is concentrated on US data.
b) Unlike previous studies we examine optimal investment portfolios that have maximum expected return and zero (or near zero) systematic risk.
c) Different implementations of the contrarian strategies result from alternative ways of identifying over and under-priced stocks. It is shown that contrarian profits are very dependent on the asset-pricing model used to estimate the magnitude of stock miss pricing and the co-variability of the investment universe
d) Liquidity is found to be another major factor affecting the magnitude of contrarian profits. The extent to which stock prices are determined by market considerations or firm specific attributes is also closely related to this factor.
e) Trading costs are introduced when calculating portfolio returns and are found to significantly affect their performance. Trading costs have largely been ignored by the literature although the strategies examined exhibit very high turnover (and hence substantial transaction costs).
f) The conventional literature calculates portfolio returns using closing stock prices which are largely unattainable. This study also examines portfolio returns which are calculated using two different types of prices: Open prices and volume-weighted average prices (VWAP). Both prices are readily and cheaply delivered by Japanese stock brokers therefore portfolio returns that are thus calculated are more realistic and feasible.
g) All the empirical studies so far examine a contrarian portfolio which is formed in period t-1 and whose performance is measured in period t. The returns of both periods use the closing price of period t-1, therefore the portfolio returns suffer from in-sample bias due to the way they are calculated. This bias results in substantially over-estimated contrarian profits as will be shown later. Use of

closing prices in the formation period and open or VWAP prices in the test period avoids this pitfall.

The chapter proceeds as follows:

Section 2.1 reviews the existing literature on contrarian profits. Section 2.2 presents the data and the methodology used. Section 2.3 replicates the Jegadeesh & Titman (1995) analysis. Section 2.4 extends the contrarian strategy of Section 2.3 by requiring that the investment portfolio is always chosen to be the maximum Sharpe Ratio portfolio. Three models are used to generate the trading signals: a simple market model, a model that uses the market return and its first order lag as factors and finally a multifactor model that uses 20 statistical factors extracted with factor analysis techniques. Section 2.5 examines market microstructure issues and proposes remedies. The profitability of this strategy is reassessed when all the biases are controlled for.

2.1 Literature review

2.1.1 Introduction

Since the advent of asset pricing models, a plethora of studies have attempted to either give support or disprove the efficient market hypothesis: the notion that all past information has been impacted in current prices and therefore it is impossible to predict future price movements and exploit them profitably. Researchers have looked for 'irregularities' or 'anomalies' in the behaviour of capital markets. The presence of empirical anomalies in asset returns suggests that empirical forms of asset pricing models are miss-specified and/or that capital markets are not efficient. The procedure, most commonly used by event studies to analyse such anomalies, is the ranking of the assets comprising the investment universe according to some attribute such as market capitalisation, accounting ratios, past asset returns etc. Assets are subsequently grouped into portfolios of 'high' and 'low' attribute values and their returns are compared. Alternatively, researchers simulate a contrarian strategy that assumes a long position in one portfolio and a short position in the other and the profit or loss generated undergoes rigorous analysis. Initially, the observed anomalous returns were attributed to miss-specification of the empirical asset pricing model employed to estimate them due to some omitted risk factor (e.g. Zarowin, 1989). It was claimed that the attribute by which stocks are ranked acts as a proxy for this factor which when included in the correct valuation model would eliminate the anomaly. However this missing factor has proved elusive and irregular returns have survived several empirical versions of asset pricing models. This explanation implies that the market is efficient and that the detected irregularities are the illusory consequence of spurious methodology. An alternative explanation was sought in the theory behavioural finance. Using the PE ratio as an example of an attribute, firms with a low (high) PE value are perceived to be 'undervalued' ('overvalued') because investors have become overly pessimistic (optimistic) and overreact after a series of bad (good) earnings announcements. Once future earnings turn out to be better (worse) than the unduly glum (buoyant) forecasts, the price adjusts. This is what Basu (1977) called the 'price-ratio' hypothesis. An important tacit admission of this interpretation is that agents do not behave rationally and therefore the market does not value assets efficiently in the short term. Such inefficiencies should be arbitraged out in the medium to long term by means of contrarian investments.

Most of the event studies employ long-horizon investment strategies to examine anomalous return patterns. These studies are reviewed in section 2.1.2 and are broadly categorised in two groups, one that seeks a behavioural rationalisation of the results and one that offers a risk-based explanation. Studies that subsequently sparked a substantial amount of debate as well as those that help the reader gain a clear understanding of the issues involved, are reviewed in greater detail than the rest. The few short-horizon contrarian studies in existence are the main focus of this chapter and so are reviewed separately in sub-section 2.1.3. Sub-section 2.1.4 reviews related methodological issues and finally sub-section 2.1.5 concludes.

2.1.2 Long-Horizon studies

Long horizon studies examine investment portfolios which are typically characterised by holding periods that range from a few months to a few years. The most influential such study is that of DeBondt & Thaler (1985) which formalised the overreaction hypothesis and generated a lot of controversy.

2.1.2.1 Behavioural Rationalisation

The notion that investors may overreact is not new. For example De Bondt and Thaler quote Keynes (1936) who noted that '...day-to-day fluctuations in the profits of existing investments, which are obviously of an ephemeral and non-significant nature, tend to have an altogether excessive, and even an absurd, influence on the market'. It is due to De Bondt and Thaler (1985, 1987) that interest in this area was renewed and the current debate was sparked. The study of De Bondt and Thaler was triggered by the work of Kahneman and Trevsky (1982) and Arrow (1982) who argue that when revising their beliefs, individuals tend to overweight recent information and underweight prior data. Individuals do not respond to new information according to Bayes' rule but rather tend to overreact to unexpected and dramatic events. De Bondt and Thaler (1985) tested the overreaction hypothesis using monthly data for the New York Stock Exchange (NYSE) for the period between January 1926 and December 1982 obtained from the Centre for Research in Security Prices (CRSP) tapes. They looked for evidence in support of overreaction, by testing two hypotheses:

(a) Extreme stock price movements in one direction will be followed by subsequent price movements in the opposite direction and

(b) The more extreme the price movements the greater the subsequent adjustments.

Only stocks that traded for at least 85 consecutive months were used. Three types of residual returns were tested (market adjusted excess returns, market model residuals, and excess returns derived from the Sharp-Linter version of the CAPM) in order to assess how different valuation models affect conclusions about market efficiency. However since all three methods are based on single index models the authors admit that their results are still susceptible to misspecification problems. De Bondt and Thaler found that whichever of the three types of residuals they used their results did not change much so they only reported results based on market-adjusted excess returns. Their particular strategy consists of 3 basic steps:

(a) Starting on January 1930 the monthly cumulative abnormal return for every stock j is calculated, over an initial portfolio formation period of 3-years, as

$$CAR_j = \sum_{t=1}^{36} (R_{jt} - R_{mt})$$

Where:

R_{jt} is the return of stock j at time t,

R_{mt} is the equally weighted market return (constant).

This step is repeated for all subsequent non-overlapping 3-year periods starting on January 1930, January 1933... January 1975. At the end of each portfolio formation period, firms are ranked according to their CAR. The extreme high and low performers are then allocated to a winner and a loser portfolio (of 35, 50 or 10 stocks) respectively.

(b) Using the equation in (a), the CARs of the winner and loser constituents are then calculated for up to 36 months during the three year period following each portfolio formation period. This period is termed the 'performance evaluation period' or test period. The Average Cumulative Abnormal Return over a period of length k months for the winner and loser portfolios is then calculated as:

$$ACAR_p(k) = \frac{1}{N_p} \sum_{i \in p} CAR_i(k)$$

Where $CAR_i(k) = \sum_{t=1}^{k} (R_{it} - R_{mt})$, k=1,...,36, p = W, L and N_p is the number of securities in portfolio p.

The difference between the ACARs is then defined as:

$DACAR(k) = ACAR_L(k) - ACAR_W(k)$, k=1,...,36.

(c) The final step is to test whether

(1) the loser portfolio outperforms the market: $ACAR_L(k) > 0$,

(2) the winner portfolio underperforms the market: $ACAR_W(k) < 0$ and most importantly

(3) the arbitrage portfolio defined as loser-winner earns positive returns: $DACAR(k) > 0$.

To carry out the tests, the $ACAR_p(k)$'s are averaged across all non-overlapping test periods for each k. .

De Bondt and Thaler found that the loser portfolio outperformed the market by 19.6% on average, three years post portfolio formation i.e. for k=36. During the same period, the winner portfolio underperformed the market by 5.0% on average. Thus the arbitrage portfolio earned 24.6% (DACAR(36) = 24.6%). In fact DAKAR was consistently greater than zero and its magnitude was increasing systematically with k. The overreaction effect was observed mostly during the second and third year of the test period and was found to be asymmetric: much larger for losers than for winners. For formation periods of one-year, price reversals were not observed. It was also noted that larger loses (gains) in the formation period are followed by larger gains (loses) in the test period. Consistent with previous work on the January effect, De Bondt and Thaler found that most of the excess returns were realized in January but that effect alone could not adequately explain the magnitude of the contrarian profits. The risks of the two portfolios, as measured by the average CAPM betas of the portfolio constituents, were also examined. CAPM betas were calculated by estimating the market model over a period of 60 months prior to portfolio formation. The average winner portfolio beta was found to be consistently and significantly larger than the loser portfolio beta. Therefore the loser portfolio not only outperforms the winner portfolio but is also less risky. This led the authors to believe that their chosen procedure probably underestimates the true magnitude of the overreaction effect.

In response to criticism of their original study by Vermaelen and Verstringe (1986) and Chan (1988) among others, De Bondt & Thaler (1987) reappraised their earlier results and also addressed unresolved issues such as:

(a) The strong seasonality in the contrarian returns,

(b) The asymmetric performance of the winner and loser portfolios,

(c) The exposure of the extreme portfolios to attributes such as size. The winner-loser effect may be yet another instance of the well documented size anomaly, and finally,

(d) the contention that the overreaction effect they observed is in effect a response to changing risk

To examine the seasonality and the risk of the winner and loser portfolio returns, the authors used the same CRSP monthly data as in their previous study. Using a 5-year formation and test period they now construct 50-stock portfolios for each of the 10-year periods starting in January of each year from 1926 to 1973. It was found that during the test period excess returns occur primarily in January for both winners and losers (more so for losers than for winners). January excess returns for both losers and winners are found to be driven mainly by reverse performance over the immediately preceding months. This is consistent with tax-loss selling for losers and a capital gains tax lock in effect for winners. A statistically significant link was also found between January returns and prior long-term performance. For losers, this negates the tax-loss selling hypothesis as an explanation of the January effect. For winners the effect is positive which contradicts the overreaction hypothesis altogether.

To test whether the contrarian excess returns can be attributed to risk differences between losers and winners, De Bondt & Thaler stack all the test period data together and estimate the Sharpe-Lintner CAPM betas of the arbitrage, winner and loser portfolios. In contrast to the 1985 results, losers are found to be riskier than winners but only slightly. Furthermore, the estimated abnormal return for the arbitrage portfolio is significantly positive and its magnitude implies that the estimated beta is insufficient to explain the portfolio's return. De Bondt & Thaler argue therefore that the risk change hypothesis fails to explain the winner-loser effect. However their results may suffer from the methodological pitfall explained by Chan (1988): Since betas change over time, De Bondt & Thaler's estimate of the abnormal return is a positively biased estimate of the true α_{L-W}. This is because time varying betas are likely to be positively correlated with the market risk premium and this covariance is included in the α_{L-W} estimate obtained by De Bondt & Thaler. Compustat data from 1966 until 1985 were used to examine whether the winner-loser effect is different from the size effect. The original (stocks ranked by CAR) winner and loser portfolios were constructed using a 4-year formation period. Portfolios were also formed by ranking stocks according to their market capitalisation (MV), book value to market (BV/MV) and asset value (AV) at the last formation period year. Significantly positive excess returns for the arbitrage portfolio were re-confirmed by replicating the original winner-loser strategy. It was found that the difference in market value between the winner and loser portfolios was less pronounced than that of the extreme MV and AV portfolios. The loser portfolio is smaller than the winner portfolio but 30 times larger than the smallest MV portfolio. Therefore the authors conclude that the winner-loser effect cannot be the same as the size effect. In contrast they notice that the portfolios which are ranked by (formation period) CAR, are coincidentally ranked by MV/BV as well and vice versa. It therefore seems more natural to characterise the winner-loser effect as an overvalued-undervalued effect. The authors also notice that the earnings of the winner and loser firms show reversal patterns that are consistent with the overreaction hypothesis. Therefore extreme price movements are predictive of subsequent earnings reversals.

Poterba & Summers (1988) assert that the observed mean reversion in stock returns is consistent with the hypothesis that stock prices are temporarily driven out of equilibrium (due to overreaction amid other things) and subsequent speculation drives them back to their fundamental values. Verity of this hypothesis would imply negative serial correlation in stock returns, and therefore contrarian profits. They examined monthly CRSP returns of both value and equally weighted NYSE indices between 1926 and 1985 and found evidence of positive serial correlation in the first year and negative autocorrelation for larger time periods. The results persist when infrequent trading is controlled for and when they switch to S&P data. There is therefore a time lag of at least one year before contrarian strategies become profitable. Similar autocorrelation patterns were observed for Canada, the UK and most of the fifteen other countries they examined.

Lakonishok, Shleifer & Vishny (1994) provide further evidence in favour of the overreaction hypothesis by showing that value stocks (hitherto known as losers) consistently outperform 'glamour' stocks (hitherto known as winners). They attribute this out-performance to the sub-optimal behaviour of the typical investor rather than to risk differences. The authors argue that 'naïve' investors tend to extrapolate recent stock performance too far into the future thus over-valuing glamour stocks and undervaluing out-of-favour or value stocks. Rational traders can realise substantial arbitrage profits by betting against this behaviour. However Shleifer and Vishny (1997) argue that there is a limit in the effectiveness of arbitrage. Rational arbitrageurs assume the short-term risk that the miss-pricing may be expanded further or last longer due to the persistence of noise traders. Furthermore, noise traders may make it impossible to find a rationally traded stock to hedge the arbitraged security. Therefore the risk involved in arbitrage may outweigh the return. Lakonishok, Shleifer & Vishny use data NYSE/AMEX stock data from 1968 until 1990 and examine the long horizon returns (of up to 5 years) of several sets of decile portfolios based on sorting firms by various measures of past and expected performance. Sales growth, earnings and cash flow are used to measure the former while price multiples of current earnings and cash flow are used to measure the latter. Portfolios are rebalanced annually thus minimising the impact of transaction costs and various market microstructure issues. The authors found that value stocks consistently outperformed glamour stocks both when simple one-dimensional and two-dimensional sorting schemes (based on combinations of past and future growth measures) were used. The superior performance persisted when the analysis was restricted to the largest 50% of stocks so it could not be attributed to the size effect.

By examining traditional risk measures (beta, standard deviations of portfolio returns) as well as comparing the performance of value versus glamour portfolios in different states of the economy, they found very little support for the view that value stocks are fundamentally riskier. Lakonishok, Shleifer & Vishny suggest that their results are due to investors consistently over-estimating the future growth prospects of glamour relative to value stocks. By comparing sales, earnings and cash flow rates of growth they found that glamour stocks have historically grown faster than value stocks. Investors expect this superior growth to continue for many years. However, evidence suggests that after a couple of years both groups of stocks had essentially the same growth rates. By tying their forecasts to past growth rates, investors become overly optimistic (pessimistic) about the growth prospects of glamour (value) stocks. Contrarian strategies that bet against these expectations produce significant profits. Finally, the authors question why have value stocks outperformed for so long despite not being fundamentally riskier? Such return differentials should vanish sooner rather than later in an efficient market. The authors think that this is because of both individual and institutional investors' preference for glamour stocks.

Dissanaike (1997) examined a sample of UK listed companies for evidence on the overreaction hypothesis. He restricted his analysis to about 1000 of the largest and better known companies whose shares are more frequently traded. By doing so, Dissanaike reduces both the effect of microstructure related biases (bid-ask spread, infrequent trading) and the possibility that his results are driven by smaller companies. Strong evidence of overreaction was found with the loser portfolio outperforming the winner portfolio by almost 100% four years after portfolio formation. Similar to the DeBondt and Thaler study, the performance of the winner and loser portfolios was found to be asymmetric. Moreover the loser portfolio displayed a strong seasonal pattern and most of its return was realised around January. This is somewhat puzzling since most UK firms have an April financial year end. The author offered as a possible explanation the participation of many US investors in the UK market who respond to their own tax regime. Using a procedure similar to Chan's (1988) to control for risk changes over time, he found that in fact the winner portfolio had a larger beta than the loser portfolio with the equity risk premium being positive. This ruled out differences in the risk of the two portfolios as a potential explanation of the results.

Having studied the evidence on return reversals, Daniel, Hirshleifer & Subrahmanyam (1998), attempt to explain why investors behave in a manner that induces such miss-pricing. They suggest that investors are overconfident, underestimating their forecast error, by believing that they have better forecast ability than they really do. Their confidence increases when public information agrees with their forecasts. As a result they tend to overreact to their private information and underreact to public signals. As time passes and their predictions are proven wrong they gradually adapt their behaviour and prices are corrected to equilibrium levels. Public events could lead to further overreaction (if confirming investor's beliefs), inducing short term momentum, and longer term price reversion as more and more public information arrives. So underreaction is possible but not necessary for a post announcement drift. They simulated two models assuming both static and changing confidence levels respectively. Their results confirmed that when positive public news agreed with investors' beliefs, there was an initial price increase followed by progressive downward correction thus implying positive short-term and negative long-term autocorrelation. Considering accounting information as noisy public information, a positive short-run and negative long-run relationship was observed between accounting ratios and price. This finding appears to be consistent with the ability of prise based measures (B/M, E/P, dividends, market value etc) to describe returns.

Finally, Gunaratne & Yosenawa (1997) studied return reversals in Japan using data for companies listed in the first section of the Tokyo stock exchange between 1955 and 1990. The authors simulated a contrarian strategy with a holding period of four years and found that past losers outperformed past winners by about 11% per annum over the holding period. By employing a simple CAPM regression, they attribute only part of the observed over-performance to risk differences and conclude that the overreaction effect is statistically and economically significant. They found seasonal patterns in the winner and loser portfolios separately but not in the reversal effect concluding that the overreaction effect is fundamentally different from the monthly seasonal pattern of stock returns.

In summary, the studies reviewed in this section attribute contrarian profits to irrational investor behaviour. It is argued that naïve investors tend to overreact to both good and bad news thus driving prices out of equilibrium. The overreaction hypothesis was alluded to by Keynes as early as 1936 but was given formal content by De Bondt and Thaler (1985). A number of subsequent studies, most notably Daniel et al (1998) and Lakonishok et al (1994), gave support to this hypothesis thus raising serious doubts about stock market efficiency.

2.1.2.2 Risk-Based Interpretations

A considerable number of researchers reacted to the overreaction hypothesis with plenty of scepticism. Fama and French (1986) compared the returns of winner and loser portfolios with those of size-sorted portfolios and claim that part of the return reversal effect is explained by the size effect. In a subsequent article (Fama & French (1988)) they examine in more detail the autocorrelation patterns induced by return reversals. They observed weak negative autocorrelation in short horizon stock returns (daily, weekly) which becomes stronger for horizons of a year or more. They suggested two possible explanations: either the market is inefficient and stock prices are temporarily driven out of equilibrium (overreaction and subsequent reversal) or the required rate of return varies with time within an efficient market framework. They examined CRSP data for all NYSE stocks between 1926 and 1985 by grouping them first into 10 equally-weighted portfolios based on size and later into 17 industry portfolios. The portfolio returns were then decomposed into a random-walk and a stationary component. The larger and more consistent the stationary component is, the larger the observed return reversals. Fama and French found that return reversals are very large for horizons between two and five years but dissipate for longer horizons. They suggested that the negative autocorrelations were due to mean reverting factor risk premiums rather than to firm-specific factors.

Zarowin argues that subsequent return differences between prior losers and winners can be explained entirely by differences in their market capitalisation. Previous research by the author (1989) suggested that firms that experienced very poor earnings recently outperformed the best earners by a statistically significant amount over the following 36 months. The poorest earners were also found to be significantly smaller than the highest earners during the portfolio formation period. Motivated by these findings and not entirely convinced by DeBondt and Thaler's (1985, 1987) claim that 'the winner-loser effect is not primarily a size effect', Zarowin (1990) re-examines the relation between size and the overreaction hypothesis, controlling for size differences between winners and losers. He starts by replicating the DeBondt and Thaler methodology and concludes that neither risk nor seasonality alone can account for the results. Interestingly, when he applies Chan's procedure to account for changing risk, the results contradict Chan's findings and losers still outperform winners significantly. To control for size differences, Zarowin sorts all firms at the beginning of the test period first according to size and then according to their prior 3-year performance. The two sorts are independent of each other and each company is assigned a pair of rankings (i, j) which denote the prior performance and size quintiles respectively, to which the firm belongs. For example, the rankings (1, 1) and (5, 1) indicate the smallest losers and the smallest winners respectively. He then applies Jensen performance tests on the five winner-loser portfolios that result from the double ranking (one for each size quintile). Zarowin finds that losers outperform winners only in January. Zarowin uses also a June 30th rather than December 31st ranking cycle to see whether the results are driven by the January effect or by overreaction in the first month of the test period. He finds that losers still outperform winners in January but not in July. Periods when losers are smaller than winners were also examined separately from periods when the opposite is true. When winners are smaller they outperform losers. This contradicts the overreaction hypothesis and is consistent with the size effect. Therefore, concludes Zarowin, the loser's out-performance is due to size differences rather than investor overreaction.

The articles presented so far attribute the contrarian profits to size differences between loser and winner stocks. If size is a good proxy for risk, as advocated by the size-effect literature, the winner and loser portfolios are fairly priced and the contrarian strategy returns are justified by their accompanying systematic risk. In accordance, the studies reviewed in the rest of this section, argue that performance differentials between winners and losers are explained by risk differences as measured by the CAPM beta. Using data on the Belgian stock market, Vermaelen and Verstringe (1986) replicated the DeBondt & Thaler study and also found evidence of an overreaction effect but argue that this effect is a rational response to risk changes. Chan (1988) argues that the risk of winners and losers changes over time and therefore the results of De Bondt and Thaler are very sensitive to the methods used. The contrarian profits seem to be very small when risk changes are controlled for. Chan observed that the market value of the winner (loser) stocks increases (decreases) dramatically, on average, over the portfolio formation or ranking period. If size is a good proxy for risk as suggested by the size-effect literature then losers become riskier than winners by the end of the formation period. A change in the market capitalisation of a firm affects the market value of its equity more than the market value of its liabilities. As the stock price falls, the debt to equity ratio increases ceteris paribus thus increasing the risk of the stock and vice versa. Therefore beta estimates over the formation period underestimate the loser portfolio beta over the test period, since the loser portfolio risk increases. The opposite holds for the winner portfolio. To test his hypothesis Chan employed the same methodology and CRSP data as De Bondt and Thaler, to construct winner and loser portfolios. However he tested the strategy over a slightly longer period (1926-1985). Formation and test period betas and abnormal returns are estimated simultaneously by estimating the parameters of the following equation:

$$r_{it}-r_{ft}=\alpha_{1i}(1-D_t)+\alpha_{2i}D_t+\beta_i(r_{mt}-r_{ft})+\beta_i D(r_{mt}-r_{ft})D_t+e_{it}$$

Where:

$t = 1$ to 72

i = loser portfolio, winner portfolio, arbitrage portfolio (loser-winner)

r_{mt} is the equally weighted CRSP index,

r_{ft} is the risk-free rate of return,

D_t is a dummy variable with D_t=0 in the formation period (t<=36) and D_t=1 in the test period (t>36),

$\hat{\beta}_i$ and ($\hat{\beta}_i - \hat{\beta}_{iD}$) are the rank and test period betas estimates respectively,

$\hat{\alpha}_{1i}$ and $\hat{\alpha}_{2i}$ are the average estimated abnormal returns of the rank and test period respectively.

The estimates of the regression parameters are averages of the parameters in individual formation and test periods. The results showed that during the formation periods, losers (winners) have large negative (positive) abnormal returns on average. Over the same periods, the arbitrage portfolio loses on average 4.56% per month. During the test periods, the contrarian strategy yields small and, after controlling for transaction costs, economically insignificant abnormal returns: 0.095%, -0.228% and 0.133% on average per month for the loser, winner and arbitrage portfolios. The aggregate t statistic for the arbitrage portfolio return is 0.88. As expected the estimated rank period betas are smaller for losers than for winners. The reverse is true for test period betas, which appears to be consistent with the change in risk explanation of contrarian profits. This conclusion contradicts De Bondt and Thaler (1985) who compared formation period betas to determine whether contrarian profits can be attributed to risk differences. Therefore the abnormal returns are very sensitive to the model and methods used to estimate them. Chan admits that the arbitrage portfolio beta (measured as the difference between the average winner and loser portfolio betas) cannot adequately explain its average monthly return during the test period. He explains the combined observation of a small abnormal return ($\alpha_{L-W} = 0.133\%$), a small beta ($\hat{\beta}_{L-W} = 0.107$) and a large return ($r_{L-W} = 0.586\%$) by the positive correlation between time-varying betas and the market risk premium. It is estimated that the CAPM explains 77% of the arbitrage portfolio return of which 55% is explained by the covariance between the beta and the market premium and 22% is explained by the average beta. It is not therefore correct to compare average returns and average betas estimated over a very long period of time because the changing betas may be correlated to the market risk premium.

Ball & Kothari (1989) tested whether the negative serial correlation in market-adjusted returns, observed by Poterba & Summers (1988), and Fama & French (1989) among others, was due to risk differences over time. Negative autocorrelation can be consistent with both changing expected returns and market miss-pricing (due to overreaction). Monthly CRSP data from 1926 to 1986 were analysed. Twenty ventile portfolios were formed at the beginning of each year for each of the following two stock rankings: their previous 5-year total return and their size. Similar to Bondt & Thaler (1985, 1987), the authors use 5-year formation and test periods and calculate buy and hold returns for each year in both periods. Market model abnormal returns and betas were also estimated for all portfolios. Significantly negative serial correlation was observed between formation and test period returns which could be a manifestation of risk changes over time. Indeed, the authors observed that extreme losers become riskier (beta increases by 78%) while extreme winners become less risky (beta reduction of 57%), as we move from the formation to the test period. The DeBondt & Thaler contrarian strategy abnormal returns were drastically reduced when betas were allowed to change and so the winner-loser effect disappears when risk changes are accounted for. Similar results were found for the size-sorted portfolios.

The studies reviewed in this section argued against the overreaction hypothesis. Instead some studies (Fama & French (1986), Zarrowin (1989)) attributed contrarian profits to size differences between the winner and loser portfolios. If size is a proxy for some underlying risk factor then contrarian returns are justified by their commensurate exposure to risk. Others (Chan (1988), Ball & Kothari (1989)) argued that the differential performance of winner and loser portfolios is explained by changes in the risk of these portfolios over time. They showed that contrarian profits became insignificant when risk changes were accounted for.

2.1.3 Short- Horizon Studies

In contrast to long horizon studies, short horizon studies examine portfolios which are characterised by holding periods that range from a few days to a few weeks. Because of the shorter holding period, some of the criticism directed to contrarian profits is no longer applicable. For example Chan's critique (1988) that contrarian profits are attributed to risk changes over time is not valid since performance is measured over time intervals which are very short for such changes to occur and affect it. The most influential such studies are those of Lo & MacKinlay (1990) and Jegadeesh and Titman (1995) both of which devise a framework for analysing the sources of contrarian profits.

Lo & MacKinlay (1990) argue that in addition to the overreaction effect, delayed reaction to information (underreaction) may also contribute to contrarian profits. If the price of stock B changes following a price change in stock A, a profit can be made from buying B subsequent to a price increase in A and vice versa. By making certain distributional assumptions on stock returns and choosing portfolio weights which are inversely proportional to each stock's performance relative to a market index, the authors are able to decompose the contrarian profits into three parts: one due to the dispersion of expected returns, another due to the serial covariance of returns and a final part due to their cross-serial covariance. The cross-serial covariance component measures the effect of delayed reaction to information on profits. By examining size-sorted portfolios, Lo & MacKinlay found that there was a definite lead-lag pattern observing large positive covariances between the returns of small stocks and the lagged returns of large stocks but not vice versa. They estimate that less than 50% of the contrarian profit is attributed to overreaction.

.Jegadeesh and Titman (1995) examine the profitability of short horizon contrarian strategies and examine the contribution of stock price overreaction and delayed reaction to such profits. They use the work of Lo and MacKinlay as a starting point, who comment that the observed profitability of contrarian strategies cannot lead to inferences about how prices react to information. The authors develop a generalised framework for identifying the different sources of contrarian profits based on how prices respond to information. They assume that stock returns are determined according to the following multifactor model:

$$r_{i,t} = \mu_i + \sum_{k=1}^{K}(b^t_{0,i,k} f_{t,k} + b^t_{1,i,k} f_{t-1,k}) + e_{i,t}$$

This model facilitates the separate examination of price reactions to common factors $f_{t,k}$, lagged realisations of common factors $f_{t-1,k}$ and firm specific information $e_{i,t}$, where $f_{t,k}$ denotes the unexpected factor realisation. It is reasonably assumed that the factors are orthogonal and unrelated to their lagged values and that $\text{cov}(e_{i,t}, e_{j,t-1})=0$ for all i $\neq$j. It then follows that:

$$\text{cov}(r_{i,t}, r_{j,t-1}) = \sum_{k=1}^{K} E(b^t_{1,i,k} b^{t-1}_{0,j,k}) \bullet \sigma^2_{f_k}$$

The model therefore relates the observed lead-lag structure of stock returns to delayed reaction to common factors. It also allows for asymmetric cross-correlations as observed in the Lo & MacKinley study where large stock returns were found to lead small stock returns but not vice-versa. Jegadeesh and Titman examine the same strategy as Lo & MacKinley where the portfolio weight for stock i at time t is:

$$w_{i,t} = -\frac{1}{N}(r_{i,t-1} - \bar{r}_{t-1})$$

where $\bar{r}_{t-1}$ is the equally weighted index return and N is the number of stocks. The contrarian profit is then given by:

$$\pi_t = -\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - \bar{r}_{t-1}) \bullet r_{i,t} \quad \text{and}$$

$$E(\pi_t) = -E\left[\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - \bar{r}_{t-1}) \bullet r_{i,t}\right] = -\sigma_\mu^2 - \Omega - \sum_{k=1}^{K}\delta_k \sigma_{f_k}^2$$

where

$$\sigma_\mu^2 = \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \bar{\mu})^2$$

$$\Omega \equiv \frac{1}{N}\sum_{i=1}^{N}\operatorname{cov}(e_{i,t} - e_{i,t-1}) \text{ and}$$

$$\delta_k \equiv E\left(\frac{1}{N}\sum_{i=1}^{N}(b_{0,i,k}^{t-1} - \bar{b}_0^t) \bullet (b_{1,i,k}^t - \bar{b}_1^t)\right)$$

The expected contrarian profit is therefore decomposed into three components:

(a) A part due to the cross-serial covariance of expected returns, $-\sigma_\mu^2$.

(b) A part due to the average serial covariance of the residual returns, $-\Omega$ and

(c) A part due to delayed reaction to factor realisations, δ_k.

If prices overreact initially to firm specific news and subsequently adjust to equilibrium levels, Ω will be negative and will have a positive contribution to contrarian profits. The term δ_k measures the cross-sectional covariance of contemporaneous and delayed factor sensitivities and may be either positive or negative. Therefore, while overreaction to firm-specific information contributes to contrarian profits, overreaction to common factors can either increase or reduce them. The authors point out that the Lo & MacKinley decomposition measures the delayed reaction effect twice thus leading to incorrect inferences. They test their decomposition on NYSE and AMEX data from 1963 to 1990 assuming a single factor model (value weighted market return and its one period lag). The estimated contrarian profit π is found to be significantly positive and the results suggest that stock prices react to the market with a one week lag. This effect is more pronounced for smaller firms. δ is found to be negative both for the whole sample and for all size quintiles therefore the lead lag structure has a positive contribution to profits. However, this contribution is found to be trivial (less than 1% of total profits). Virtually all profit is attributed to the large negative auto-covariance of the error terms implying strong overreaction to firm-specific news (for lack of a better explanation). Similar results are obtained when the betas are allowed to change over time. Return reversals can therefore result to substantial contrarian profits and their primary cause is the reversal of the firm specific component of returns.

Lehmann (1990) tested a short horizon contrarian strategy using weekly CRSP data on AMEX and NYSE stocks from July 1962 and December 1986. He used formation periods which ranged from 4 days to 52 weeks. Stocks were assigned portfolio weights proportional to the deviation of their formation period return from that of an equally weighted index comprising all eligible stocks. Lehmann found that substantial profits could be made even after accounting for substantial transaction costs. The arbitrage portfolio gained profits in 85-94% of the weeks depending on the investment horizon Most of the loser portfolio profits occurred in the week immediately following the formation period and dissipated thereafter. The winner portfolio had losses in the first week and profits in the following four weeks. The lack of persistence in the reversal effect could be due to the market being efficient in the long run. The author believes that price reversals are due to lack of short-term market liquidity, caused by the inability of market makers to meet demand from impatient traders. Supply pressures are alleviated in the long run and prices return to their fundamental values. Risk changes cannot explain the profits of the short horizon contrarian strategy because systematic short run changes in fundamental values should be insignificant in an efficient market. A potential caveat of strategy is that it may suffer from bid-ask spread, lagged reaction and price pressure effects.

Chang, McLeavey & Rhee (1995) examined the existence of short term contrarian profits in Japan using data between 1975 and 1991 on companies listed in both sections of the Tokyo Stock Exchange. They also considered how these profits are affected by firm size and seasonal patterns. In order to examine the persistence of contrarian profits, they tested holding periods of one up to six months. They found that profits were significant and persisted after differences in systematic risk and size were accounted for. However profits dissipated quickly after the third month and became negative in the fifth and sixth months. Like Gunarante & Yonesawa (1997), they found that contrarian profits did not exhibit strong seasonal patterns and they derived more or less equally from both the winner and loser portfolios.

To summarize, the studies reviewed in this section showed that there exist significant short term contrarian profits. However, in addition to the overreaction hypothesis, these profits are also consistent with delayed reaction to factor realizations. Jegadeesh and Titman (1995) extended the work of Lo & MacKinlay (1990) and provided a framework for examining the sources of such profits. In contrast to Lo & MacKinlay, they showed that, almost all the profit is attributed to overreaction to firm specific events and only a negligible proportion is due to delayed factor reaction.

2.1.4 Methodological Issues

This section reviews a number of studies that focus their criticism on the procedure followed to evaluate the performance of contrarian strategies. These studies argue that contrarian returns are susceptible to a number of microstructure biases and so are not reliable. They identify a number of methodological issues that need to be addressed in order to draw valid inferences about the profitability of contrarian strategies. Estimates of stock and by extension portfolio returns are most commonly affected by bid-ask bias. This issue is explored in Conrad & Kaul (1993). They build on a paper by Blume and Stambaugh (1983) who show that single period returns are positively biased. Researchers usually observe a closing price which may be a bid or an ask price. The observed price may be written as:

$$OP_{it} = (1+\vartheta_{it})P_{it} = P_{it} + e_{it}$$

where OP is the observed price, P is the true price, $E(\vartheta_{it}) = 0$, ϑ_{it} is independent of ϑ_{ik} and P_{ik} for all k. The observed return is then given by:

$$OR_{it} = \frac{OP_{it}}{OP_{it-1}} - 1 = \frac{1+\vartheta_{it}}{1+\vartheta_{it-1}}(1+R_{it}) - 1$$

where R_{it} is the true return. Therefore:

$$E(OR_{it}) = E\{(1+\vartheta_{it})/(1+\vartheta_{it-1})\}[1+E(R_{it})] - 1$$

According to Jensen's inequality $E\{(1+\vartheta_{it})/(1+\vartheta_{it-1})\}>1$ and using a Taylor series approximation: $E(OR_{it}) = E(R_{it}) + \sigma^2(\vartheta_{it-1})$. So single period observed returns are positively biased estimates of true returns. By cumulating single period returns over a long period of time, long-term contrarian strategies cumulate also the bid-ask bias. This bias increases linearly with the measurement interval and is substantially greater for low rather than high priced stocks. If loser firms are on average priced lower than winner firms, the long horizon arbitrage portfolio return will be substantially over-estimated. A large part of the perceived long-term abnormal contrarian return will therefore be spurious. The procedure for cumulating single period returns over long periods of time (i.e. computing CARs) is also conceptually flawed because it implicitly rebalances portfolios to equal weights each period (e.g. month) thus generating substantial transaction costs which are not taken into account. The authors suggest that a more appropriate measure of portfolio performance over long intervals is the holding period return (i.e. the buy and hold return measured over the entire interval). This measure minimises the bid-ask spread bias as well as the implicit transaction costs. Using data on NYSE stocks between 1926 and 1988 and applying the DeBondt & Thaler procedure, Conrad & Kaul found that the average price for losers is $11.48, substantially lower than the average price of $38.576 for winners. After confirming the DeBondt & Thaler results, they used buy and hold returns and found that the arbitrage portfolio earns negative returns in the non-January months. The all-month returns are consistently lower, compared to the DeBondt & Thaler procedure, but still positive. Therefore the January effect accounts entirely for the portfolio's positive performance, contrary to the overreaction hypothesis.

Kaul & Nimalendran (1990) examine the possibility that the observed serial correlation in stock returns may be due to measurement errors rather than investor overreaction. They evaluated the performance of three portfolios of small, medium and large firms respectively using three measures: conventional close price-to-close price returns R_T, bid price-to-bid price returns R_B and their difference $R_D = R_T - R_B$ which measures the bid-ask spread effect. They found that R_T exhibit strong negative autocorrelation in the short term which becomes positive in the long term. The same autocorrelation pattern, only much weaker and only for small firms, occurs when R_B is used. The authors show that the short term negative autocorrelation is due to weekday returns being less volatile than weekend returns. Therefore, the authors conclude, return reversals are more likely due to bid-ask spread rather than investor overreaction. Bid-ask errors were actually found to explain over 50% (23%) of the small (large) firm variance.

Ball, Kothari, and Shanken (1995) build on the work of Conrad and Kaul (1993) and highlight a number of problems in measuring both raw and risk adjusted returns in the context of the DeBondt and Thaler methodology. They first show that losers are on average priced very low hence their returns are very sensitive to measurement errors and other microstructure effects (bid-ask spread, liquidity and transaction costs). A $1/8 increase in the purchase price reduces the average 5-year buy and hold return by 25%. As is shown in other contrarian studies as well, most of the strategy's profitability is due to loser stocks. Therefore contrarian returns are very susceptible to the same biases as loser returns and so very unreliable. Furthermore, the distribution of loser stock returns is highly skewed to the right and so their mean is considerably larger than their median. Comparisons of average loser and winner returns should therefore be done with caution. By simply changing the formation period to June rather than December and even ignoring transaction costs, both raw and abnormal loser returns are drastically reduced implying that the DeBondt and Thaler estimates of contrarian performance are not robust. In fact the risk adjusted performance of the June-end portfolio becomes negative, regardless of the CAPM version used. December-end contrarian returns derive mainly from the winner portfolio and cannot therefore be explained by year-end tax-loss selling. Finally, the authors examine the contrarian portfolio beta at different states of the market and, in agreement with DeBondt and Thaler, find that it is higher in up-market than down-market states. They notice however that, although attractive, the higher up-market beta is accompanied by a not so desirable negative alpha. Ball, Kothari, and Shanken conclude that measurement errors are present in both raw and risk adjusted returns. These errors are more acute for contrarian portfolios because they tend to invest in extremely low priced stocks.

Studies, which provide evidence that stock prices over- or underreact to certain events, argue against market efficiency, since prices do not reflect all available information. Fama (1998) (who introduced event studies) refutes this claim because:

(a) The observed frequencies of both over- and underreaction are the same. Therefore they both have an equally random chance of occurring, which is consistent with the efficient market hypothesis (EMH).

(b) Long-run anomalies are very sensitive to the different methods and models used to estimate expected returns. Most anomalies disappear when different approaches are used so they can be thought of as chance events.

(c) Finally, for a model to be considered as an alternative to the EMH, it must describe reality better than the EMH.

The models used in such studies do not describe reality perfectly so they generate biased results. In contrast to Conrad & Kaul (1993), Fama argues that buy-and-hold abnormal returns accentuate the biases introduced by averages of monthly abnormal returns or cumulative abnormal returns and suggests the use of value- rather than equally-weighted portfolios. He shows that, with the exception of small firms whose returns are in any way not described well by available models, anomalous returns can disappear when either the sample period or the portfolio-weighting scheme or the valuation model is changed. Therefore, the author concludes, the results of most event studies are not reliable because they are sensitive to the methods used. Anomalous returns are most probably observed because of specific samples, the use of wrong methods and valuation models that don't explain reality properly.

2.1.5 Summary

The existence of negative serial correlation patterns in stock returns has cast doubt on the efficient market hypothesis. Such patterns can make future returns predictable and may result in risk-less arbitrage profit by means of a contrarian strategy. The question whether this profit is economically or statistically significant has sparked an intense debate. Two schools of thought have emerged. The first one argues that return reversals are economically exploitable and are the result of irrational investor behaviour. Based on survey data, Kahneman and Trevsky (1982) and Arrow (1982) argued that individuals are not rational, Baysian decision makers but rather tend to overreact to unexpected and dramatic events. DeBondt and Thaler were the first to launch an empirical investigation into this claim and found evidence in support of the overreaction hypothesis. A plethora of both empirical (e.g. Fama & French (1988), Poterba & Summers (1988), Lakonishok, Shleifer & Vishny (1994), Lo & MacKinlay (1990), Lehmann (1990), Jegadeesh and Titman (1995)) and theoretical (e.g. Daniel, Hirshleifer & Subrahmanyam (1998), Shleifer and Vishny (1997)) studies followed providing support to the same hypothesis.

Non-converts to the overreaction hypothesis (e.g. Vermaelen and Verstringe (1986), Chan (1988), Ball & Kothari (1989)) argue that the observed contrarian returns are accompanied by commensurate risk as measured by the CAPM beta. Alternatively the superior performance of loser stocks is attributed to their smaller market capitalisation (e.g. Zarowin (1989, 1990), Fama and French (1986)). As long as size is a good proxy for risk, contrarian returns are consistent with efficiently functioning stock markets. Finally a group of non-partisan studies (e.g. Fama (1998), Ball, Kothari, and Shanken (1995), Kaul & Nimalendran (1990), Conrad & Kaul (1993), Blume and Stambaugh (1983)) point out several procedural errors common in event studies that argue in favour or against market efficiency. They show that the measured stock and portfolio returns are plagued by market microstructure induced biases. Furthermore the results of the aforementioned event studies are sensitive to the different methods and models used to estimate expected returns. Therefore the evidence, presented by both the efficient market hypothesis and the overreaction hypothesis advocates, is debatable.

2.2 Methodology and Data

As it has emerged from the previous section, there are three main thrusts to the criticism of the advocates of the overreaction hypothesis. It was argued that contrarian profits:

(a) are explained by differences in the market capitalisation of the winner and loser portfolios

(b) are explained by the changing risk of these portfolios over time

(c) are spurious in nature because of bid/ask and other microstructure biases in measured portfolio returns.

This section describes in detail how this study attempts to address each of these issues and how the methodology for assessing the profitability of contrarian strategies can be improved.

By concentrating our analysis on a short-term strategy the problems associated with long-horizon strategies are alleviated. For example, time-varying risk can no longer explain the performance of the arbitrage portfolio since the risk of the long and short portfolios does not change very much from one week to the next. As mentioned above, measured returns may suffer from infrequent trading and bid-ask biases. With regard to the former, the entire sample is broken into two sub-samples, consisting of liquid and illiquid shares respectively and the results are compared. Liquid shares are characterised by relatively large daily trading volumes as a proportion of the total number of outstanding shares. The procedure used to assign companies to either of the two samples consists of two steps: The median of the traded volume divided by the number of shares outstanding for each company over the entire sample period is calculated first. The cut-off point of the two samples is then defined as the median of these medians. Companies with a median less (greater) than the cut-off point are assigned to the illiquid (liquid) sub-sample respectively.

Use of buy and hold weekly returns reduces the bid-ask bias but does not eliminate it. Furthermore, the closing price at the Tokyo Stock Exchange (TSE) is defined as the last traded price for the day and is unattainable by any simulated strategy. This renders the simulation results unrealistic. To make the performance of the simulated strategy more plausible we use open or volume weighted average prices (VWAP) to measure portfolio returns. Open prices at the (TSE) are determined by an open auction whereby individual buy and sell orders are aggregated and then the price that equates supply with demand is calculated. As such, open prices are not susceptible to bid/ask bias. Anecdotal evidence suggests that a large proportion of the average daily volume is traded at the open price. Provided that the extra volume generated by our simulated strategy is not very large relative to the average daily traded volume, it should in principle be absorbed by the market at the open auction without having a major effect on the price. Alternatively, portfolio returns may be measured using volume weighted average prices. As the name suggests, a VWAP for a given stock is defined as the volume weighted average of all the prices at which trades for that stock occurred in a given day. Such prices are available from 1996 onwards from Bloomberg[1]. Many stock brokers guarantee execution of their clients' orders at VWAP for a slightly higher fee compared to other types of orders because the broker assumes part of the execution risk. For example, a market open order fee is around 10 basis points whereas the fee for a VWAP order ranges from 12.5 to 15 basis points. Both VWAP and open prices therefore eliminate the bid-ask bias in measured portfolio returns.

All the empirical studies so far examine an arbitrage portfolio which is formed at the end of period t-1 using all available information including the closing price at t-1. Its performance in period t is subsequently measured as the ratio of the closing price at t and the closing price at t-1. In real life though the portfolio positions are not established until the open of the market in period t, therefore the portfolio return suffers from in-sample bias. This bias is more severe for short rather than long-horizon strategies and results in substantially over-estimated contrarian profits as will be shown later. This pitfall is avoided by measuring portfolio returns between the beginning of period t (using the open price at t) and either the end of period t (using the close price at t), or the beginning of period t+1 (using the open price at t+1).

Another common argument against the overreaction hypothesis is that contrarian profits are due to differences in the market capitalisation or the risk of the winner and loser portfolios. However, the portfolio weights in the event studies reviewed herein were not chosen to simultaneously maximize expected return and minimize risk. In short the portfolios examined in the extant literature are not on the efficient frontier and as such they are not efficient. Inferences about market efficiency drawn from evidence based on non-efficient investment portfolios cannot therefore be reliable. In order to counteract this argument, we examine an alternative contrarian

[1] Bloomberg Inc is a commercial provider of real time and historical market data

strategy, which results from maximizing the expected Sharpe Ratio of the investment portfolio. By maximising the Sharpe ratio, we choose arbitrage portfolios that are characterised by minimum risk for any given expected return. By definition, the risk of the arbitrage portfolio is equal to the tracking error between the long and short portfolios. Therefore maximum Sharpe ratio arbitrage portfolios are characterised by minimum risk differences between their long and short sides. The Sharpe Ratio is defined as the average weekly portfolio return divided by its standard deviation and measures the return received for each unit of risk borne by the portfolio

$$SR = \frac{\bar{R_P}}{\sigma_P}$$

The portfolio standard deviation is equal to the square root of its variance, which is given by: $w'Vw$, where w is a Nx1 vector of portfolio weights and V is the NxN variance-covariance matrix of all stocks considered in the optimisation problem. Assuming that stock returns are fully described by a K factor model:

$$R_{it} = \mu_i + \sum_{k=1}^{K} b_{ik} f_k + e_{it} \quad (2.2.1)$$

then

$$V = BV_f B' + \Omega$$

Where μ_i is the unconditional expected return, e_{it} is the residual or firm specific component, f_k is the kth factor realisation and b_{ik} is the sensitivity of stock i to the kth factor, V_f is a KxK variance-covariance matrix of factor returns, B is a NxK matrix of factor sensitivities and Ω is a NxN diagonal matrix with the stock specific variances along the diagonal. Furthermore, by adding appropriate constraints to the objective function we can maximise the expected Sharpe ratio of the arbitrage portfolio while at the same time minimising its sensitivity to specific factors. The portfolio sensitivity to factor k is given by $\sum_i w_i b_{ik}$. Assuming that the factor sensitivities at time t are good forecasts of factor sensitivities at time t+1, the portfolio sensitivity to factor k at time t+1 can be minimized by imposing the following constraint to the optimisation problem: $\sum_i w_i b_{ik} = 0$. The same constraint can be used to minimise the arbitrage portfolio's exposure to any given attribute, like size for example. An additional constraint sets the sum of the weights to 0 thus ensuring that we have a zero net investment.

Therefore optimal portfolio weights are derived by solving the following constrained optimisation problem:

$$\text{Max } SR = \frac{\bar{R}_P}{\sigma_P}$$

$$\text{Subject to} \sum_i w_i b_{ik} = 0, \text{ k=1, 2...and}$$

$$\sum_i w_i = 0$$

By setting the portfolio sensitivity to factor k equal to zero at time t does not necessarily imply zero sensitivity at time t+1. The optimisation problem is conditional on information available at time t. If factor sensitivities are time varying, it is impossible to completely avoid exposure to any given factor unless we have perfect foresight of future factor sensitivities. Notice that when portfolio weights are multiplied by a non-zero constant c the Sharpe Ratio remains unchanged since $\frac{\sum cw_i R_i}{\sqrt{cw'Vwc}} = \frac{c\sum w_i R}{c\sqrt{w'Vw}} = SR$ and so the optimisation problem remains unchanged. If, as in Grinold & Kahn (1995), c is chosen so that c=$1/\sum w_i R$ then the numerator in the objective function is always 1 and the maximization problem becomes equivalent to the following:

<u>Optimisation Problem 2.2.1</u>

$$\text{Min } f = \sigma_P \equiv h'Vh \equiv h'(BV_f B'+\Omega)h$$

Subject to $$\sum_i h_i b_{ik} = 0, \text{ k=1, 2...}$$

$$\sum_i h_i = 0$$

and $$\sum h_i R = 1$$

Hence we minimize the denominator of SR subject to $\sum h_i R$ =1, where $h_i = cw_i$, in addition to the old constraints. The market model can be regarded as a special case of

2.2.1 with K = 1. The 1st order conditions for the optimisation problem 2.2.1 are then given by:

$$Vh - \lambda_1 b - \lambda_2 r - \lambda_3 h = 0$$
$$h'r = 1$$
$$h'b = 0$$
$$h'I = 0,$$

Where: $\lambda_1, \lambda_2, \lambda_3$ are the Lagrange multipliers, r is a Nx1 vector of expected returns, b is a Nx1 vector of factor sensitivities and I is a Nx1 vector of ones. The above can be solved for $h, \lambda_1, \lambda_2, \lambda_3$ to give:

Closed Form Solution 2.2.1

$$h = V^{-1}(\lambda_1 b + \lambda_2 r + \lambda_3 I)$$

$$\lambda_1 = \frac{AB(CF - DE + ABF(1 - 1/C))}{(AB - C^2)(AD^2 - ECD + E^2 B - ABF)}$$

$$\lambda_2 = \frac{AB(E^2 - AF) + EC(AD - EC)}{(AB - C^2)(AD^2 - ECD + E^2 B - ABF)}$$

$$\lambda_3 = \frac{AD - EC}{AD^2 - 2ECD + E^2 B - ABF + C^2 F}$$

Where $A = b'V^{-1}b$, $B = r'V^{-1}r$, $C = r'V^{-1}b$, $D = r'V^{-1}I$, $A = b'V^{-1}I$ and $F = I'V^{-1}I$ are all scalars

The weights resulting from the closed form solution 2.2.1, sum to 0 but neither the long nor the short side weights add up to 1 necessarily, implying that both portfolios have a positive (under-invested) or negative (over-invested) cash component at each period. In order to have fully invested portfolios we divide all weights by the sum of the long side weights. The new long and short portfolio weights will thus add up to 1 and -1 respectively. As explained before, this transformation leaves the Sharpe Ratio unaffected. In order to assess how different valuation models affect conclusions about market efficiency, we use both a single index model and a commercially available, multifactor APT type model to generate the inputs to the optimisation process. To the best of our knowledge, such work has not been carried out before in the context of contrarian literature.

The available data consists of 2069 daily observations from January 1994 until May 2002, on the open and closing prices and traded volume spanning a universe of 2359 Japanese companies downloaded from DataStream. The sample comprises 1500 and 576 companies listed in the 1st and 2nd section of the Tokyo stock exchange respectively as well as 314 dead companies. The dead companies sample also includes companies listed in regional exchanges, since DataStream does not provide Stock Exchange information for dead companies. Included in this sample were also subsidiaries of non-Japanese multinational companies, which were manually weeded out from the sample. Weekly returns are calculated by taking every 5th closing price for all stocks in the sample starting from observation 1. The reason for doing so is that each 'weekly' return thus calculated carries 5 trading days worth of information. It is assumed that during 'market' holidays (i.e. when the Stock market is closed) there are no corporate or other news releases that can significantly affect stock prices. There are 5 non-overlapping weekly return series that can be generated starting from observations 1 to 5 respectively. The 1st such series is used to derive all the results presented in this chapter. Results for the remaining 4 series are characterised by slight quantitative differences which are of no consequence to the conclusions drawn herein. The formula used to calculate returns is $R_t = P_t/P_{t-1} - 1$. All the strategies tested require the estimation of a simple market or a multifactor model. Factor exposure estimates for the later are provided by Advanced Portfolio Technologies[2], a company that provides such information commercially to financial institutions. All strategies are simulated from 24-Jul-1995 until 21-May-2002 and use the same sample of companies so that the

[2] APT use internationally recognized codes to identify individual companies such as SEDOLS, ISIN numbers and local exchange codes. DataStream on the other hand use their own proprietary code but also provide SEDOLS as part of the data for each company in their database. These SEDOLS were used to match DataStream with APT data. There are 31 companies in total for which the data cannot be matched. This is because either their SEDOL code is not available or APT does not provide coverage.

results of the simulations are comparable. At each period t, the companies included in the analysis must:

(a) Have more than 30 non-missing weekly returns in the last 78 weeks so as to minimise biases induced by infrequently traded or less-established firms.
(b) Have a non-missing return for period t.
(c) Be part of the APT sample

When the last restriction is relaxed the results do not change substantially with signs and orders of magnitude still the same and only slight numerical differences (3^{rd} or 4^{th} decimal place). Not all companies meet these criteria at all times. Their number varies with a minimum of 1514, a maximum of 1935 and a median of 1767 companies used at different times. The min, max and median number of companies available at different times for the series of weekly returns which are calculated starting from observations 2 to 5 are [1555, 1941, 1781.5], [1549, 1926, 1782], [1488, 1933, 1783] and [1589, 1939, 1787] respectively. Prices with an associated traded volume of zero are set to missing since they are artificial. Finally, estimation of CAPM betas requires the subtraction of a risk free rate of return from the market and the stock returns. In the US this is usually the T-Bill rate. In Japan there is no equivalent rate. Researchers have previously used the call money rate and the 30-day Gensaki (repo) rate. However interest rates in Japan have been very close or equal to zero throughout our sample period, therefore using raw instead of excess returns should make no difference to our results. For example annual interest rates on Certificates of Deposit[3] with terms of less than 30 days from Jan 1995 until May 2002 averaged 0.44%, that's 44 basis points. Since we use weekly data, the equivalent weekly rate should be used as the risk free rate. That is equal to 0.44/52 = 0.0086% which is 0.86 basis points. The Japan Inter-bank 1 Month offered rate over the same period, averaged 47 basis points annually i.e. 0.9 basis points weekly. This represents 0.4% of the average weekly movement of the equally weighted market index over the same period which is equal to 215 basis points.

To summarise therefore this study attempts to rectify several methodological problems identified in the literature review. We simulate a strategy with a holding period of one week which is too short a time for substantial changes in the risk profiles of the winner and loser portfolios to occur. Unlike previous studies we examine optimal investment portfolios that have maximum expected return and zero exposure to systematic risk and/or size thus countering the argument that results are driven by

[3] Source: Bank of Japan website, data is available from January 1995 until present

risk differences in the winner and loser portfolios. In order to mitigate the impact of microstructure biases we use auction determined open prices and volume weighted average prices to estimate portfolio performance. We also split the sample in two halves and examine illiquid companies separately from liquid ones. Portfolio returns are calculated net of trading costs which have largely been ignored by the literature although contrarian returns are very sensitive to them due to the high turnover of the strategy. Unlike previous studies our strategy is simulated entirely out of sample and so portfolio returns do not suffer from in-sample bias. This bias results in substantially over-estimated contrarian profits as will be shown later.

2.3 The Jegadeesh-Titman Decomposition

2.3.1 Ex-Ante Return Decomposition

Table 25 displays the average coefficient values when equation (2.2.1)[4] is estimated over the entire sample using the market return and its 1st lag as regressors. As in Jegadeesh-Titman (JT) (1995), the market returns used to estimate (2.2.1) are value weighted but those used to calculate the portfolio weights are equally weighted. The portfolio weight assigned to stock i at time t is $w_{i,t} = -\frac{1}{N}(R_{i,t-1} - R_{m,t-1})$, where the subscript 'm' indicates the market. Simulated portfolio returns are calculated from 24-Jul-1995 until 21-May-2002. Delta is an estimate of the quantity given by $\delta_k \equiv E\left(\frac{1}{N}\sum_{i=1}^{N}(b_{0,i,k}^{t-1} - \bar{b}_0^t)\bullet(b_{1,i,k}^{t} - \bar{b}_1^t)\right)$, which is the expected value of the covariance between contemporaneous and lagged factor sensitivities. Delta is used to estimate the component of the contrarian profit attributed to delayed reaction to factor realisations.

The coefficient of the market lag is positive but the average T-statistic is very small and so it does not seem to be significant on average. A closer examination reveals that about 32% of the stocks have a statistically significant positive lagged market coefficient value. About 64% of the sample has insignificant lagged-market sensitivity and the rest has significantly negative sensitivity. Therefore over one third of the sample has a statistically significant response to past market returns. The Delta estimate is positive suggesting that delayed reaction to factor realizations will have a negative contribution to the expected contrarian profit. Table 26 shows the components of the estimated contrarian profits for the whole, liquid and illiquid samples. The component, $-\sigma_\mu^2 \times 10^3$, measures the part of the return attributed to the cross-sectional variation of stock returns. Stocks with higher than average expected returns tend to have higher than average realized returns and therefore reduce contrarian profits. The term $-\Omega \times 10^3$ measures the part of the return due to overreaction to firm specific information. Finally, the component $-\delta\sigma_{VWm}^2 \times 10^3$ is the contribution of delayed reaction of stock prices to common factor realizations.

[4] Equation (2.2.1) is: $R_{it} = \mu_i + \sum_{k=1}^{K} b_{ik} f_k + e_{it}$

Table 25 Jegadesh & Titman Decomposition, Sensitivities to contemporaneous and lagged value weighted market returns				
	Constant	Market	Lag(Market)	Delta Estimate
Whole Sample	0.0010 (0.3115)	0.9015 (5.8728)	0.1476 (1.0185)	0.0302
Liquid Sample	0.0007 (0.3323)	1.0533 (8.0419)	0.1341 (0.8691)	0.0248
Illiquid Sample	0.0012 (0.2159)	0.7490 (4.6543)	0.1611 (1.1098)	0.0397

Table 25a Jegadesh & Titman Decomposition, Sensitivities to contemporaneous and lagged equally weighted market returns				
	Constant	Market	Lag(Market)	Delta Estimate
Whole Sample	0.0003 (0.1632)	0.9738 (6.6418)	0.0217 (0.2523)	-0.0484
Liquid Sample	0.0001 (0.1673)	1.1030 (8.6214)	-0.0190 (-0.2799)	-0.0001
Illiquid Sample	0.0005 (0.0710)	0.8440 (5.8007)	0.0625 (0.5786)	-0.0864

Table 26 Jegadesh & Titman Decomposition of Contrarian Profits					
		$-\sigma_{\mu}^{2}\times 10^{3}$	$-\Omega\times 10^{3}$	$-\delta\sigma_{VWm}^{2}\times 10^{3}$	Total
Whole Sample	Value	-0.0439	0.3464	-0.0234	0.033%
	Proportion	-0.1334	1.0515	-0.0710	
Liquid Sample	Value	-0.0229	0.1935	-0.0192	0.023%
	Proportion	-0.1008	0.8527	-0.0846	
Illiquid Sample	Value	-0.0650	0.5020	-0.0308	0.047%
	Proportion	-0.1376	1.0620	-0.0652	

As expected the contribution of the delayed reaction to common factors is negative and most of the return comes from overreaction to the firm-specific component of returns. An important observation is that the average overreaction return for the illiquid sub-sample is more than twice as large as that of the liquid sub-sample suggesting that most of the strategy return comes from the less liquid stocks in the sample. Table 27 provides estimates of the relative contribution of the different sources of contrarian profits allowing for time varying factor sensitivities. According to Jegadeesh & Titman (1995) this is done by estimating the parameters of the following equation:

$$\pi_t = \alpha_0 + \alpha_1 (R_{VWm,t-1} - \bar{R}_{VWm})^2 + \gamma \vartheta_{t-1} + u_t$$

Where π is the contrarian return and $\theta_t = \frac{1}{N}\sum_{i=1}^{N} e_{i,t}^2$. Estimates of contrarian profits due to delayed reaction to the common factors and to overreaction are given by $\alpha_1 \sigma_{VWm}^2$ and $\gamma\left(\frac{1}{T}\sum_{t=1}^{T} \vartheta_{t-1}\right)$ respectively. An estimate of ϑ is obtained using the residuals from equation. (2.2.1). These results reinforce the results in table 26. It is worth noting that the largest part of the return is due to overreaction, for all three samples. The delayed reaction to common factors contributes negatively to the strategy profits for all samples but this contribution is much larger for the liquid sample than for the illiquid sample. This result in itself would lead us to believe that the prices of illiquid stocks react more promptly and fully to the market, which seems counterintuitive. Table 25 though shows that the coefficient of the lag of the market return is on average very small and insignificant. Moreover, the coefficient of the market return is on average almost equal to 1 for the companies in the liquid sample but significantly less than 1 for the companies in the illiquid sample. This may be so because the market return is constructed as a value weighted index and is therefore more correlated with the larger companies in the sample, which also happen to be the most liquid. An alternative explanation is that the returns of illiquid companies are driven more by company specific factors rather than market considerations. To gain some insight into which interpretation may be true, we re-produce the results of Tables 25 and 27 in tables 25a and 27a respectively, using the returns of an equally weighted market index. The results are remarkably similar when equally weighted returns are used. The average market return coefficient for liquid stocks is still considerably larger than for illiquid stocks. Delayed reaction to factors seems to contribute very little to the profits of the illiquid sample. This, in conjunction with the lower average correlation of these stocks with the market, suggests that their returns are driven to a lesser extent by market considerations.

Table 27 **Jegadesh & Titman Contrarian Profits Conditional on Lagged Factor Realizations using value weighted market returns**					
	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\gamma \times 10^3$	$\alpha_1 \sigma_{VWm}^2 \times 10^3$	$\gamma\left(\frac{1}{T}\sum_{t=1}^{T}\vartheta_{t-1}\right)\times 10^3$
Whole Sample	-0.0463 (-0.5237)	-67.9895 (-2.3118)	105.2815 (5.2736)	-0.0527 [-0.1600]	0.4130 [1.2539]
Liquid Sample	0.0016 (0.0134)	-109.2188 (-2.6616)	74.7987 (2.9656)	-0.0847 [-0.3731]	0.2981 [1.3134]
Illiquid Sample	-0.0385 (-0. 5887)	-7.8604 (-0.3553)	131.4952 (8.6316)	-0.0061 [-0.0129]	0.5053 [1.0690]

Table 27a **Jegadesh & Titman Contrarian Profits Conditional on Lagged Factor Realizations using equally weighted market returns**					
	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\gamma \times 10^3$	$\alpha_1 \sigma_{VWm}^2 \times 10^3$	$\gamma\left(\frac{1}{T}\sum_{t=1}^{T}\vartheta_{t-1}\right)\times 10^3$
Whole Sample	-0.0805 (-0. 8382)	-68.4401 (-3.9642)	125.3999 (5. 2203)	-0.0618 [-0.1875]	0.4561 [1.3846]
Liquid Sample	-0.0112 (-0.0931)	-127.8514 (-5.3975)	91.4778 (3.1902)	-0.1154 [-0.5085]	0.3389 [1.4932]
Illiquid Sample	-0.0425 (-0.5965)	14.4470 (1.0837)	137.7368 (7.4955)	0.0130 [0.0276]	0.4892 [1.0349]

2.3.2 Ex-Post Return Attribution

The return decomposition proposed by Jegadeesh & Titman breaks down the expected portfolio return into different components. An alternative method of return attribution, which is widely used by investment professionals and also appears in Bachmann-Dubois (1998) (BD), decomposes the realised portfolio return into different components. This method treats weights as constants rather than random variables since they are calculated as a function of realized returns. According to BD, if (2.2.1) describes stock returns then the strategy return at time t is given by:

$$\pi_t = \sum_{i=1}^{N} w_i R_{it} = \sum_{i=1}^{N} w_i\left(\mu_i + \sum_{k=1}^{K} b_{ik} f_k + e_{it}\right) = \sum_{i=1}^{N} w_i \mu_i + \sum_i \sum_k w_i b_{ik} f_k + \sum_{i=1}^{N} w_i e_i$$

So the strategy return can be broken into 3 parts: an idiosyncratic part consisting of the weighted sum of the idiosyncratic stock returns, a systematic part attributed to the influence of common factors including lagged factors and a residual part attributed to over and underreaction to firm specific news.

Table 28
Ex-Post Return attribution: Simple market model with market lag

Portfolio			Total	a	b_0	b_1	Residual
Jegadeesh & Titman Portfolio	Whole Sample	Proportion	1	-0.1093	0.0506	-0.0331	1.0918
		Mean*10³	0.3294	-0.0360	0.0167	-0.0109	0.3596
		T-Stat,H0: X = 0	9.4916	-8.1396	0.9109	-1.6215	11.8959
	Liquid Sample	Proportion	1	-0.1657	0.0413	-0.1098	1.2342
		Mean*10³	0.2269	-0.0376	0.0094	-0.0249	0.2801
		T-Stat,H0: X = 0	4.968	-6.5245	0.3642	-2.7291	8.2495
	Illiquid Sample	Proportion	1	-0.0713	0.0601	0.0187	0.9926
		Mean*10³	0.4727	-0.0337	0.0284	0.0088	0.4692
		T-Stat,H0: X = 0	11.949	-10.914	2.5922	1.4717	12.0852

Table 28 presents the results of this decomposition. Estimates of the factor sensitivities of stock returns are obtained from equation (2.2.1) which is estimated for each period t using the most recent 78 weekly returns. This allows for time variability in the factor sensitivities. Stocks with fewer than 30 returns at time t (i.e. in the last 78 weeks) are excluded from all calculations for that period, thus avoiding biases induced by infrequently traded or less-established firms. T-statistics are corrected for serial correlation of order up to 5. The 1st value in this row is the T-statistic of the average weekly strategy return, which rejects the null that the mean return is 0 for all samples. The average weekly return for the whole sample is 0.032% and the annualized Sharpe Ratio is 3.51. It is evident from Table 28 that, for all samples, the largest proportion of the contrarian profit is attributed to the residual return which is associated with overreaction. The contribution of the lagged factor value is negative for the whole and liquid samples and positive but very small for the illiquid sample, which is in keeping with the results in Table 26. The average return for the illiquid sample is more than twice as large as that of the liquid sample. This result is again in keeping with the results in Tables 26 and 27. Table 26 shows that the expected contrarian profit for the illiquid sample is 0.4062 compared with 0.1514 for the liquid sample. Table 27 shows that the estimates of contrarian profits due to delayed reaction to the common factors and to overreaction for the liquid and illiquid samples are [-0.0847, 0.2981] and [-0.0061, 0.5053] respectively. The fact that most of the strategy profits come from the illiquid part of the sample implies that the strategy's performance in real life would be much poorer than on paper. Illiquid stocks are traded infrequently and in small amounts, therefore a large part of the strategy's profit would not be readily realizable. Furthermore, even small traded nominal values would have a relatively large impact on the price of such shares thus dissipating the potential profit before it is realized.

Table 30
Jegadeesh & Titman Portfolio Ex-Post Return attribution: Simple market model

		Total	a	b_0	Residual
Whole Sample	Proportion	1	-0.1102	0.0517	1.0584
	Mean*10^3	0.3294	-0.0363	0.0170	0.3487
	T-Stat,H0: X = 0	9.4916	-7.8408	0.9397	12.3316

2.3.3 Market Risk of Contrarian Returns

A stock-portfolio is a collection of securities and as such is a synthetic stock itself. The tools used to analyse stock returns should therefore be used to assess the properties of portfolio returns as well. One such tool is the multifactor model used to estimate stock betas with respect to a number of factors. When a given portfolio's returns are influenced by common factors, the effect can be measured by regressing the portfolio returns on the factor realizations, as in equation (2.3.3.1):

$$\pi_t = a + \sum_i b_i f_{it} + e_t,\ f_i : \text{Factor i} \quad (2.3.3.1)$$

Two factors of interest in this study are the market index and its lag and equation (2.3.3.1) in this case becomes:

$$\pi_t = a + b_0 R_{VWm,t} + b_1 R_{VWm,t-1} + e_t \qquad (2.3.3.2)$$

This regression estimates the market beta of the portfolio return. The portfolio beta is by definition equal to the covariance between the portfolio and the market return divided by the variance of the market return. The beta of the market return is equal to one while a risk free asset has a Beta equal to zero. A very small beta therefore would imply a small covariance between the portfolio and the market return i.e. a relatively low risk asset. Alternatively, the estimated beta is by definition equal to the difference between the betas of the long and short sides of the portfolio. The intercept term a is the familiar Jensen performance index. Table 29 presents estimates of regression (2.3.3.2).

Table 29
Regressions of Contrarian Returns on a volume weighted market index and its first lag

	a	b_0	b_1
Whole Sample	0.0003 (10.6792)	0.0043 (3.9489)	-0.0003 (-0.2650)
Liquid Sample	0.0002 (6.1220)	0.0051 (3.5516)	-0.0019 (-1.3441)
Illiquid Sample	0.0004 (16.6287)	0.0032 (3.4391)	0.0015 (1.6124)

The coefficients of the market and the lagged market return are both very small in magnitude indicating very small correlation between the portfolio and the market returns. The T-statistic of the market beta is statistically significant so the beta, although very small, is not zero. The constant term is also statistically significant implying that the mean portfolio return is greater than zero. The regression results in Table 29 then show that the contrarian strategy return is on average larger than zero and bears very small correlation with the market return. It can therefore be assumed that although a very small part of the average portfolio return can be attributed to the assumption of market risk, the market does not play a dominant role in determining such returns. The contrarian portfolio return is in large part free of systematic risk as is also confirmed by the return attribution results in Table 28. The coefficient of the lagged value of the market index is negative, so the strategy returns are negatively correlated with the previous period's market index value. This is in agreement with the results in Tables 25 and 27, which indicate that delayed reaction to common factors contributes negatively to the strategy profits.

2.3.4 The Jegadeesh-Titman Decomposition Using Time-Varying Betas

Results so far have been derived by estimating the 2-factor version of equation 2.2.1 over the entire sample. Therefore the factor sensitivities are constant over time. Alternatively 2.2.1 can be estimated by using a rolling window regression, as above, thus allowing betas to vary over time. Estimates of the JT return components are obtained for each period and then averaged and their means tested as in Bachmann-Dubois (1998). Results are presented in Table 31. Again, most of the return is attributed to overreaction to firm specific information. The component that measures the contribution of delayed reaction to factor realizations is statistically insignificant for all samples. A noticeable difference with the results in Table 26 is the size of the contribution of the cross-sectional variation of expected returns, which now appears to be much larger and significant.

Table 31
Jegadeesh & Titman Decomposition of Contrarian Returns using time varying betas

Portfolio			$-\sigma_{\mu}^{2}\times10^{3}$	$-\Omega\times10^{3}$	$-\delta\sigma_{VWm}^{2}\times10^{3}$
Jegadeesh & Titman Portfolio	Whole Sample	Proportion	-0.6953	1.1497	-0.0690
		Mean*10^3	-0.2290	0.3787	-0.0227
		T-Stat,H0: X = 0	-3.5584	24.8627	-0.9867
	Liquid Sample	Proportion	-0.5678	1.3754	-0.0824
		Mean*10^3	-0.1289	0.3121	-0.0187
		T-Stat,H0: X = 0	-9.0874	23.4499	-1.7512
	Illiquid Sample	Proportion	-0.8097	1.0692	-0.0778
		Mean*10^3	-0.3828	0.5054	-0.0368
		T-Stat,H0: X = 0	-2.5466	22.7762	0.6828

2.3.5 Summary

The results of the Jegadeesh-Titman analysis are dependent on the portfolio weights attributed to each stock in each period, which are proportional to a simple market residual. Therefore the results should in principle not hold when the chosen weights are not simple linear functions of each stock's performance relative to the market index. Furthermore, these weights are thought to maximise the expected contrarian return because larger deviations imply larger reversals. However, large deviations may simply reflect a stock's larger volatility or a larger standard error for the stock's estimated factor sensitivities. The authors provide a convenient and fast way to estimate the magnitude of the expected profit from a specific contrarian strategy, as well as, to what extent this profit bears systematic risk. If the analysis suggests that the estimated profit is significantly larger than zero and only a small part comes from delayed reaction to common factors then one should attempt to further refine the strategy and maximize the expected profit. If on the other hand, the estimated profit is not significantly positive, this should not be interpreted as lack of potential for contrarian profits in the given market. The tested strategy is by no means the strategy with the best risk/reward potential. The desirability of the portfolio tested is questionable since the weights chosen do not maximize expected return nor do they minimize the portfolio's expected exposure to common factor risk.

2.4 Maximum Sharpe Ratio Portfolios

This section presents results for our particular version of the contrarian strategy which involves the use of portfolios which are optimal with respect to their expected Sharpe ratio. As mentioned in the methodology section both a single index model and a multifactor APT type model were used to generate the inputs to the optimisation process. Sub-section 2.4.1 presents results for the single factor asset pricing model while sub-section 2.4.2 presents results for the multifactor model. Finally sub-section 2.4.3 examines the portfolio returns for seasonal patterns

2.4.1 Optimal Portfolios with a Single Factor Asset Pricing Model

The closed form solution to the portfolio optimisation problem requires estimates of the expected returns and variance-covariance matrix of the stocks that comprise the investment universe. These estimates may be derived using a single or a multifactor approach to modelling stock returns. This section will examine optimal portfolios based on the single factor approach.

2.4.1.1 Portfolio Formation

The results in section 2.3 indicate that delayed reaction to factor realisations contributes very little to contrarian profits. The sensitivity to the first lag of the market return is very small on average; however it is statistically significant for 36% of the stocks. Therefore, equation 2.2.1 will be estimated using the market return and its first lag in order to produce the inputs for the closed form solution (2.2.1). Normality tests and portfolio performance results are presented in Tables 32 and 33 respectively. Return attribution results are included in tables 34 and 35. Both tables were derived by using the ex-post return attribution procedure described in Section 2.3. The only difference is that Table 34 presents t-statistics for the null hypothesis that the various return components are equal to zero. In contrast Table 35 presents one tailed tests for two separate null hypotheses:

(a) That the various return components account for 3% or less of the total portfolio return and

(b) That the various return components account for -3% or less of the total portfolio return.

If (a) is accepted and (b) is rejected, the return component accounts for less than 3% in absolute value of the total portfolio return. The scheme used by Lo & MacKinley and Jegadeesh & Titman to allocate portfolio weights to individual securities does not guarantee that these weights add up to 1. This implies that at any time either of the long or short portfolios is over or under invested thus making return comparisons over time spurious. In order to make the JT strategy comparable with the optimised portfolio strategy, both the short and the long portfolio weights are transformed so that they sum up to –1 and 1 respectively. This new portfolio is called the 'JT Portfolio'.

As it has emerged from the literature review, many of the sceptics attribute the contrarian strategy returns to differences in either the average market capitalisation or in the systematic risk between the long and short portfolios. This compelled us to impose two sets of restrictions on the optimal portfolio weights. The first set requires that:

(a) The portfolio sensitivity to the market is zero and

(b) The portfolio sensitivity to the market lag is zero

The vector of historical betas is used as a forecast of period t+1 betas. The exposure of the resulting portfolio to the market index depends on the quality of this forecast. This portfolio is called 'Zero Risk'. The second set of restrictions requires that:

(a) The portfolio sensitivity to the market is zero and

(b) The average size of the long portfolio equals that of the short portfolio

For each stock, size is calculated every 52 weeks as the average market capitalisation over the last 200 trading days (i.e. roughly one calendar year). This portfolio is called 'Zero Size'. Using equation 2.2.1, the residual return for each stock j is calculated as:

$$e_j = R_{j,t} - a_{jt} - b_{j0t} R_{VWm,t} - b_{j1t} R_{VWm,t-1},$$

Where R_j is the stock j return, R_{VWm} is the market return and a_j is the constant of the regression or the stock j abnormal return. The opposite of this residual is taken to be the expected stock return for time t+1. Using the closed form solution (2.2.1) we then get a vector of weights for period t+1, given all the information up to time t. The portfolio return for t+1 is calculated as $R_{P,t+1} = h'_{t+1|X_t} R_{t+1}$, where R is an Nx1 vector of period t+1 returns and N is the number of stocks in the investment universe. The variance-covariance matrix is estimated by: $\tilde{V} = B'V_m B + \Omega$, where B is a Nx2 matrix of market and market lag betas, V_m is the covariance matrix of the market return and its lag and Ω is an NxN diagonal matrix with the variances of the residual stock returns along the diagonal.

2.4.1.2 Performance Comparisons

Table 33 shows that the Sharpe Ratio of the 'Zero Risk' and 'Zero Size' portfolios is 7.81 and 7.99 respectively. In comparison, the JT portfolio has a Sharpe Ratio of 4.68. Thus, by simply changing the way in which portfolio weights are allocated, we managed to improve the strategy's performance significantly in terms of the reward-to-risk ratio. The average weekly return of the JT strategy is both larger and more volatile than that of the optimal portfolio (1.48% vs. 1.27% and 1.29%) and therefore less certain. This is also reflected in the associated t-statistic which is larger for the optimised portfolio returns due to their much smaller standard deviation. The t-statistic values reject the null hypothesis that the average weekly portfolio return is less than or equal to 0.5% for all three portfolios. All the portfolio return series have a few observations that are more than three standard deviations away from their mean. These observations will certainly bias the portfolio beta estimates and will also affect the Sharpe-Ratio estimates. A closer examination of the returns, showed that the average value of all the outlying observations is positive, suggesting that there are more positive than negative outliers. One way of dealing with such observations is truncation, i.e. observations larger (smaller) than the mean plus (minus) three standard deviations are set equal to the mean plus (minus) three standard deviations This will result in both a smaller mean return and associated standard deviation. Table 32 only reports the Berra-Jarque statistic for the truncated portfolio returns. Sharpe ratio values for the raw portfolio returns are reported in brackets in Table 33. The raw return Sharpe Ratio value is always smaller than that corresponding to the truncated returns. This is because although truncation reduces the mean portfolio return, it reduces the standard deviation even more thus resulting in a larger Sharpe Ratio.

Table 32
Normality Statistics of Optimal Portfolios with a Single Factor Asset Pricing Model

Portfolio			Berra-Jarque	Skewness	Kurtosis
Jegadeesh & Titman Portfolio	Whole Sample	Arbitrage	44.6400	-0.2431	1.7182
		Long	26.3943	-0.0537	1.3689
		Short	17.3725	-0.0664	1.1059
	Liquid Sample	Arbitrage	55.3576	-0.3148	1.8862
		Long	22.7639	-0.1927	1.2155
		Short	15.2141	-0.0037	1.0424
	Illiquid Sample	Arbitrage	33.0560	-0.1731	1.4971
		Long	40.3030	0.2411	1.6267
		Short	18.8235	-0.1652	1.1115
Zero Risk Portfolio	Whole Sample	Arbitrage	12.5016	-0.2300	0.8255
		Long	12.4995	0.0669	0.9354
		Short	14.7079	0.0960	1.0068
	Liquid Sample	Arbitrage	18.7016	-0.1847	1.0951
		Long	8.7647	0.0249	0.7897
		Short	14.7364	-0.0192	1.0252
	Illiquid Sample	Arbitrage	3.2848	-0.1268	0.4127
		Long	17.9917	0.1770	1.0769
		Short	15.4816	-0.2824	0.8870
Zero Size Portfolio	Whole Sample	Arbitrage	8.7577	-0.1680	0.7160
		Long	12.3118	0.0725	0.9265
		Short	14.3190	-0.0961	0.9929
	Liquid Sample	Arbitrage	18.8079	-0.1877	1.0966
		Long	8.7361	0.0246	0.7884
		Short	14.7924	-0.0203	1.0271
	Illiquid Sample	Arbitrage	3.2128	-0.1251	0.4085
		Long	17.9806	0.1774	1.0763
		Short	15.3587	-0.2806	0.8843

Table 33

Performance Statistics of Optimal Portfolios with a Single Factor Asset Pricing Model

Portfolio			a	b_0	b_1	R Square	Average Return	Sharpe Ratio
Jegadeesh & Titman Portfolio	Whole Sample	Arbitrage	0.0145 (12.11)	0.1726 (4.07)	-0.0080 (-0.19)	0.0479	1.48% (8.31)	4.68 (4.34)
		Long	0.0071 (6.07)	1.0020 (24.19)	0.0850 (2.05)	0.6378	0.81%	1.52 (1.52)
		Short	0.0076 (8.13)	-0.8306 (-24.97)	-0.0742 (-2.22)	0.6523	0.67%	1.81 (1.53)
	Liquid Sample	Arbitrage	0.0106 (7.33)	0.1906 (3.72)	-0.0020 (-0.04)	0.0400	1.07% (4.06)	2.85 (2.66)
		Long	0.0059 (4.66)	1.1177 (25.02)	0.0874 (1.95)	0.6531	0.68%	1.18 (1.17)
		Short	0.0049 (4.41)	-0.9344 (-23.8)	-0.0714 (-1.81)	0.6305	0.39%	0.98 (0.78)
	Illiquid Sample	Arbitrage	0.0202 (17.9)	0.1379 (3.45)	-0.0014 (-0.03)	0.0346	2.09% (12.44)	6.97 (6.52)
		Long	0.0087 (7.42)	0.8235 (19.9)	0.0697 (1.68)	0.5429	0.97%	2.06 (2.03)
		Short	0.0118 (11.8)	-0.6827 (-19.3)	-0.0441 (-1.24)	0.5286	1.11%	3.13 (2.83)

Table 33 Continued

Portfolio			a	b_0	b_1	R Square	Average Return	Sharpe Ratio
Zero Risk Portfolio	Whole Sample	Arbitrage	0.0123 (20.79)	0.1282 (6.14)	0.0040 (0.19)	0.1016	1.28% (11.44)	7.81 (7.22)
		Long	0.0064 (8.27)	0.8418 (30.49)	0.0626 (2.26)	0.7364	0.71%	1.76 (1.75)
		Short	0.0062 (8.75)	-0.7144 (-28.40)	-0.052 (-2.06)	0.7080	0.57%	1.78 (1.61)
	Liquid Sample	Arbitrage	0.0105 (14.45)	0.1455 (5.67)	-0.0008 (-0.03)	0.0881	1.08% (7.54)	5.47 (5.26)
		Long	0.0058 (7.03)	0.9802 (33.54)	0.0744 (2.54)	0.7717	0.65%	1.42 (1.42)
		Short	0.0049 (6.19)	-0.8325 (-29.60)	-0.0601 (-2.13)	0.7248	0.43%	1.20 (1.07)
	Illiquid Sample	Arbitrage	0.0148 (28.65)	0.0977 (5.34)	0.0083 (0.45)	0.0790	1.54% (14.74)	10.88 (9.69)
		Long	0.0072 (9.04)	0.6718 (23.67)	0.0474 (1.66)	0.6274	0.79%	2.26 (2.22)
		Short	0.0080 (11.29)	-0.5726 (-22.85)	-0.0418 (-1.66)	0.6108	0.75%	2.70 (2.50)

Table 33 Continued

Portfolio			a	b_0	b_1	R Square	Average Return	Sharpe Ratio
Zero Size Portfolio	Whole Sample	Arbitrage	0.0124 (21.31)	0.1286 (6.24)	0.0063 (0.30)	0.1046	1.29% (11.61)	7.99 (7.36)
		Long	0.0065 (8.36)	0.8405 (30.47)	0.0622 (2.25)	0.7362	0.72%	1.78 (1.77)
		Short	0.0063 (8.8)	-0.7138 (-28.3)	-0.0520 (-2.05)	0.7067	0.57%	1.79 (1.63)
	Liquid Sample	Arbitrage	0.0105 (14.44)	0.1452 (5.66)	-0.0002 (-0.006)	0.0878	1.08% (7.53)	5.47 (5.25)
		Long	0.0058 (7.03)	0.9802 (33.52)	0.0749 (2.55)	0.7716	0.65%	1.42 (1.42)
		Short	0.0049 (6.18)	-0.8328 (-29.6)	-0.0599 (-2.12)	0.7245	0.43%	1.06 (1.19)
	Illiquid Sample	Arbitrage	0.0148 (28.6)	0.0974 (5.32)	0.0081 (0.44)	0.0784	1.54% (14.71)	10.86 (9.68)
		Long	0.0072 (9.04)	0.6715 (23.7)	0.0470 (1.65)	0.6271	0.79%	2.26 (2.22)
		Short	0.0080 (11.3)	-0.5728 (-22.9)	-0.0416 (-1.66)	0.6111	0.75%	2.69 (2.50)

By examining the abnormal returns of the portfolios that are formed over the entire sample of companies (Table 33), it emerges that they are fairly symmetric with the long and short sides contributing more or less equally to the arbitrage profits. This is not true when the total portfolio returns are compared; the long side of the arbitrage portfolio seems to contribute slightly more than the short side (roughly 55% and 45% respectively). When the liquid sample is examined, the long portfolio contributes substantially more than the short portfolio for all strategies. In contrast, by examining the illiquid sample, the optimised portfolios are symmetric while the short side contributes relatively more for the JT strategy. The illiquid sample portfolio returns are substantially higher than their liquid sample counterparts for all strategies. Taking the 'Zero Size' strategy as an example, the illiquid sample portfolio outperforms significantly the liquid sample portfolio both in terms of average return and Sharpe Ratio. The average difference of the two return series is 0.46% and its associated t-statistic of 6.55 suggests it is significantly different from zero at the 5% level. Furthermore, the market betas for the illiquid sample's long and short portfolios are lower than their liquid sample counterparts. This implies that the illiquid portfolio returns are rather driven by factors other than the market, such as reaction to firm specific events and microstructure effects. Conrad & Raul (1993) and Ball, Kothari & Shanken (1995) among others have argued that small capitalisation stock returns are more susceptible to measurement errors such as the bid-ask bias. Illiquid stocks tend to be also small in size. The average market capitalization in the sample under investigation is 129,767.8 and 296,166.2 million yen for the illiquid and liquid stocks respectively. The market impact of any given transaction will be relatively larger for illiquid stocks, thus resulting in larger price movements. This makes it more likely that prices of illiquid stocks overreact to firm specific news, which in turn induces higher correlation between current residual and future total returns. Therefore higher returns and lower market betas are symptomatic of measurement errors and lack of liquidity.

2.4.1.3 Return Attribution and Risk Analysis

Table 33 reports the sensitivity of the various portfolio returns to the market index and its first lag over the entire sample period. The market return coefficient is very small in magnitude but statistically significant despite choosing the portfolio weights so that the formation period portfolio beta is always zero. This is partly because the variance-covariance matrix, the stock betas and the stock residual returns are all estimated with error. This makes it very difficult to calculate weights that eliminate systematic risk completely. Another reason is that when time varying betas are assumed, historical betas are not very good forecasts of future betas. An interesting result is obtained when the variance-covariance matrix, the stock betas and the stock residual returns are all estimated using all available time points (i.e. betas are assumed to be constant over time). Portfolio weights are again calculated using equations (2.2.1) but now the vector of Betas and the Variance-Covariance matrix are the same in each period t. The only thing that changes is the vector of expected returns for t+1. All of the average portfolio return in this case is attributed to the residual stock returns by construction as is evident in the table that follows. Nevertheless, the portfolio return has a statistically significant regression coefficient for the market return.

	a	b_0	b_1	**Residual**
Proportion	0.0001	-0.00%	0.00%	99.99%
Mean Value	0.000149%	-0.000045%	0.000054%	1.41%
Regression Value	0.0136	0.1219	0.0076	
T-Statistic	23.12	5.87	0.36	

This result highlights the difficulties in disentangling portfolio returns. Caution should be applied when interpreting results. Although the portfolio beta above is zero by construction, the regression of the portfolio return on the market return rejects the hypothesis that the portfolio beta is zero. It should be borne in mind that betas are estimated with error. Therefore, despite one's best efforts, the optimal portfolio will most likely have a true beta that is not exactly equal to zero. The best that can be done is to construct a portfolio with a very low beta so that the impact of the market on the portfolio return is so small that can be ignored. It can then be argued that stock betas do not really affect portfolio returns. The importance of statistically significant betas should not be over-stated. The explanatory power of the regression is very weak as shown by the R-Square value. The R-Square is an estimate of the proportion of the total variance of the portfolio return explained by the market return and its lag. In this case, the proportion is about 9% as it is also indicated by the small beta values. In agreement with the JT analysis in Section 2.3, the market lag coefficient is insignificant across all portfolios indicating the absence of wide-spread delayed reaction to factor realisations.

All portfolios have positive and statistically significant abnormal returns. This raises questions regarding short-term market efficiency and lends support to the overreaction hypothesis. The abnormal portfolio returns should be zero in an efficient market. In contrast, as is obvious from Table 34, the abnormal stock return a contributes negatively to all arbitrage portfolio profits. This contribution is much larger in magnitude and more significant for the JT portfolio. A possible explanation is that this strategy uses market adjusted returns as trading signals. In the context of a CAPM type valuation model, this return consists of the abnormal return a, the residual return and a part equal to $(b_{j0t} - 1) * R_{VWm,t}$. Therefore the strategy will tend to short high a stocks and buy low a stocks with the arbitrage portfolio having a negative net exposure to a. For the same reason the JT portfolio seems to have a larger proportion of its return attributed to the market beta although the associated t-statistic indicates that it is not significant. However, as mentioned before, the large portfolio-return volatility accounts for the low t-statistic value.

Less than 2% of the average return of the optimised portfolios is attributed to the market index. The rather large associated t-statistics indicate that this proportion is not zero. Once again, the large t-statistic values are a consequence of the low portfolio volatility. It has therefore emerged that high t-statistics are associated with low portfolio volatility and vice versa. This may suggest that the tested null hypothesis should be changed. Comparison of individual return components to zero may be unproductive since a contribution value of 2% is just as insignificant. Table 35 compares return contributions to 3% and -3% of the average portfolio return. Evidently, the substantial negative contribution of the abnormal return is significantly larger (in absolute value) than 3% for the JT strategy. Both the market index component and the lag market component account for less than 3% of the average return for all portfolios. The largest proportion of the return is by far attributed to the residual stock performance, which is associated with overreaction to firm specific news, thus providing overwhelming support to the overreaction hypothesis. T-statistics for the a, b_0, b_1 and **Residual** columns are compared against a critical value of 1.9671 and - 1.9671 for the right and left tail test respectively (2.5% confidence level).

Table 34
Return Attribution for Optimal Portfolios with a Single Factor Asset Pricing Model

Portfolio			Total	a	b_0	b_1	Residual
Jegadeesh & Titman Portfolio	Whole Sample	Proportion	1	-11.59%	3.77%	-1.54%	109.36%
		T-Statistic	12.57	-10.19	1.02	-1.20	15.25
	Liquid Sample	Proportion	1	-16.44%	4.17%	-2.94%	115.21%
		T-Statistic	7.59	-8.62	0.80	-1.54	9.50
	Illiquid Sample	Proportion	1	-7.74%	3.83%	-0.90%	104.81%
		T-Statistic	6.36	-12.75	1.61	-0.93	18.72
Zero Risk Portfolio	Whole Sample	Proportion	1	-1.60%	1.89%	1.68%	98.02%
		T-Statistic	18.82	-1.98	5.24	5.50	19.53
	Liquid Sample	Proportion	1	-2.16%	1.74%	1.56%	98.86%
		T-Statistic	14.02	-1.86	4.39	4.38	14.40
	Illiquid Sample	Proportion	1	-0.96%	2.08%	1.74%	97.14%
		T-Statistic	21.82	-1.87	5.66	6.6	22.92
Zero Size Portfolio	Whole Sample	Proportion	1	-1.56%	1.90%	1.70%	97.95%
		T-Statistic	19.02	-2.01	5.33	5.87	19.68
	Liquid Sample	Proportion	1	-2.15%	1.74%	1.56%	98.86%
		T-Statistic	14.01	-1.86	4.38	4.37	14.39
	Illiquid Sample	Proportion	1	-0.95%	2.08%	1.74%	97.13%
		T-Statistic	**21.79**	-1.86	5.66	6.60	22.87

Table 35
Return Attribution for Optimal Portfolios with a Single Factor Asset Pricing Model

Portfolio			a	b_0	b_1	Residual
Jegadeesh & Titman Portfolio	Whole Sample	Proportion	-11.59%	3.77%	-1.545	109.36%
		H0: X <= 0.03*PR	-12.84	0.20	-3.55	14.84
		H0: X>=-0.03*PR	-7.55	1.83	1.14	15.67
	Liquid Sample	Proportion	-16.45%	4.09%	-2.94%	114.82%
		H0: X <= 0.03*PR	-10.17	0.21	-3.12	9.19
		H0: X>=-0.03*PR	-7.03	1.36	0.026	9.68
	Illiquid Sample	Proportion	-7.74%	3.83%	-0.90%	104.81%
		H0: X <= 0.03*PR	-17.66	0.32	-4.05	18.14
		H0: X>=-0.03*PR	-7.79	2.84	2.17	19.21
Zero Risk Portfolio	Whole Sample	Proportion	-1.605	1.89%	1.68%	98.02%
		H0: X <= 0.03*PR	-5.70	-3.07	-4.31	18.94
		H0: X>=-0.03*PR	1.73	13.56	15.32	20.13
	Liquid Sample	Proportion	-2.16%	1.74%	1.56%	98.86%
		H0: X <= 0.03*PR	-4.45	-3.18	-4.05	13.97
		H0: X>=-0.03*PR	0.73	11.96	12.83	14.84
	Illiquid Sample	Proportion	-0.96%	2.08%	1.74%	97.14%
		H0: X <= 0.03*PR	-7.73	-2.52	-4.76	22.21
		H0: X>=-0.03*PR	3.99	13.84	17.96	23.62

Table 35 Continued						
Portfolio			a	b_0	b_1	**Residual**
Zero Size Portfolio	**Whole Sample**	**Proportion**	-1.56%	1.90%	1.70%	97.95%
		H0: X <= 0.03*PR	-5.81	-3.08	-4.49	19.01
		H0: X>=-0.03*PR	1.86	13.70	16.17	20.21
	Liquid Sample	**Proportion**	-2.15%	1.74%	1.56%	98.86%
		H0: X <= 0.03*PR	-4.45	-3.18	-4.06	13.95
		H0: X>=-0.03*PR	0.73	11.96	12.80	14.82
	Illiquid Sample	**Proportion**	-0.95%	2.08%	1.74%	97.13%
		H0: X <= 0.03*PR	-7.73	-2.51	-4.77	22.16
		H0: X>=-0.03*PR	4.01	13.83	17.97	23.57

2.4.2 Optimal Portfolios with a Multi-Factor Asset Pricing Model

2.4.2.1 Model Description

A company called APT (Advanced Portfolio Technologies) estimate a multi-factor model using weekly return data on about 1800 companies. The sample of companies is selected based on length of trading history, market capitalisation and liquidity criteria. Using factor analysis they extract 20 factors and provide quarterly updates of the set of factor loadings (sensitivities) for all stocks in the investment universe. Robust regression techniques are used to estimate factor loadings for assets outside the sample. The factor returns are linear combinations of stock returns that best explain their historical variance-covariance matrix. The chosen number of 20 factors is coincidental; when the model was developed, FORTRAN did not support dynamic allocation of arrays so the number of 20 factors was settled on since most markets could be modelled adequately with about 15 factors and 20 was a cautious estimate. The 20 factor model has the same form as equation 2.2.1, the only difference being that the term μ_i is now replaced by r_f, the risk free rate of return. All factor returns have an expected value of 0 and are orthogonal by construction. These properties afford us with computational ease of quantities such as the systematic variance-covariance matrix of stock returns which is given by: B*B', where B is the NxK matrix of factor loadings, N is the number of stocks and K the number of factors. Each row of B contains the factor loadings for each stock in the investment universe. So the inner product of row j of B provides an estimate of the systematic variance for stock j. Factor returns are not provided so they have to be estimated from the supplied sets of factor loadings and our sample of stock returns. Residual returns may then be estimated using (2.2.1) The process for estimating factor returns is as follows:

Equation (2.2.1) may be rewritten as:

$$R_t = BF_t + e_t$$

Where:

R is the Nx1 vector of stock returns, B is the NxK matrix of factor sensitivities, F is the Kx1 vector of factor returns and e is the Nx1 vector of residual returns.

The variance-covariance matrix of residual returns is given by, Ω an NxN diagonal matrix with residual variances along the diagonal. If the risk-free rate is not known, the term can be absorbed in the equation, so that we can write:

$$R_t = XZ_t + e_t,$$

Where now X = [B I], I is a Nx1 vector of ones and $Z = [F \; r_f]$

The weighted least-squares solution to this problem is:

$$\tilde{Z} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}R \qquad (2.4.1)$$

Using (2.4.1), we can generate estimates of the time series of factor returns and the risk free rate for each period t and subsequently the residual stock returns can be calculated.

The next sub-section examines two maximum Sharpe Ratio portfolios, when the inputs to the optimisation problem, namely estimates of the expected returns and the variance-covariance matrix of the stocks in the optimisation universe, are calculated using the 20-factor model described above. The first portfolio results from solving the Optimisation Problem (2.2.1) without imposing any constraints on the exposure of the portfolio to various factors or attributes. This portfolio will be called '**APT Unconstrained**'. The second portfolio is constrained to have zero exposure to size as in section 2.4.1 and will be called '**APT Zero Size**'. Results are presented in Tables 36 to 40.

Table 36
Normality Statistics for Optimal Portfolios with a Multi-Factor Asset Pricing Model

Portfolio			Berra-Jarque	Skewness	Kurtosis
APT Unconstrained	Whole Sample	Arbitrage	0.2736	-0.0101	0.1384
		Long	16.9724	0.0738	1.0911
		Short	17.7703	-0.0813	1.1148
	Liquid Sample	Arbitrage	7.6495	-0.0688	0.7263
		Long	12.8647	0.0212	0.9577
		Short	17.2291	-0.0426	1.1061
	Illiquid Sample	Arbitrage	2.2635	0.1221	-0.3194
		Long	30.3619	0.2672	1.3723
		Short	18.7161	-0.2193	1.0698
APT Zero Size	Whole Sample	Arbitrage	0.0698	0.0123	0.0662
		Long	16.8553	0.0755	1.0868
		Short	17.5756	-0.0785	1.1094
	Liquid Sample	Arbitrage	7.5854	-0.0711	0.7222
		Long	12.8963	0.0204	0.9587
		Short	17.2630	-0.0432	1.1070
	Illiquid Sample	Arbitrage	2.3578	0.1262	-0.3236
		Long	30.4695	0.2672	1.3751
		Short	18.5842	-0.2177	1.0667

Table 37
Performance Statistics for Optimal Portfolios with a Multi-Factor Asset Pricing Model

Portfolio			a	b_0	b_1	R Square	Average Return	Sharpe Ratio
APT Unconstrained	Whole Sample	Arbitrage	0.0149 (24.84)	0.1279 (6.00)	0.0136 (0.63)	0.0979	1.55% (13.15)	9.34 (8.55)
		Long	0.0076 (8.11)	0.9501 (28.53)	0.0794 (2.37)	0.7101	0.86%	1.81 (1.80)
		Short	0.0075 (9.60)	-0.8145 (-29.24)	-0.0705 (-2.52)	0.7202	0.69%	1.91 (1.72)
	Liquid Sample	Arbitrage	0.0126 (17.90)	0.1420 (5.68)	0.0101 (0.40)	0.0886	1.30% (9.09)	6.77 (6.50)
		Long	0.0068 (6.96)	1.0624 (30.51)	0.0812 (2.32)	0.7368	0.79%	1.49 (1.51)
		Short	0.0058 (6.83)	-0.9176 (-30.42)	-0.0705 (-2.34)	0.7356	0.52%	1.29 (1.15)
	Illiquid Sample	Arbitrage	0.0185 (29.84)	0.1089 (4.95)	0.0164 (0.74)	0.0693	1.93% (15.85)	11.38 (10.00)
		Long	0.0087 (8.92)	0.7862 (22.70)	0.0777 (2.23)	0.6082	0.96%	2.28 (2.24)
		Short	0.0101 (12.22)	-0.6666 (-22.72)	-0.0677 (-2.230)	0.6087	0.96%	2.93 (2.71)

Table 37 Continued

Portfolio			a	b_0	b_1	R Square	Average Return	Sharpe Ratio
APT Zero Size	Whole Sample	Arbitrage	0.0150 (24.96)	0.1277 (6.00)	0.0132 (0.61)	0.0977	1.56% (13.22)	9.40 (8.60)
		Long	0.0076 (8.13)	0.9496 (28.53)	0.0794 (2.38)	0.7100	0.86%	1.81 (1.80)
		Short	0.0076 (9.60)	-0.8141 (-29.18)	-0.0707 (-2.52)	0.7193	0.69%	1.92 (1.72)
	Liquid Sample	Arbitrage	0.0126 (17.89)	0.1419 (5.68)	0.0104 (0.41)	0.0885	1.30% (9.14)	6.77 (6.50)
		Long	0.0068 (6.97)	1.0623 (30.51)	0.0814 (2.33)	0.7368	0.79%	1.51 (1.52)
		Short	0.0058 (6.84)	-0.9176 (-30.39)	-0.0708 (-2.33)	0.7353	0.52%	1.29 (1.15)
	Illiquid Sample	Arbitrage	0.0185 (29.79)	0.1084 (4.92)	0.0161 (0.73)	0.0686	1.93% (15.62)	11.37 (9.98)
		Long	0.0087 (8.91)	0.7858 (22.69)	0.0775 (2.22)	0.6081	0.96%	2.28 (2.24)
		Short	0.0101 (12.12)	-0.6670 (-22.74)	-0.0677 (-2.29)	0.6091	0.96%	2.93 (2.71)

Table 38
Return attribution for the APT Unconstrained portfolio using the 20 factor model

	Whole Sample		Liquid Sample		Illiquid Sample	
Source	**Proportion**	**T-Stat**	**Proportion**	**T-Stat**	**Proportion**	**T-Stat**
Total	1.0000	19.45	1.0000	21.29	1.0000	14.81
Factor 1	0.0003	0.92	-0.0002	-0.61	-0.0009	-0.78
Factor 2	-0.0007	-1.42	-0.0001	-0.14	-0.0013	-1.36
Factor 3	-0.0005	-1.74	0.0002	0.51	-0.0030	-4.21
Factor 4	-0.0001	-0.47	0.0000	-0.05	-0.0004	-1.01
Factor 5	0.0001	0.93	0.0002	0.98	-0.0003	-0.83
Factor 6	0.0004	1.67	0.0003	1.46	0.0011	1.90
Factor 7	-0.0002	-1.53	-0.0002	-1.17	-0.0001	-0.12
Factor 8	-0.0001	-0.47	0.0001	0.57	-0.0004	-0.82
Factor 9	-0.0002	-1.56	-0.0005	-2.33	-0.0004	-1.01
Factor 10	0.0000	0.02	0.0000	-0.25	0.0000	0.09
Factor 11	0.0000	-0.06	-0.0005	-2.24	0.0004	1.00
Factor 12	0.0000	0.02	-0.0001	-0.58	0.0003	1.30
Factor 13	0.0002	0.78	0.0000	-0.01	0.0003	1.28
Factor 14	-0.0002	-0.85	-0.0002	-0.90	-0.0002	-0.63
Factor 15	-0.0002	-1.70	0.0001	0.34	-0.0003	-0.81
Factor 16	-0.0001	-0.43	0.0001	0.46	-0.0004	-1.09
Factor 17	-0.0002	-1.73	0.0002	1.55	-0.0001	-0.42
Factor 18	0.0000	-0.17	0.0001	0.90	-0.0006	-1.95
Factor 19	-0.0001	-0.70	0.0000	-0.12	-0.0004	-1.49
Factor 20	-0.0001	-0.38	0.0002	1.27	0.0000	-0.17
RF-Rate	0.0000	0.46	0.0000	0.65	0.0001	1.48
Residual	1.0017	19.11	1.0003	20.98	1.0065	14.75

Table 39
Return attribution for the APT Zero Size portfolio using the 20 factor model

	Whole Sample		Liquid Sample		Illiquid Sample	
Source	**Proportion**	**T-Stat**	**Proportion**	**T-Stat**	**Proportion**	**T-Stat**
Total	1.0000	19.48	1.0000	14.81	1.0000	21.23
Factor 1	0.0003	1.11	-0.0009	-0.76	-0.0005	-1.24
Factor 2	-0.0004	-0.70	-0.0012	-1.35	0.0000	-0.07
Factor 3	-0.0007	-1.91	-0.0030	-4.22	-0.0001	-0.26
Factor 4	0.0000	-0.05	-0.0004	-0.99	-0.0003	-0.86
Factor 5	0.0003	1.87	-0.0003	-0.78	0.0002	0.70
Factor 6	0.0005	1.97	0.0011	1.95	0.0006	2.37
Factor 7	-0.0001	-1.09	-0.0001	-0.15	-0.0006	-1.99
Factor 8	-0.0001	-0.36	-0.0004	-0.80	0.0001	0.60
Factor 9	-0.0002	-1.51	-0.0004	-0.95	-0.0006	-2.30
Factor 10	0.0000	0.22	0.0000	0.08	-0.0003	-1.20
Factor 11	0.0000	-0.28	0.0004	0.94	-0.0002	-1.01
Factor 12	0.0000	-0.32	0.0003	1.41	-0.0001	-0.32
Factor 13	0.0001	0.62	0.0003	1.16	-0.0001	-0.23
Factor 14	-0.0001	-0.55	-0.0002	-0.63	0.0000	-0.17
Factor 15	-0.0002	-1.80	-0.0003	-0.82	0.0000	-0.05
Factor 16	0.0000	-0.19	-0.0003	-1.05	0.0001	0.25
Factor 17	-0.0002	-1.50	-0.0001	-0.39	0.0001	0.81
Factor 18	0.0000	-0.01	-0.0006	-1.94	0.0001	0.87
Factor 19	-0.0001	-0.72	-0.0004	-1.52	-0.0001	-0.29
Factor 20	-0.0001	-0.38	-0.0001	-0.21	0.0001	0.83
RF-Rate	0.0000	-0.60	0.0001	1.46	0.0000	1.07
Residual	1.0011	19.16	1.0064	14.76	1.0015	21.26

Table 40
Return Attribution for Optimal Portfolios with a Multi-Factor Asset Pricing Model Using the Market Model

Portfolio			a	b_0	b_1	Residual
APT Unconstrained	Whole Sample	Proportion	-0.0898	0.0291	0.0135	1.0472
		H0: X <= 0.03*PR	-21.00	-0.07	-1.85	20.22
		H0: X>=-0.03*PR	-10.48	5.19	4.88	21.41
	Liquid Sample	Proportion	-0.1071	0.0275	0.0117	1.0680
		H0: X <= 0.03*PR	-17.67	-0.19	-1.93	15.54
		H0: X>=-0.03*PR	-9.94	4.49	4.38	16.44
	Illiquid Sample	Proportion	-0.0704	0.0315	0.0155	1.0236
		H0: X <= 0.03*PR	-25.49	0.13	-1.69	22.25
		H0: X>=-0.03*PR	-10.26	6.18	5.30	23.59
APT Zero Size	Whole Sample	Proportion	-0.0895	0.0286	0.0120	1.0489
		H0: X <= 0.03*PR	-21.11	-0.12	-2.04	20.25
		H0: X>=-0.03*PR	-10.51	5.21	4.76	21.45
	Liquid Sample	Proportion	-0.1071	0.0273	0.0117	1.0681
		H0: X <= 0.03*PR	-17.67	-0.20	-1.92	15.55
		H0: X>=-0.03*PR	-9.94	4.48	4.39	16.45
	Illiquid Sample	Proportion	-0.0705	0.0315	0.0155	1.0235
		H0: X <= 0.03*PR	-25.46	0.14	-1.68	22.19
		H0: X>=-0.03*PR	-10.25	6.20	5.29	23.53

2.4.2.2 Performance Evaluation

Restricting the portfolio exposure to size to be zero does not alter its performance significantly if at all (Table 37). Size does not seem to influence the returns of any of the portfolios examined. Nevertheless, size is very closely related to liquidity. When the universe is split into liquid and illiquid stocks and the strategy is implemented separately on each sub-sample the resulting portfolios are drastically different. It seems therefore that when the entire sample is used, the optimisation process yields portfolios, which are fairly neutral with respect to their exposure to size and to the factors used to calculate the inputs of the optimisation problem. The average size difference between the long and the short side of the unconstrained portfolio is 490 million yen (4.1 million USD) compared with an average size of 221 billion for the entire sample. Both the 'APT Unconstrained' and 'APT Zero Size' portfolios have a higher Sharpe Ratio and average weekly return compared to the portfolios in Section 2.4.1. The weekly return of the 'APT Unconstrained' portfolio is on average 0.28% (7.24) larger than the return of the 'Zero Risk' portfolio and the return difference is statistically significant as shown by the T-statistic value in brackets. The weekly return of the 'APT Zero Size' portfolio is on average 0.27% (7.12) greater than that of its market model counterpart ('Zero Size') and 0.08% (0.94) larger than the average return of the 'JT Portfolio'. Although the average portfolio return is only slightly higher than that of the JT portfolio, the Sharpe Ratio is almost twice as large. So when the objective is to maximise the Sharpe Ratio, the same average weekly return can be obtained but with only half the volatility associated with it. This shows that the portfolio examined by JT is not on the efficient frontier and hence rather undesirable since investors can attain the same return for less risk. Drawing conclusions about market efficiency on the basis of such a portfolio can be specious. Both the 'APT Zero Size' and 'Zero Size' portfolios are formed using the same procedure to calculate portfolio weights and the same investment universe. The only difference is that different models are used to provide estimates of the variance-covariance matrix and the expected stock returns. So the differences in the portfolio performance can only be attributed to differences in the quality of the inputs to the portfolio formation procedure. It seems that the 20–factor model is more precise in estimating the systematic component of the return, thus leading to more accurate estimates of the part of the return closely related to over- or underreaction to firm specific events. Furthermore, better estimates of the variance-covariance matrix of the investment universe, lead to the formation of more efficient portfolios.

The regression (2.3.3.2) results for the APT portfolios are very similar to the results for the portfolios in section 2.4.1. The portfolio beta is again very close to zero and the r-square of the regression is still low indicating that only a very small part of the total variance of the portfolio return is explained by the market. The return attribution tables 38 and 39, constructed using the 20 factor model, show that 100% of the return is attributed to stock residual returns with the average return attributed to all the other factors being negligible. In contrast the market model decomposition in Table 40 shows that both APT portfolios have a significant negative contribution from the stock abnormal return, a. Return proportions attributed to the market are less than 3%, similar to the portfolios examined in section 2.4.1. The portfolio, which is formed using the illiquid part of the sample, outperforms significantly its liquid sample counterpart. Therefore most of the portfolio performance is attributed to the less liquid stocks in the sample. This may be a cause for concern regarding the feasibility of the strategy. If scale is the main concern, the liquid sample results indicate that a healthy

Sharpe Ratio can be achieved by simply concentrating on the more liquid stocks. The strategy can then be implemented by investing nominal amounts that range from very small to very large since a liquid market should be able to absorb such amounts without any serious adverse price movements. If on the other hand, scale is not very important, the strategy can be implemented in its original form.

2.4.3 Seasonal Patterns in Portfolio Returns

Table 41 breaks down the returns off all the portfolios examined so far, into the parts attained in each month of the year. Associated t-statistics are in brackets. All months yield a positive return on average for all portfolios so there is no serious concentration of performance on any given month. April returns are the highest for the first three portfolios and the second highest for the APT portfolios. Most Japanese companies have a March financial year end so at first glance it would appear that there is a tax-loss selling effect. However the Japanese tax code does not share the same peculiarities with the US one. There are three other potential explanations for the higher April returns.

(a) Many Japanese banks have been facing insolvency for a number of years. One very significant asset in their books is large blocks of other firm's shares. There is a concerted effort around the end of each financial year to prop up the value of such shares and therefore allow many banks to meet the solvency criteria.

(b) There is a fundamental shift towards value shares towards the financial year end. Most firms go ex-dividend in March and companies whose share value has been depressed during the year present a good value investment because of their higher dividend yield. Shares of these companies are sold again after their ex-dividend date elapses.

(c) There is anecdotal evidence that the government sometimes intervenes directly to support an otherwise demoralised stock market.

Table 41
Contrarian Return Seasonality

	JT	Zero Risk	Zero Size	APT Zero Risk	APT Zero Size
January	1.81% (2.74)	1.44% (4.81)	1.50% (5.15)	2.29% (7.65)	2.30% (7.71)
February	1.59% (3.48)	1.14% (4.31)	1.14% (4.32)	1.45% (5.23)	1.45% (5.24)
March	1.54% (4.35)	1.49% (9.79)	1.48% (9.77)	1.56% (9.49)	1.56% (9.48)
April	2.28% (3.39)	1.76% (4.42)	1.76% (4.47)	2.04% (6.15)	2.04% (6.15)
May	2.05% (5.40)	1.50% (8.73)	1.50% (8.73)	1.69% (8.70)	1.69% (8.74)
June	1.45% (3.69)	0.97% (6.89)	0.97% (6.98)	1.15% (6.42)	1.14% (6.44)
July	0.75% (3.44)	1.00% (6.11)	1.01% (6.32)	1.22% (7.54)	1.22% (7.56)
August	1.23% (3.53)	1.07% (6.16)	1.08% (6.29)	1.34% (6.22)	1.34% (6.29)
September	0.97% (2.15)	0.99% (4.11)	1.00% (4.22)	1.23% (5.62)	1.23% (5.69)
October	2.05% (4.69)	1.62% (8.89)	1.65% (8.97)	1.98% (9.02)	1.99% (8.99)
November	0.94% (1.99)	1.17% (5.15)	1.19% (5.24)	1.30% (4.83)	1.31% (4.91)
December	1.05% (2.32)	1.13% (4.04)	1.14% (4.03)	1.38% (5.02)	1.38% (5.04)

2.5 Feasibility of contrarian returns.

All the portfolios examined so far yield substantial returns with little exposure to systematic risk. It is paradoxical that although this has been public knowledge for many years, these strategies still continue to yield large returns on paper. One would assume that investors would welcome the opportunity to make some relatively low risk profits until the opportunity disappeared. Shleifer and Vishny (1997) argued that limits to the effectiveness of arbitrage explain the persistence of contrarian profits over time. Another reason may be that when implemented, such strategies yield substantially different results than on paper. This section will show that the contrarian strategies, as perceived and analysed in the extant academic literature, have a strong positive bias and are highly unrealistic.

The returns used to calculate the strategy's performance are usually calculated as the ratio of the difference between two closing prices. This is fine when unrealised returns are calculated and as long as the particular investment is not cashed (liquidated). However, these prices are not feasible. The composition of the portfolio for period t+1 is determined after the closing price at time t becomes known. This price is therefore unattainable during the holding period. The starting value of the portfolio will be determined in the trading day immediately following period t. (the length of each period could be 5, 25, etc days, depending on the periodicity of the returns we analyze) and will depend on the prices at which the portfolio holdings are obtained. A more realistic candidate for the book price of the portfolio holdings would be the open price of the trading day following period t. This is particularly true for the Japanese stock market where most of the day's traded volume is transacted at the open auction. This price will generally be quite different from the closing price of the formation period and as will be shown next, measuring portfolio returns between closing prices overstates portfolio performance. The type of contrarian strategy under investigation assumes that investors overreact to firm specific events therefore driving the stock price too high or too low from what is otherwise justified by the firm's fundamental value. This anomaly will eventually be corrected as contrarian investors step in and take opposite positions. It is reasonable to assume that as more and more investors start to think that a certain price movement is overdone and pluck up the courage to build opposite positions, the price will revert instantly to a new level when the market re-opens and it will start accelerating towards its fair value. This effect will erode the potential contrarian profit. It will also induce high negative correlation between the residual return in period t and the return between the closing price of period t and the opening price of period t+1. The correlation should increase as we move towards the end of period t+1. This is demonstrated in the table that follows:

	CO	CC	5D
Avg. Corr.x 100	- 9.43	-9.97	-11.34
T-Statistic	-37.82	-36.28	-46.53

The CO column shows the average correlation coefficient between the residual return in period t and the return calculated between the close price of period t and the open price of period t+1. Column CC shows the correlation coefficient between the residual return in period t and the return calculated between the closing price of period t and the closing price of the 1st day of period t+1. Finally, column 5D shows the average correlation coefficient between the residual return in period t and the return calculated between the close price of period t and the close price of period t+1 (i.e. the closing price of day 5 in period t+1). Evidently, the average correlation coefficient increases as we move from CC to 5D but the CO coefficient is 83% of the 5D coefficient. Therefore a large part of the return reversal occurs before the market even opens for trading. The above result is reinforced by breaking down daily stock returns into a component measured by the difference between the log of the opening price of day t+1 and the log of the closing price of day t, and a component measured by the difference between the log of the closing price of day t+1 and the log of the opening price of day t+1. The former part is unattainable. Averages over the entire sample are then examined.

Average Proportion of Daily return attributed to time between:	
Close(t)-Open(t+1)	**Open(t+1)-Close(t+1)**
11.85%	88.15%

As can be seen more than 10% of the average daily return occurs while the market is closed implying that, when measured from closing price to closing price, the portfolio performance is overstated by at least 10%. The price at the end of the holding period may be available but it is still not realizable. The closing price in the Tokyo Stock Exchange is defined as the last traded price so the simulated trade price (i.e.

closing price at t+1) will be quite different from the realised price. Return calculations based on this type of price are also very susceptible to the well documented bid-ask bias. Furthermore, the added volume from the portfolio trade will have an adverse impact on the closing price itself, especially when liquidity is low, thus making the reported prices unattainable. The open price on the other hand is formed using an open auction and so there is no bid-ask spread. Quite a substantial proportion of the daily volume is traded at this price so the portfolio trade will be readily feasible and its market impact will be relatively smaller. Open prices therefore are better candidates for assessing the simulated portfolio performance. Volume weighted average prices (VWAP) are also good candidates for simulating the contrarian strategy. As the name suggests, VWAPs are calculated as the volume weighted average of all the traded prices during a given trading day. Many stock brokers guarantee delivery of such prices for a small fee (the author has traded using VWAPs at a cost of around 12 basis points in Japan). Volume weighted average prices are therefore highly feasible, immune to bid-ask biases and not very susceptible to market impact (as long as the additional traded volume from the strategy remains a small proportion of the total volume).

Trading costs have been largely ignored thus leading to grossly overstated portfolio returns. All the portfolios so far are subject to 100% turnover over each holding period implying very high trading costs that could seriously hamper the portfolios' performance. Furthermore, a position is taken in all the stocks in the investment universe even for those with very small residual returns (noise trading) thus assuming contrarian positions on stocks that seem to be fairly priced. This will also have an adverse effect on portfolio performance.

The effects on contrarian profits of the all the issues mentioned before are further analysed by re-examining the **'APT Unconstrained'** portfolio with a few modifications. A trading cost of 20 basis points per trade is assumed for both when the position is established and when it is liquidated. Given that the average cost of trading in Japan ranges from 7bp to 15bp depending on the type of order, the cost assumed here is intentionally higher to account for the probable market impact of the trade. During portfolio formation, the investment universe is sorted by the size of the residual return and it is split into 10 deciles. The eight deciles in the middle are then excluded from the portfolio formation process so that only stocks with a reasonably high residual in absolute value are considered. Both volume weighted and open price based returns are used to evaluate portfolio performance. The tables that follow present performance and risk statistics for strategy returns calculated using the two types of price mentioned before.

APT Unconstrained Portfolio Performance, Entire Sample						
Return Type	**Berra Jarque**	**Skewness**	**Kurtosis**	**Sharpe Ratio**	**Mean Return**	**T-Stat**
Open Price	9.6419	0.2191	0.7048	3.48 (3.37)	1.00%	8.65
VWAP	7.1957	0.2456	0.5222	2.92 (2.83)	0.76%	7.29

APT Unconstrained Portfolio: Beta Estimates, Entire Sample				
Return Type	a	b_0	b_1	**R-Square**
Open Price	0.0096 (9.11)	0.1982 (5.29)	0.0141 (0.37)	0.0777
VWAP	0.0075 (7.60)	0.1708 (4.91)	0.0043 (0.12)	0.0676

APT Unconstrained Portfolio Performance						
Sample	**Berra Jarque**	**Skewness**	**Kurtosis**	**Sharpe Ratio**	**Mean Return**	**T-Stat**
Liquid-Open	8.4317	-0.0743	0.7617	1.92 (1.85)	0.60%	4.99
Illiquid-Open	21.6100	0.3561	1.0180	4.47 (4.14)	1.55%	10.26
Liquid-VWAP	11.0728	0.0224	0.8882	1.72 (1.64)	0.49%	4.24
Illiquid-VWAP	20.1627	0.0160	1.1997	3.53 (3.41)	1.16%	8.42

As expected, there is a drastic drop in the annualised Sharpe Ratio values for both return measures. The average weekly portfolio return, net of trading costs, is still significantly larger than 0.5% but much lower than before. Therefore portfolio performance is grossly overstated when measured using close price returns and ignoring trading costs. When trading costs are taken into account and Open Price returns are used to measure its performance, the original **'APT Unconstrained'** portfolio yields 1.004% (compared to 1.55% before) on average per week with a

Sharpe Ratio of 3.48. Omission of trading costs and use of close price returns overstates the portfolio performance by 0.55%. However, by reducing turnover, contrarian profits still remain significant when more realistic assumptions are made in measuring portfolio performance. When the strategy is simulated over the sub-sample of illiquid stocks, it outperforms significantly its liquid sample counterpart. This is true for both open and VWAP price returns, therefore there is more than just measurement error driving the superior performance of the illiquid sub-sample. Illiquid stocks seem to overreact more intensely to firm specific news.

Conclusion

The aim of this chapter is to examine the existence and significance of contrarian profits in the Japanese stock market. The analysis started with the implementation of the analytical framework provided by JT on data for the Tokyo stock exchange constituent companies from January 1995 until May 2002. The results suggested that a strategy like the one examined by JT can lead to significant contrarian profits. The main source of these profits is overreaction to firm specific events rather than delayed reaction to factor realisations. However the strategy simulated by JT examined a portfolio that was not optimal with respect to its expected return/risk trade-off. The analysis was then extended by examining portfolios on the efficient frontier. The objective was to maximise the expected Sharpe Ratio of a contrarian portfolio. This was equivalent to maximising the portfolio's expected return while at the same time minimizing its volatility. Initially, a simple market model was used to generate estimates of the inputs to the optimisation process. The single index optimal portfolio had a much higher Sharpe ratio than the original JT portfolio. As the complexity of the model increased by adding more factors, so did the Sharpe Ratio reflecting the better quality of the inputs to the optimisation process. When a 20-factor APT type model was used, the Sharpe ratio of the investment portfolio became almost twice as large as that of the JT portfolio.

All the portfolios tested, appeared immune to lagged factor realisations, so the main source of the contrarian profits was overreaction to firm specific events. This was also supported by the return attribution tables which showed that more than 98% of the portfolio return was related to residual stock returns. When the investment universe was split into liquid and illiquid stocks and the contrarian strategy was implemented separately on each sub-sample, the liquid sample portfolio consistently underperformed the illiquid sample portfolio almost by half. Illiquid stocks were found to be more prone to overreaction since their prices are more responsive to demand surges or supply squeezes. The average market Beta was smaller for illiquid than for liquid stocks. This is because illiquid stock prices are driven mainly by firm specific events rather than the market.

Both the Jegadeesh & Titamn (1995) paper and the present study provide a framework for examining a specific class of contrarian strategies, namely strategies that are based on estimates of residual stock performance. Any inference drawn by this analysis cannot be universally applied to all contrarian strategies. Even if the type of strategy tested in this paper proved to be unprofitable or infeasible, this does not mean that the Japanese stock market is efficient and arbitrage opportunities are non-existent altogether. Nevertheless, the strategy tested seems to generate significant profits with the likely assumption of very little systematic risk. The profits are still significant when trading costs are imposed and more realistic assumptions are made regarding the prices at which the portfolio is traded. This raises questions regarding the short-term efficiency of the Japanese stock market.

CHAPTER 3

Pairs Trading in Japan

Introduction

Since its introduction in 1970 by Fama, a vast volume of modern finance literature has been dedicated to the examination of the efficient market hypothesis. According to the strong version of the efficient market hypothesis, all available information is impounded in stock prices and as a consequence efficient markets are characterised by the absence of arbitrage opportunities. A corollary of the efficient market hypothesis is the law of one price: equivalent future payoffs with identical risk profiles should carry the same price. If the prices are different then a riskless profit can be made by selling the expensive and buying the cheap of the two otherwise equivalent payoffs. Practitioners have been engaging in trading pairs of highly correlated securities whose relative prices appear to diverge from their perceived equilibrium level in the belief that the law of one price will eventually drive the two prices back to a level justified by their risk profiles. The sources of the correlation between securities can vary from the purely fundament to the purely statistical. There are relatively very few studies that examine the behaviour of the relative prices of securities linked by a fundamental relationship. For example some papers examine the price differential between voting and non-voting shares of the same company (e.g. Dittman, 2001) while others examine the behaviour of shares of the same company which are traded on different exchanges (e.g. Froot & Dabora, 1999). Besides these fundamentally linked securities though, there are a large number of companies that have similar exposures to a set of common factors that are believed to describe the market adequately. The shares of such companies will exhibit high systematic correlation because of their similar risk profiles. For example competing companies that belong to the same industry group are faced with similar risks and their shares will very likely be highly correlated (e.g. Coca-Cola vs. Pepsi). The aim of this chapter is to (a) develop a framework for identifying and analysing pairs of highly correlated stocks (whatever the reason) and (b) to examine whether deviations of relative stock prices from their equilibrium level can be profitably exploited by using a simple pairs trading rule on Japanese stock market data. An attempt is also made to examine the sources of such profits by drawing analogies between the pairs trading strategy and the contrarian strategy examined by Jegadeesh & Titman (1995) in their very influential article.

The chapter proceeds as follows: Section 3.1 reviews the relevant literature on the behaviour of fundamentally linked securities; Section 3.2 develops the methodology, describes the trading rule and presents the data used to derive the empirical results and finally Section 3.3 presents the results.

3.1 Overview and relevant literature

The concept of market efficiency, introduced by Fama (1970), is of crucial importance as it constitutes a measure of the ability of financial markets to fulfil their economic role of resource allocation. The strong version of the Efficient Market Hypothesis (EMH, hereafter) asserts that all available information is reflected in stock prices (Fama 1991). A more testable form of the EMH is the weak form and is defined as the lack of arbitrage opportunities (Ross, 1987) or the non-existence of trading profits net of costs (Jensen, 1978). Over the last 3 decades, research on market efficiency and asset pricing models across different markets has been overwhelming. However studies suggest that apparent arbitrage opportunities may be illusory due to market imperfections, such as liquidity risk or pitfalls in the methodology employed (e.g. Ball, Kothari & Shanken, 1995).

Pairs trading is a trading strategy widely used by practitioners (Singh, 2002) to exploit perceived pricing anomalies between pairs of highly correlated securities but has nevertheless received little attention from the academic community. The existence of statistically significant profits from the strategy violates the 'no-arbitrage' definition of the efficient market hypothesis and so has very serious implications for the efficiency of relative asset pricing in particular and for market efficiency in general. As the name suggests, the strategy aims to identify pairs of securities whose returns are highly correlated; the implication being that the price of either stock relative to the other will be moving around a mean value over time. The high correlation of the returns will ensure that observed relative price deviations from their mean will eventually be corrected and relative prices will revert to their expected values. If the deviation is large enough (to cover trading costs) and the correction is not instantaneous then it can be economically exploited by selling short and buying equal nominal amounts of the over-performing and under-performing stocks respectively.

The sources of the correlation can be manifold. For example companies within the same industry group that face similar conditions both in terms of demand for their product and supply for primary resources used to produce it will most likely experience relatively high correlation in their returns. This correlation stems from the fact that these companies face similar risks, for example Coca-Cola and Pepsi in the US. The same can be true for companies from different industries. In both cases the underlying relationship between the companies is of a statistical rather than physical nature so such pairings of stocks are commonly referred to as 'statistical'. Different classes of shares of the same company (e.g. voting/non voting, common/preference) will also exhibit very high correlation due to the fact that they all represent shares of equity on the same underlying assets. So will shares of the same company traded on different exchanges (commonly known as 'dual listings') and shares of companies with large cross-ownership interests (e.g. companies with a parent/child relationship). In the first two cases there is a complete overlap in the underlying assets of the correlated shares. In the last case the overlap is partial but in all three cases it represents a more fundamental relationship between the paired shares so such pairs are usually referred to in the professional jargon as 'fundamental pairs'. One major source of risk for the strategy stems from the possibility that what is perceived as a deviation from the expected relationship may transpire to be a permanent shift or even breakdown of the relationship. In this case the expected reversal will never materialise and substantial loses may occur if the relative price of the two stocks moves further away from its perceived equilibrium value. Fundamental pairs are less risky in that respect since the underlying relationship is stronger and therefore more stable over time.

There are no studies that examine the behaviour of the relative price of statistical pairs of securities and only few published papers examine the relationship between the prices of fundamentally linked securities. The majority of these papers focus on the behaviour of the voting premium which is defined as the price differential between voting and non-voting shares of the same company. It will however be instructive to present a few of these papers since there are obvious similarities between the two types of pairs. In a recent study, Dittman (2001) analyses the relationship between voting and non-voting shares of 10 German companies. His study is motivated by a finding common in many previous empirical studies (e.g. Kunz & Angel (1996), Lease, McConnell & Mikkelson (1983), Rydqvist (1996), Zingales (1994)) namely that the voting premium is stationary around a mean value determined by the stock's characteristics. Assuming that log prices behave like random walks, as standard theory and empirical work suggests (Fama, 1970), stationarity of the voting premium implies that the log prices of the voting and the non-voting shares are cointegrated. As the cointegration hypothesis between voting and non-voting shares had not been tested rigorously before, Dittman does so using daily data on ten such pairs of shares traded at the Frankfurt stock exchange. More specifically he tests for the existence of fractional cointegration as opposed to classical cointegration. A linear combination of two series is fractionally or classically cointegrated if it is a long or short memory process respectively. Deviations from the equilibrium value of a long memory process die out eventually (Cheung & Lai, 1993) but tend to last much longer than a short memory process. Therefore adjustment to equilibrium values is faster for classically than fractionally cointegrated series, classical cointegration being a special case of fractional cointegration. It is showed that seven out of the ten pairs examined are indeed cointegrated and that the cointegrating relationship residuals are long memory processes. Dittman argues that the presence of cointegration between securities raises questions about efficiency since, as has been argued before, cointegration is incompatible with efficient markets.

An intense debate about using cointegration analysis to test the efficient market hypothesis was sparked since the advent of this technique. Granger (1986) stated that assets cannot be cointegrated in an efficient market since otherwise one price could be used to forecast the other using the error correction model (ECM) derived from the cointegrating system. If for example the price of the voting shares relative to the non-voting shares is larger than the equilibrium price suggested by the cointegrating equation, then the voting (non-voting) share price must decrease (increase) relative to the non-voting (voting) share price for equilibrium to be restored. It would therefore seem that cointegration is incompatible with market efficiency since according to the strong form of the EMH efficient markets compound all past information into present prices. However some studies like Sephton & Larsen (1991) point out that cointegration test results depend critically on the assumed model or the period analysed. Cointegration tests tend to accept the null of no cointegration more frequently as we increase the number of lagged differences included in the cointegrating regression for residual based tests or the VAR order of the model used to conduct the Johansen test. Others like Hakkio & Rush (1989) note that the EMH is a joint hypothesis that (a) investors are risk neutral and (b) they make rational use of all available information so that speculators have a zero expected return. Violation of either hypothesis will lead to rejection of the joint hypothesis but does not mean that the market is inefficient. Furthermore, as Fama (1991) noted, the necessity to rely on a particular asset-pricing model in many empirical tests of the EMH adds yet another facet to the joint hypothesis. Fama argues that stock prices can be predictable in an efficient market. The strong form of the EMH therefore does not have much economic content and has no connection to the existence of arbitrage profits. A weaker but economically more sensitive version of the EMH is that of Jensen (1978): market efficiency implies that economic profits from trading are zero, where economic profits are risk-adjusted returns net of all costs. Fama (1991) suggests that 'event studies are the cleanest evidence we have on efficiency (the least cumbered by the joint hypothesis problem)'. Event studies, pioneered by Fama et al (1969), enable us to test the hypothesis that new information is rapidly incorporated into asset prices, and that the information currently available cannot be used to derive future abnormal returns. Dwyer & Wallace (1992) argue that with market efficiency defined as the lack of arbitrage opportunities, the existence of cointegrated assets is not equivalent to market inefficiency. In a more recent study Ferre & Hall (2002) built on the work of Dwyer & Wallace and by analysing the relationship between efficiency and cointegration in the foreign exchange market they conclude that cointegrated exchange rates do not necessarily result from an inefficient market. In contrast they provide a theoretical example where lack of cointegration among the exchange rates resulted in violation of the no-arbitrage condition and thus market inefficiency. Ferre & Hall illustrate that the error correction model (ECM) is an expression that can be obtained from any cointegrated system under both efficient and inefficient market conditions. Therefore it is the precise form of the ECM rather than its mere existence that may convey some information about efficiency. More importantly the authors show that since empirical work only deals with partial systems given the intractability of the whole economy, examining efficiency using cointegration can lead to wrong conclusions because of the serious effect of the omitted variables on the results of the analysis.

Froot & Dabora (1999) analyse pairs of large 'Siamese-twin' multinational companies where the distribution of cash flows between them is fixed in their charter. More specifically they examine the shares of Royal Dutch Petroleum versus Shell PLC, Unilever N.V versus Unilever PLC and SmithKline Beecham class A ordinary shares traded in London versus Class E shares traded in New York. All these twins pool their cash flows and their shares represent claims on a fixed proportion of each pooled cash flow. Therefore their share prices should move together at a ratio equal to the proportion of the cash flows. Froot & Dabora find that the relative prices of the twin stocks they examined do not actually behave in that manner but in contrast they are highly correlated with the value of their respective stock market indices. Their evidence suggests that the price differentials of the twin stocks contain unit roots and they are cointegrated with their stock market indices. This means that the price differences are not mean reverting and tend to move together with stock index differences. The authors argue that since all the shares under investigation are among the largest and most liquid in the world, additional costs and informational advantages usually associated with cross-border trading cannot explain the results. The location where each share trades seems to be the overriding factor determining its price. They suggest three possible sources for this market segmentation namely tax-induced investor heterogeneity, noise from irrational traders that tends to affect domestic stocks more than foreign traded stocks and institutional inefficiencies. As the authors admit though, none of these explanations is complete.

In summary, despite its popularity with practitioners, pairs trading has attracted little attention from the academic community. The term 'pair' refers to securities which are highly correlated because they have either some fundamental underlying relationship or similar exposures to market-wide risk factors. In either case there is a compelling reason for the prices of the two securities to move together over time. This co-movement lends it self nicely to analysis by cointegration techniques. The existence of cointegrated assets is identified by some authors (e.g. Granger, 1986) with inefficient markets. This is disputed by others (e.g. Sephton & Larsen 1991, Dwyer & Wallace 1992, Ferre & Hall, 2002) who point out the weaknesses of using cointegration as a market efficiency test. A cleaner way to examine market efficiency pioneered by Fama (1969) is the use of event studies.

3.2. Methodology and data

3.2.1 Introduction

In this section an event study will be simulated in order to examine the efficiency of the pricing of highly correlated securities. The centrepiece of the study is a pairs trading strategy which comprises three basic steps:

(a) The parsimonious calculation of correlations between all securities in the investment universe.

(b) The statistical analysis of the prices of pairs of securities that appear to be strongly correlated, and finally

(c) Based on the results from step (b), the implementation of a trading rule that sells the overvalued and buys the undervalued asset.

The strategy is tested using the same data on Tokyo Stock Exchange traded shares as in Chapter 2. One specific asset pricing model is used, namely the multifactor model provided by Advance Portfolio Technologies and described in detail in Chapter 2.

3.2.2 The Data

The available data consists of 2069 daily observations from January 1994 until May 2002, on the open and closing prices and traded volume spanning a universe of 2359 Japanese companies downloaded from DataStream. The sample comprises 1500 and 576 companies listed in the 1st and 2nd section of the Tokyo stock exchange respectively as well as 314 dead companies. The dead companies sample also includes companies listed in regional exchanges, since DataStream does not provide Stock Exchange information for dead companies. Included in this sample were also subsidiaries of non-Japanese multinational companies, which were manually weeded out from the sample. The strategy tested makes also use of the stocks' factor exposure estimates obtained from a multifactor model provided by Advanced Portfolio Technologies (APT), a company that provides such information commercially to financial institutions. APT provides coverage for a wide range of listed companies in Japan and other developed markets. The DataStream and APT datasets were merged barring 31 companies in total which could not be matched. Prices with an associated traded volume of zero are set to missing since they are not real.

All strategies are simulated from 6-Feb-1996 until 24-May-2002 and use the same sample of companies so that the results of the simulations are comparable. In order to minimise biases induced by infrequently traded or less-established firms, at each period t:

(a) The companies included in the analysis must have more than 260 non-missing daily closing prices in the 520 days prior to the pairs formation date

(b) The price ratio of a pair of securities must have a non-missing value for period t.

(c) The price ratio of a pair of securities must have at least 260 non-missing observations in the 520 days prior to period t.

3.2.3 Asset Pricing models and relative prices

Market efficiency and the law of one price command that cash flows with similar values and risk profiles should have similar prices. As was seen in section 3.1 there is some evidence suggesting that, ceteris paribus, the relative price of highly correlated securities tends to move around a mean value. In this section it will be shown that the co-movement of the prices of highly correlated shares is compatible with a general form of asset pricing model.

The price of a share and its rate of change are determined by the value of the cash flow and its risk characteristics of the company respectively. Shares represent claims on risky cash flows so cash flows with very similar risk profiles should imply share prices that move almost in lockstep. Let's assume that a K-factor asset pricing model provides an adequate description of stock returns. The returns of all N stocks in the investment universe can then be written:

$$R = X^{*}f + u$$

Where R is an N vector of continuously compounded stock returns, X is an N by K matrix of stock factor exposures, f is a K vector of factor returns and u is an N vector of specific returns with zero expected value that cannot be explained by the K factors. Then the continuously compounded returns of stocks i and j are given by:

$$R_{i,t} = X_{ri} f_t + u_{i,t}$$

and

$$R_{j,t} = X_{rj} f_t + u_{j,t}$$

respectively, where X_{rn} is the nth row of X. Applying the expectation operator on both sides of the above equations yields:

$$E[R_{i,t}] = X_{ri} E[f_t]$$

and

$$E[R_{j,t}] = X_{rj} E[f_t]$$

Let's assume that stocks i and j have very similar risk characteristics, therefore $X_{ri} \approx X_{rj}$. Also $R_{n,t} = \log(\frac{P_{n,t}}{P_{n,t-1}})$, $n = i, j$ by definition. The difference of the expected returns of i and j then becomes:

$$E[R_{i,t}] - E[R_{j,t}] = (X_{ri} - X_{rj}) E[f_t] \approx 0 \Rightarrow$$

$$E[R_{i,t}] \approx E[R_{j,t}] \Rightarrow$$

$$E[\log(\frac{P_{i,t}}{P_{i,t-1}})] \approx E[\log(\frac{P_{j,t}}{P_{j,t-1}})] \Rightarrow$$

$$E[\log(\frac{P_{i,t}}{P_{i,t-1}}) - \log(\frac{P_{j,t}}{P_{j,t-1}})] \approx 0 \Rightarrow$$

$$E[\log(\frac{P_{i,t} P_{j,t-1}}{P_{i,t-1} P_{j,t}})] \approx 0 \Rightarrow$$

$$E[\log(\frac{P_{i,t}}{P_{j,t}}) + \log(\frac{P_{j,t-1}}{P_{i,t-1}})] \approx 0 \Rightarrow$$

$$E[\log(\frac{P_{i,t}}{P_{j,t}})] \approx -E[\log(\frac{P_{j,t-1}}{P_{i,t-1}})] \Rightarrow$$

$$E[\log(\frac{P_{i,t}}{P_{j,t}})] \approx E[\log(\frac{P_{i,t-1}}{P_{j,t-1}})]$$

The above relationship implies that the expected log-ratio of the prices of two securities with similar factor exposures will remain more or less constant over time. Therefore extreme deviations from the expected price-ratio should at face value present arbitrage opportunities because they are not sustainable: the price-ratio should in time revert to its mean value.

Two standard assumptions for asset pricing models are that the specific returns u are uncorrelated with the factor returns f and that cov $(u_i, u_j) = 0$ for $i \neq j$. The N by N covariance matrix V of stock returns is then given by:

$$V = XFX' + \Omega,$$

where Ω is the N by N diagonal matrix of residual variance. When the model is well defined and has good explanatory power, the diagonal terms of Ω are very small compared to those of V, i.e. the largest part of the stock variance is explained by the factor model. The covariance between stocks i and j is then given by:

$$V(i, j) = X_{ri} * F * X_{rj}',$$

where F is the covariance matrix of factor returns. The correlation between i and j is given by:

$$Corr(i, j) = \frac{V(i,j)}{\sqrt{V(i,i) + \Omega(i,i)}\sqrt{V(j,j) + \Omega(j,j)}},$$

while the systematic correlation i.e. the part of the total correlation induced by exposure to the common factors is given by:

$$Corr(i, j) = \frac{V(i,j)}{\sqrt{V(i,i)}\sqrt{V(j,j)}}$$

In the extreme case where i and j have identical factor exposures, $X_{ri} = X_{rj}$, we have that V(i,j)=V(i,i)=V(j,j). Furthermore if the variances of i and j are adequately explained by the factor model, $\Omega(i,i)$ and $\Omega(j,j)$ are negligible and $Corr(i,j)$ approaches 1. Therefore stocks that have similar factor exposures have also high systematic correlation. Their total correlation will also be high only if the factor model describes their returns adequately. Thus high systematic correlation does not imply high correlation in general. If the specific component dominates the stock returns of any given pair of stocks, their price paths will most likely be divergent. Although such a pair of stocks will become a candidate for trading on the basis of their similar factor exposures, their relative price may not exhibit the desirable mean reverting behaviour. Cointegration analysis will aid in identifying such pairs and therefore exclude them from the investment universe.

3.2.4 Calculation of correlations

Calculating the covariance matrix of all the stocks in our investment universe can be very complicated and computationally expensive. Factor models provide a parsimonious way for calculating the covariance matrix since all that is needed is the covariance matrix of the factor returns and each stock's residual variance, thus drastically reducing the number of necessary computations. Furthermore, structural multifactor risk models allow for the convenient breakdown of a stock's risk structure into two distinct parts: one attributed to the stock's exposure to a set of common risk factors and the other attributed to the stock's idiosyncratic behaviour.

As mentioned before, estimates of the multifactor model are provided by Advanced Portfolio Technologies (APT). The model is estimated using weekly returns on about 1800 companies listed on the Tokyo stock exchange. The sample of companies is selected based of length of trading history, market capitalisation and liquidity criteria. Using factor analysis they extract 20 factors and provide quarterly updates of the set of factor exposures (sensitivities) for all stocks in the investment universe. Robust regression techniques are used to estimate factor loadings for assets outside the sample. The factor returns are linear combinations of stock returns that best explain their historical variance-covariance matrix. The chosen number of 20 factors is coincidental; APT observed that most markets could be modelled adequately with about 15 factors so 20 is a cautious estimate. All factor returns have an expected value of 0 and are orthogonal by construction so F = I. Each row of X contains the factor loadings for each stock in the investment universe, so the inner product of row j of X provides an estimate of the systematic variance for stock j. These properties afford us with computational ease of quantities such as the systematic covariance matrix of stock returns. The correlation coefficient between stocks i and j is now equivalent to:

$$Corr(i,j) = \frac{V(i,j)}{\sqrt{V(i,i)}\sqrt{V(j,j)}} = \frac{X_{ri}FX'_{rj}}{\sqrt{X_{ri}FX'_{ri}}\sqrt{X_{rj}FX'_{rj}}} = \frac{X_{ri}X'_{rj}}{\sqrt{X_{ri}X'_{ri}}\sqrt{X_{rj}X'_{rj}}}$$

The factor model is estimated quarterly so correlations also change quarterly. After calculating the systematic correlation matrix, all its elements above the main diagonal are sorted in descending order and the pairs of stocks that correspond to the largest 5% of the correlations are formed into a list of candidate pairs for trading.

3.2.5 Statistical analysis of relative prices

It has been shown so far that stocks with comparable risk profiles exhibit high systematic correlation as well as high total correlation provided that the systematic component dominates their returns. Equivalence of the risk profiles also translates into relative stock prices that oscillate around a constant expected value. The expected value of the relative price will remain stable for a long time as long as the overall risk exposures of the pair also remain similar over this period. However companies are living entities thus changing all the time. Each share represents a claim on a series of cash flows resulting from a collection of projects undertaken by the company. The period intervening between inception and implementation of a project is normally measured in years rather than months. Each project carries its own risks that affect the overall company risk. As new projects come to fruition the company risk profile changes accordingly. Unless two companies are faced with the same opportunity set, these changes will not be similar. It is not therefore likely that the systematic correlation between a particular pair of stocks will be stable over time. This is even more true for statistical than for fundamental pairs and is reflected in the correlation matrix which is gradually changing from one period to the next. Therefore the prices of a pair of highly correlated stocks may eventually start diverging so it becomes imperative that before assuming a trading position the stability of the relative price is examined. This should be done over a period of time of some specified length, prior to the trading decision. Testing for the stability of the relative price of the pair is equivalent to testing for the presence of unit roots. The testing procedure chosen for this study is the Augmented Dickey-Fuller test[1] (henceforth ADF). The time series on which the test is applied is calculated as the log of the ratio of the two stock prices that make up the pair. In 3.2.3 it was shown that $E[\log(\frac{P_{i,t}}{P_{j,t}})] \approx E[\log(\frac{P_{i,t-1}}{P_{j,t-1}})]$. It then follows that the price ratio of a pair can be modelled as:

[1] The Phillips-Perron test was also used and the results were qualitatively the same

$$y_t = a + \delta \cdot t + \rho y_{t-1} + e_t,$$

where $y_t = \log(P_{it} / P_{jt}) = \log(P_{it}) - \log(P_{jt})$.

The regression estimated for the augmented test is:

$$y_t = \zeta_1 \Delta y_{t-1} + \zeta_2 \Delta y_{t-2} + \ldots + \zeta_{p-1} \Delta y_{t-p+1} + a + \delta \cdot t + \rho y_{t-1} + e_t$$

The time trend is included because unless the two stocks are identical, their factor exposures and consequently their expected returns will be slightly different thus resulting in slightly different growth rates for the two prices. The price ratio will trend upwards (downwards) when the numerator grows faster (slower) than the denominator and in the case of a stable pair it will be trend stationary. The number of the lagged differences in the augmented regression is determined using the Schwarz criterion (Hubrich, Lutkepohl & Saikkonen, 2001, pp 29). The Schwarz criterion is one of few commonly used criteria for choosing the order of the autoregressive model above and has the desirable property that it chooses the correct model with probability as the number of observations goes to infinity. All the pairs whose price ratio accepts the null hypothesis of a unit root are eliminated from the list of candidate pairs. The remaining pairs are actually used to simulate the trading rule described in the next section.

Since $y_t = \log(P_{it}) - \log(P_{jt})$, testing the log ratio for stationarity is equivalent to testing for cointegration between the log prices of the pair and imposing the restriction that the cointegrating vector is equal to [1, -1]. Alternatively, the Johansen procedure may be used to test for cointegration without imposing any restrictions. A direct estimate of the cointegrating vector is now obtained as a by-product of the test procedure and can be used to estimate the equilibrium price of either stock in the pair with respect to the other. Therefore a separate set of results is presented for the trading strategy, using the Johansen procedure to test for cointegration and estimate the cointegrating vector. The Schwarz criterion is again used to determine the VAR order of the model that is assumed to describe the two log prices. Before testing for the existence of a stationary linear combination of the pair of prices, the individual series must be tested in order to ensure they are not stationary. If either price is found to be stationary, or the null hypothesis of zero cointegrating vectors is accepted, the pair is eliminated from the list of candidate pairs. The rest of the pairs are used to simulate the trading rule.

As mentioned above (Sephton & Larsen, 1991), testing for cointegration is notoriously complicated. A set of variables may be found to be cointegrated or not by simply changing the length of the period over which the test is conducted. The period length chosen to conduct the cointegration tests is 104 weeks. This coincides with the length of the price histories that APT used to estimate their model and is therefore impounded in the systematic correlation estimates thus maintaining consistency.

3.2.6 The trading rule

After eliminating the non-correlated and non-stationary pairs from the list, we are left with a shortlist of pairs that have been stationary over the past 104 weeks. Each pair's relative price, calculated as the log of the price ratio, should oscillate around a mean value. Stationarity confers a certain degree of confidence that large deviations of the log ratio from that mean value will eventually get corrected and the ratio will move back towards its stationary mean. In other words, when the two prices are found to be cointegrated and they start diverging from each other, the built in error correction mechanism will ensure that the prices start converging eventually towards their long-term relative value. A profit can then be made by selling short the relatively expensive and buying the relatively cheap stock. The implicit assumption made here is that the pair will continue to be cointegrated over the strategy's holding period. This is not necessarily true for the reasons given in the previous section. What is perceived as a relatively large deviation from the mean may be movement towards a new equilibrium level or even worse a permanent breakdown in the relationship between the two stocks. The situation just described constitutes a main source of risk for the strategy and necessitates the imposition of a rule that liquidates a given position when the accrued losses exceed a given limit. This rule is known as a stop loss rule. Likewise, aggressive profit taking may be enforced by closing positions as soon as their return exceeds a certain limit. Section 3.3.4 presents results when a stop loss and a profit taking rule are imposed on the strategy. When the strategy is simulated using the ADF test on the relative share price, the log of the price ratio is detrended and demeaned using all the valid observations in the last 13, 26 and 52 weeks preceding the trading date. The resulting series is the residual from the equation: $y_t \equiv \log(\frac{P_{it}}{P_{jt}}) = a + \delta \cdot t + u_t$, which has a zero mean by construction. If the value of the last residual prior to the trading date is larger than 3.5 times its standard deviation then on the trading date equal nominal amounts of stocks i and j are sold short and bought respectively. If the residual value is smaller than minus 3.5 standard deviations then stock i is bought and stock j is sold short. The different periods over which the mean values of the relative prices are calculated will result in different, though in the case of stationary pairs, unbiased estimates of the true mean. This will assist in testing the robustness of the strategy as well as its sensitivity to the choice of estimate for the mean relative price value. When the strategy is simulated using the Johansen procedure to test for cointegration, the cointegrating vector is standardised so that its first element is always 1 and is then used to estimate the cointegrating equation's residuals: $u_t = \log(\tilde{P}_{it}) - cv(2) * \log(\tilde{P}_{jt})$, where cv(2) is the second element of the cointegrating vector and $\tilde{P}_t$ is the demeaned and detrended price. The value of the last residual prior to the trading date is again compared with plus or minus 3.5 standard deviations and long and short positions are opened accordingly. Relative prices deviate from their mean because either stock starts growing faster than its expected return would indicate. Since any stock is highly correlated with a number of other stocks, when its price starts growing faster, more than one of the associated relative prices will also start diverging. Any given stock may then be a member of more than one pairs which satisfy the trading rule. Trading all these pairs would then result in building a very large position in the particular security within a day thus potentially having an adverse effect on its price given its liquidity status. The overall portfolio performance would also become very sensitive to the behaviour of this stock. In order to prevent this situation only the pair with the highest correlation is actually traded for each stock. Finally the pairs of positions thus constructed are held until one of the following events occurs:

(a) The residual u_t described above changes sign or

(b) The price history for either of a pair's components ends

3.2.7 Position weighting schemes

One of the main criticisms of event studies is that their results can be attributed to the different risk profiles of the long and the short sides of the investment portfolio. Statistically significant excess returns occur because the portfolio has a significant net exposure to one or more risk attributes such as size, price/earnings ratio, book value etc. In order to assess the impact of such exposure on the performance of the pairs trading strategy, three alternative ways of calculating the hedge ratio for each pair are employed resulting in three types of investment portfolios. The hedge ratio for a pair is the ratio of the nominal size of the long relative to the short position and can be chosen so as to minimise the pair's exposure to a certain attribute. The three types of pairs examined in this study are:

(a) cash-neutral pairs whereby the amount invested in the long side of the pair exactly offsets the short side resulting in zero net cash exposure. The hedge ratio is always 1 and there is no cash held or borrowed as part of the investment portfolio.

(b) risk-neutral pairs whereby the hedge ratio is chosen to minimise the overall systematic risk of the pair at the time of its inception. The systematic risk of the pair is calculated using the APT model and finally

(c) size-neutral pairs whereby the hedge ratio is chosen to eliminate the pair's exposure to size. Size is measured by market capitalisation and a pair's exposure to size is measured by $HR*MC_L-1*MC_S$, where HR is the hedge ratio and MC_L and MC_S are the market capitalisation of the long and short securities respectively.

The maximum nominal value of a pair's long or short side is one million yen in absolute value. The nominal value of the pair's other component stock is less than or equal to one million yen depending on which of the weighting schemes is used.

3.2.8 Performance evaluation

At the end of each trading day, a portfolio of pairs is formed using the procedure described above. All the positions are actually established when the market opens again the following trading day. Individual positions are terminated when either of the criteria described in section 3.2.6 is met. Therefore on any given day the overall investment portfolio consists of the remaining parts of a number of overlapping portfolios formed since the beginning of the simulation period. Jegadeesh & Titman (1993) argue that examining portfolios with overlapping periods increases the power of the tests applied to the performance of the strategy. They look at portfolios with fixed investment horizons whereby each portfolio is held for a fixed period of time. On any given day, Jegadeesh & Titman calculate each overlapping portfolio's return as the average of the returns of its constituents and the overall portfolio return as the average of the returns of all the overlapping portfolios. This calculation assumes that the overlapping portfolios are rebalanced at the end of each day so that their relative weights remain constant over the entire holding period. The same is assumed for individual holdings within each overlapping portfolio. This calculation offers computational ease however it is neither realistic nor correct because it ignores the impact of transaction costs. The small adjustments entailed by the continuous rebalancing are very costly given the size of the amounts involved and no real life fund manager would actually do that. At the end of each day therefore, each security's weight with respect to the overall investment portfolio is adjusted to reflect the security's performance during that day. Next day's returns are calculated on the basis of these new weights. The daily returns used to evaluate portfolio performance are measured between the open price of days t-1 and t. Using open prices to calculate returns eliminates the bid-ask bias that plagues most studies that use high frequency returns. Open prices at the Tokyo Stock Exchange (TSE) are determined by an open auction whereby individual buy and sell orders are aggregated and then the price that equates supply with demand is calculated.

3.2.9 Summary

In this section it was shown that securities with similar risk profiles have highly correlated expected returns implying that their respective prices move more or less in parallel as long as the risk similarities persist. The co-movement of the prices allows one to deduce the value of one asset relative to the other. Cointegration techniques are most suitable for analysing this relationship and are employed herein to test for its stability over time and to estimate the long term equilibrium value of one price as a function of the other. This leads to the estimation of a 'fair value' which lends it self to comparison with the actual value of the asset. Large deviations between the two values have serious implications about the efficiency of the relative pricing of the two assets and are exploited by a pairs trading rule described above in detail. A number of overlapping buy-and-hold portfolios are created as a consequence, which constitute the overall strategy portfolio. The use of overlapping portfolios increases our confidence in the tests carried out on the strategy portfolio. Portfolio returns are measured using auction-determined open prices thus eliminating the bid ask bias inherent in high frequency data. The strategy is simulated entirely out of sample, meaning that no prior knowledge of future information is assumed at any point during the simulation. Results and inferences are presented in the next section.

3.3. Results

3.3.1 Introduction and preliminary statistics

This section presents the results of the trading strategy described in section 3.2.6 above. As mentioned before several variants of the strategy can be implemented depending on the method used to test for the stability of the relationship between two securities over time. Sub-section 3.3.2 presents the results when the 20-factor APT model is used to calculate the systematic correlation matrix of the investment universe and the augmented Dickey-Fuller test is used to assess the stationarity of the perceived relationship between a pair of securities. Sub-section 3.3.3 presents the results when the systematic correlation matrix is still calculated using the 20-factor APT model but the Johansen methodology is used to both test for the existence and estimate the parameters of a possible stationary linear combination of the prices of a pair of highly correlated stocks. Sub-section 3.3.4 presents results for the strategy used in sub-section 3.3.2 when both a stop-loss and a profit taking rule are used in addition to the existing criteria for terminating a position. Finally sub-section 3.3.5 examines their various sources of all the different portfolio returns.

As mentioned in the introduction to the chapter, the motivation for the pairs trading strategy is the observation that the price ratio of highly correlated securities oscillates around a mean value. If these oscillations are wide enough to cover transaction costs then an arbitrage profit can be made. An obvious question is whether this pattern of behaviour is also displayed by other random combinations of stocks and is not an exclusive characteristic of highly correlated pairs of securities. In order to answer it all the possible pairs of securities in the investment universe are ranked in order of the systematic correlation of their constituents. The top and bottom percentiles of pairs are then allocated into two groups of high and low correlation pairs respectively and the daily first difference of the log-price ratio is calculated for each pair over the three years preceding the pair formation date. This is equivalent to calculating the return of a pair that holds one share of the first security long and one share of the second security short. The first order autocorrelation coefficients of these returns are an indicator of the presence or lack of mean reversal in the pairs' returns. The following table displays the results:

Pair Formation Date	High Correlation Pairs	Low Correlation Pairs
31/12/1996	-0.14567	-0.026937
31/03/1997	-0.14488	-0.026136
30/06/1997	-0.14072	-0.022776
30/09/1997	-0.13387	-0.021447
31/12/1997	-0.14657	-0.01633
31/03/1998	-0.16084	-0.0034715
30/06/1998	-0.16307	-0.014081
30/09/1998	-0.17156	-0.02279
31/12/1998	-0.17743	-0.039738
31/03/1999	-0.1838	-0.042784
10/07/1999	-0.18177	-0.034359
10/10/1999	-0.18285	-0.037865
13/01/2000	-0.18455	-0.036373
14/04/2000	-0.18783	-0.036631
28/06/2000	-0.18858	-0.038372
21/09/2000	-0.18925	-0.044001
31/12/2000	-0.19391	-0.047113
28/03/2001	-0.18582	-0.056017
18/06/2001	-0.18341	-0.056163
28/09/2001	-0.15345	-0.067605
19/12/2001	-0.14605	-0.064799
27/03/2002	-0.14582	-0.062746

It is evident that the high correlation pairs have on average consistently larger autocorrelation coefficients than their low correlation counterparts. Furthermore all the coefficients are negative indicating the presence of mean reversion and possible arbitrage opportunities which the trading strategy in the next two sections will attempt to exploit. The table also shows that there are several pair formation dates. On each of these dates a new set of factor exposures (for the APT factor model) becomes available and, as mentioned in the methodology section, the correlation matrix of the investment universe is calculated using the following formula

$$Corr(i,j) = \frac{V(i,j)}{\sqrt{V(i,i)}\sqrt{V(j,j)}} = \frac{X_{ri}FX_{rj}^{'}}{\sqrt{X_{ri}FX_{ri}^{'}}\sqrt{X_{rj}FX_{rj}^{'}}} = \frac{X_{ri}X_{rj}^{'}}{\sqrt{X_{ri}X_{ri}^{'}}\sqrt{X_{rj}X_{rj}^{'}}}$$

as described in section 3.2.4. The ADF test is also conducted on each of these dates for all pairs using the last 104 weeks of data. The resulting set of stationary pairs remains fixed until the next set of factor exposures becomes available. An implicit assumption made here is that these pairs will remain stationary until the next pair formation date. To test this assumption the ADF test was conducted again on the pairs that were initially identified as stationary, including the roughly 65 daily observations until the next pair formation date. The following table displays the results.

Pair Formation Date	ADF Pass Rate
31/12/1995:	0.73993
31/03/1996:	0.72682
30/06/1996:	0.84188
30/09/1996:	0.76208
31/12/1996:	0.64292
31/03/1997:	0.74981
30/06/1997:	0.67143
30/09/1997:	0.57483
31/12/1997:	0.74094
31/03/1998:	0.76641
30/06/1998:	0.72227
30/09/1998:	0.77145
31/12/1998:	0.71605
31/03/1999:	0.65373
10/07/1999:	0.75242
10/10/1999:	0.77392
13/01/2000:	0.74271
14/04/2000:	0.69962
28/06/2000:	0.75567
21/09/2000:	0.79602
31/12/2000:	0.74518
28/03/2001:	0.71943
18/06/2001:	0.75611
28/09/2001:	0.66904
19/12/2001:	0.75164

The ADF Pass rate shows the percentage of pairs that still test stationary at the 1% level, 65 days after formation. On average 73% of pairs remain stationary between formation dates during the entire simulation period. Trading opportunities arise within the pool of stationary pairs when a price ratio moves 3.5 times its standard deviation away from its estimated mean value. Three sets of mean and standard deviation estimates are calculated over the last 13, 26 and 52 weeks respectively resulting in three different portfolios of pairs namely P1, P2 and P3. Given the fact that, as will be shown in the subsequent sections, the average holding period for any of these strategy variants is at most 67 days we can be fairly confident that most of the pairs will remain stationary during their holding period.

Table 42 Cash-Neutral Portfolios			
	P1 (13 Weeks)	P2 (26 Weeks)	P3 (52 Weeks)
	Portfolio Return Statistics		
Normality Test	848	978	1,855
Critical Value	5.9910	5.9910	5.9910
Skewness	0.4320	0.7660	1.0090
Kurtosis	3.5220	3.5790	4.9680
Average Return	0.1640%	0.1160%	0.0630%
T-Statistic (5%)	8.18	5.54	2.88
Sharpe Ratio	3.3400	2.5800	1.4500
Average Profit/Loss	276,885	293,937	263,086
Total Profit/Loss	428,618,224	455,014,112	407,257,893
Average Portfolio Value	279,084,794	433,494,586	657,962,782
Historic Daily VAR @ 5%	-1,357,228	-2,075,573	-3,283,463
STD's Away From The Mean	1.3802	1.3665	1.3261
	Position Return Statistics		
Normality Test	1,790,636	4,839,447	1,634,853
Skewness	4.9910	7.2580	5.8610
Kurtosis	62.3040	109.6550	70.3020
Sharpe Ratio	7.8700	7.2700	7.4300
Average Daily Return	0.7660%	0.6380%	0.4770%
T-Statistic (5%)	36.56	30.51	26.85
Average Total Return	3.9710%	4.7930%	5.2730%
Total Number of Pairs	10,794	9,493	7,724
Average Daily Holdings	140	217	331
Average Holding Period	20.0200	35.3600	66.2600
Systematic Risk	0.1797	0.1766	0.1752
Average Pair Beta	0.2445	0.2407	0.2432
Average MCap Difference	-10,890,107	-25,782,369	-47,655,709
P(Pair Return > 0)	74.4%	74.6%	74.1%
P(Pair Return < 0)	25.6%	25.4%	25.90%

3.3.2 Multifactor model, augmented Dickey-Fuller test implementation

Table 42 displays the various performance measures for the three cash-neutral portfolios of pairs. Cash neutral pairs are formed by using all the proceeds from the sale of the short stock to buy shares of the long stock thus keeping zero cash. The nominal amount sold and bought is always 1,000,000 Yen. The upper part of Table 42 labelled '**Portfolio Return Statistics**' displays attributes of the resulting long-short portfolio of equities while the lower part shows various statistics for the individual pairs. The Normality Test line shows the Berra-Jarque statistic and is obvious that the all three portfolio returns are highly non-normal. All three portfolio returns are positively skewed implying that large positive returns are more common than large negative returns. The kurtosis estimates for P1 and P2 are around 3 which is the kurtosis of the normal distribution. Therefore the portfolio returns are not characterised by relatively frequent large gains or losses. This is not entirely true for P3 whose kurtosis is close to 5. The average daily portfolio return ranges from 0.164% to 0.116%, to 0.063% for portfolios P1, P2 and P3 respectively and are all statistically significant. The annualised returns are 42.64%, 30.16% and 16.38% which, at least for P1 and P2, are also economically significant considering that trading costs have been removed. The Sharpe Ratio of the portfolios exhibits the same pattern as the portfolio returns: it starts with a large value for P1 and finishes with a small value for P3 reflecting a smaller reward for each unit of risk undertaken. So far it seems that the portfolio performance deteriorates substantially as the length of the window over which the mean and the standard deviation of the pairs' price ratio are calculated, increases. The average daily profit and loss for the three portfolios is 276K, 293K and 263K Yen respectively. However the total profit figures are just over 400 million yen for all portfolios so in that sense P3 performs just as well as P1 and P2. It is also noticed that the number of pairs decreases and the average holding period for each pair increases as we move from P1 to P3. In fact portfolio P3 yields a similar outcome by turning over 3000 and 2000 fewer pairs than P1 and P2 respectively. This outcome though is characterised by higher volatility. The associated historical VAR numbers are calculated at the 5% confidence level and represent the daily loss that is smaller than 95% of all the daily gains and losses that were realised during the simulation period for each portfolio. The absolute VaR figure increases as we move from P1 to P3. Taken at face value this pattern indicates that the potential daily loss is larger for P3 than P1 and therefore P3 is riskier than P1. This assertion is consistent with the fact that the P1 portfolio returns have a higher Sharpe Ratio as mentioned above. Nevertheless, as Duffie & Pan (1997) suggest, 'if the main concern is measuring the VaR of direct exposure to the underlying market a more relevant measure of tail fatness is the number of standard deviations represented by the associated critical values of the return distribution'. In this case the 5% critical value of the daily gain/loss distribution is slightly larger for P1 than for P3 or P2. This indicates that the daily gains and losses are slightly closer to their mean value for P2 and P3 than for P1.

In all three cases the critical VaR values represent roughly -1.3 standard deviations, fewer than in the case of the normal distribution whose 5% critical value is -1.65 standard deviations away from the mean. Concentration of potential outcomes around their mean is a desirable attribute for any successful investment strategy since there is less likelihood of unexpected disastrous outcomes occurring. It also indicates that the strategy's performance is fairly consistent throughout the simulation period and cannot be attributed to a few sporadic and very large gains. This assertion is also reinforced by Figure 3 which shows the cumulative gain/loss for each portfolio. The slope of the curve at a particular point is equal to the gain or loss of the portfolio at that point in time. All three curves are smoothly sloping upwards without any protracted periods of consistently negative slopes. There are also no large jumps or breaks in the diagrams that would indicate the presence of one-off, large gains or losses.

Comparison of the individual position attributes provides a more detailed insight to the strategy's performance. As mentioned before, both the position turnover and the total number of positions decrease as we increase the length of the window over which the mean value and the standard deviation of the pairs' price ratio is calculated indicating that reversal to the mean becomes slower. The average daily return for each pair is defined as the total position return divided by the number of days over which the pair is held. The numbers shown in the row labelled '**Average Daily Return** ' in the second part of the table are calculated by taking the cross-sectional average of this measure over the total number of pairs held in each portfolio over the entire simulation period. As is obvious the average daily position return declines as we move from P1 to P3. The total position return exhibits the opposite pattern reflecting merely the fact that pairs are held longer in P3 than in P1. The normality test indicates that the distribution of the average daily position returns is not normal. However, the distributions of these returns are quite comparable for all portfolios as reflected in the skewness and kurtosis numbers which are very close across the board. All three groups of returns have again positive skewness which roughly means that large positive returns are more common than large negative returns. The kurtosis numbers also indicate fat tails for the distributions of the three groups of returns. The similarity of the position return distributions is further reinforced by the closeness of the corresponding Sharpe Ratio values.

Figure 3

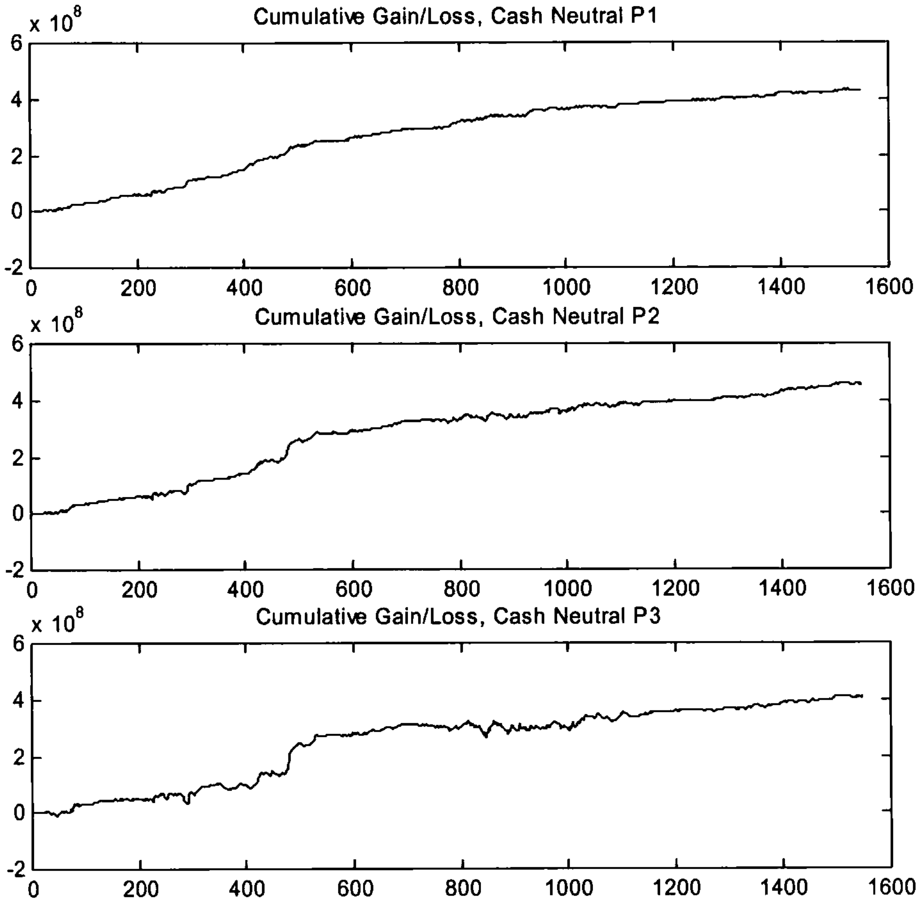
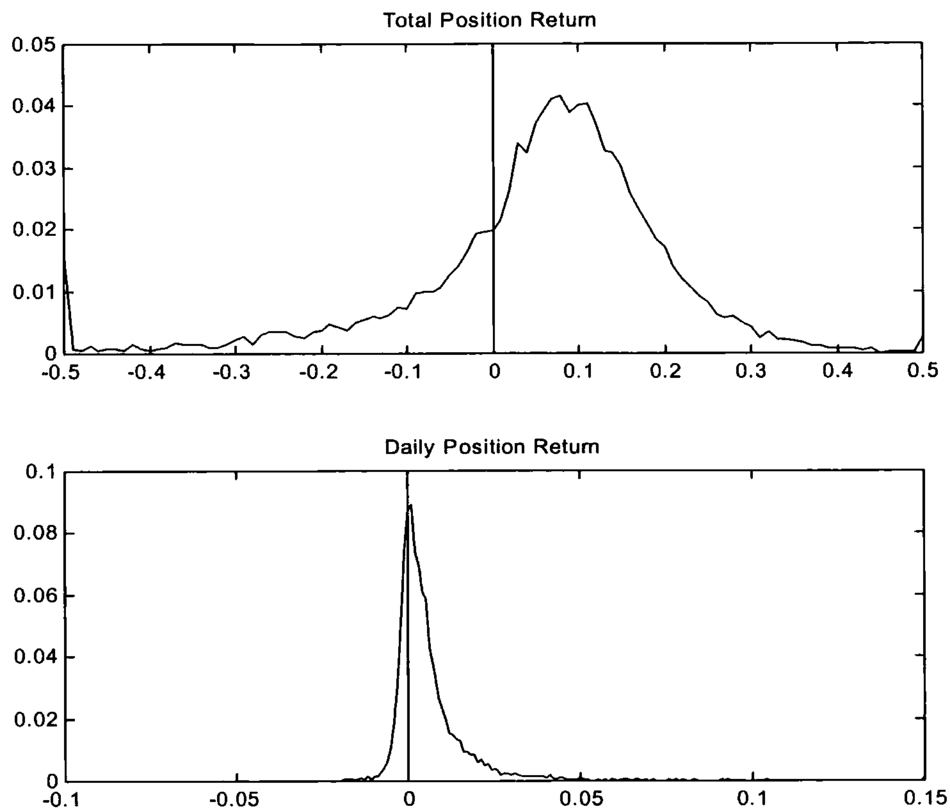

Cumulative Gain/Loss, Cash Neutral P1
x 10^8
6
4
2
0
-2
0
200
400
600
800
1000
1200
1400
1600
Cumulative Gain/Loss, Cash Neutral P2
x 10^8
6
4
2
0
-2
0
200
400
600
800
1000
1200
1400
1600
Cumulative Gain/Loss, Cash Neutral P3
x 10^8
6
4
2
0
-2
0
200
400
600
800
1000
1200
1400
1600

Figure 4



The Sharpe Ratio in this case is defined as the ratio of the cross-sectional average and the standard deviation of the mean daily position return. The Sharpe Ratio figures are again annualised. The last two rows of the table show the proportion of the pairs that yield a positive or negative return respectively. These numbers are also quite similar for all three portfolios. Portfolio P1 has slightly more pairs that have a negative return but overall, about 74% of all positions have a positive return after transaction costs are accounted for which is quite impressive. This implies that only one in four positions held will lose money notwithstanding the fact that the whole trading process is devoid of any human intervention and that there are no stop loss rules in effect. Human supervision could help improve the overall performance by avoiding altogether certain positions (for example buying stock faced with imminent bankruptcy) and by improving the timing of others. Stop loss rules can help mitigate the magnitude of negative outcomes thus both increasing the average gain and decreasing volatility. A graphic display of the distributions of the total position return and the daily position return for portfolio P2 is given by Figure 4. The top half of the graph plots the total returns for all pairs ever held in portfolio P2. The bottom half plots the distribution of the daily returns. For both distributions most of the area under the curve is to the right of the zero return vertical line. Furthermore, it can be seen that the total return distribution has more extreme negative outcomes (returns less than -50%) than positive which reinforces the assertion that the portfolio performance is quite consistent and cannot be attributed to a few lucky strikes. It also highlights the necessity of a stop-loss rule.

The average pair systematic risk is equal to about 18% for all three portfolios of pairs. The systematic risk of a pair is equivalent to the systematic tracking error between the long and the short side of the pair. The average pair beta is negligible for all portfolios and so the strategy's performance cannot be attributed to exposure to market risk. An intriguing result is that the average pair exposure to size decreases as we move from P1 to P3. It was mentioned before that the average holding period also increases as we move from P1 to P3. It would appear therefore that the slower reversal to the mean is associated with larger differences in the market capitalisation of the pair's constituents. There is a vast body of literature on the so called 'size effect' namely the observed over-performance of small capitalisation stocks compared to large capitalisation stocks. All the cash neutral portfolios have negative exposure to size, i.e. the stocks held long have on average smaller market capitalisation than the ones sold short. The presence of the size effect would therefore intensify the out-performance of the short by the long side thus improving the overall portfolio performance. This might indicate that part of the portfolios' performance could well be attributed to the size difference between the pairs' constituents. However this exposure has to be very large on average in order to affect performance. Portfolio P3 which has the largest absolute exposure seems to be the worst performing portfolio. Moreover the two middle quartile points for the average market capitalisation of all the companies in the investment universe over the entire simulation period are 13,762,682,000 and 104,567,588,000. This means that 50% of the investment universe has an average size difference that is larger than 90,804,906,000 which is almost 2000 times the average exposure of P3. Therefore the average size exposure of all three portfolios is rather small to have any effect. A more systematic way to determine how size differences affect performance is to simulate the strategy again by forming size neutral pairs. The magnitudes of the long and the short side of the pair are chosen in a proportion that eliminates the pair's net size exposure. The new proportions assign a larger weight to the long side of the pair to compensate for its smaller market capitalisation. The constituent pairs of the size neutral portfolios P1, P2 and P3 are identical to their cash neutral counterparts. The only thing that is different is the hedge ratio between the long and the short side of each pair. Table 43 displays the results.

Table 43 **Size-Neutral Portfolios**			
	P1 (13 Weeks)	**P2 (26 Weeks)**	**P3 (52 Weeks)**
	Portfolio Return Statistics		
Normality Test	618	437	1,349
Critical Value	5.9910	5.9910	5.9910
Skewness	0.1840	0.4950	0.8050
Kurtosis	3.0730	2.4070	4.2800
Average Return	0.1750%	0.1310%	0.0720%
T-Statistic (5%)	8.73	6.52	3.48
Sharpe Ratio	3.4200	2.8500	1.6700
Average Profit/Loss	217,255	238,801	207,540
Total Profit/Loss	336,310,575	369,664,108	321,272,072
Average Portfolio Value	205,323,266	317,297,866	480,795,247
Historic Daily VAR @ 5%	-1,152,684	-1,764,684	-2,929,138
STD's Away From The Mean	1.3646	1.3811	1.4248
	Position Return Statistics		
Normality Test	2,986,438	5,353,176	3,783,186
Skewness	5.5160	7.0240	7.0620
Kurtosis	80.7370	115.4840	107.4970
Sharpe Ratio	6.8600	6.7300	6.3000
Average Daily Return	0.8120%	0.6690%	0.5020%
T-Statistic (5%)	32.47	29.22	24.4
Average Total Return	4.1880%	5.2510%	5.5930%
Total Number of Pairs	10,794	9,493	7,724
Average Daily Holdings	140	217	331
Average Holding Period	20.0200	35.3600	66.2600
Systematic Risk	0.2078	0.2045	0.2020
Average Pair Beta	0.4706	0.4699	0.4649
Average MCap Difference	0	0	0
P(Pair Return > 0)	71.1%	70.8%	69.2%
P(Pair Return < 0)	28.9%	29.2%	30.79%

As is evident, the average daily returns and the Sharpe Ratios are marginally increased for all portfolios. This means that the portfolio returns have become slightly less volatile. The kurtosis numbers are smaller for the size-neutral portfolios meaning that the portfolio returns exhibit relatively fewer extreme outcomes. This in turn results in smaller historical VAR numbers for the size-neutral portfolios. The individual position returns present a slightly different story. The average total position return is again slightly increased for all portfolios but the standard deviation as well as the kurtosis of those returns has also increased resulting in a smaller return-standard deviation ratio. Nevertheless the main qualitative characteristics of the return distributions remain the same both at the portfolio and at the individual position level. All returns exhibit positive skewness and large kurtosis numbers as in the cash neutral case. The proportion of the positions exhibiting a positive return is slightly lower than before. The smaller number of positive outcomes coupled with their larger average size reflects the larger standard deviation of these outcomes. This might in turn imply that the size-portfolios are slightly riskier than their cash neutral counterparts, an assertion also supported by the larger systematic risk numbers. The average pair betas are also larger than before but still small for all portfolios.

Table 44
Risk-Neutral Portfolios

	P1 (13 Weeks)	P2 (26 Weeks)	P3 (52 Weeks)
	Portfolio Return Statistics		
Normality Test	840	1,339	2,183
Critical Value	5.9910	5.9910	5.9910
Skewness	0.4740	0.8820	1.0820
Kurtosis	3.4810	4.2010	5.4000
Average Return	0.1610%	0.1110%	0.0590%
T-Statistic (5%)	8.17	5.35	2.68
Sharpe Ratio	3.3600	2.5100	1.3700
Average Profit/Loss	228,848	240,361	215,987
Total Profit/Loss	354,256,361	372,078,141	334,348,317
Average Portfolio Value	231,865,308	361,235,637	546,882,617
Historic Daily VAR @ 5%	-975,377	-1,508,250	-2,465,164
STD's Away From The Mean	1.3802	1.354	1.3331
	Position Return Statistics		
Normality Test	1,320,128	3,213,581	2,556,605
Skewness	4.7970	6.8880	6.5120
Kurtosis	53.3220	89.0770	88.1720
Sharpe Ratio	7.5800	7.0000	7.0700
Average Daily Return	0.7300%	0.6100%	0.4570%
T-Statistic (5%)	35.59	29.74	26.09
Average Total Return	3.9360%	4.7200%	5.1150%
Total Number of Pairs	10,794	9,493	7,724
Average Daily Holdings	140	217	331
Average Holding Period	20.0200	35.3600	66.2600
Systematic Risk	0.1417	0.1396	0.1384
Average Pair Beta	0.2459	0.2440	0.2414
Average MCap Difference	-11,497,120	-30,516,284	-51,664,975
P(Pair Return > 0)	73.0%	73.3%	72.1%
P(Pair Return < 0)	27.0%	26.7%	27.9%

Finally, Table 44 presents results for the risk-neutral portfolios of pairs. The hedge ratio of risk neutral pairs is chosen so as to minimise the total systematic risk of the pair as measured at inception by the APT 20 factor model. As before, the constituent pairs of the risk neutral portfolios P1, P2 and P3 are identical to their cash and size neutral counterparts and only the proportion of the amount bought relative to the amount sold for each pair is different. Starting with the portfolio return statistics, the Sharpe Ratio values are comparable to all the other cases examined so far and, like before, decline as we move from P1 to P3. The same holds true for the average daily portfolio returns. All portfolios display positive skewness and kurtosis which grows larger as we move from P1 to P3. As mentioned before, positive skewness indicates a larger concentration of outcomes to the right of the mean. Portfolio P3's relatively large skewness is also accompanied by large kurtosis. Therefore, although P3 may have relatively more and larger positive outcomes, it also has more frequent and relatively large negative outcomes thus making the portfolio inherently riskier and with a smaller average return. This is also reflected in the historical daily VAR numbers. P3's VAR is more than double that of portfolio P1. Compared to the cash and size neutral portfolios, the risk neutral portfolios have lower VARs than their peers. It might therefore appear that the VAR numbers improve as we increase the number of risk factors with respect to which the exposure of the portfolios is minimised. The average pair systematic risk is also naturally smaller for the risk neutral portfolios. Nevertheless, these portfolios have also slightly lower average returns thus resulting in similar or slightly lower Sharpe ratios than their cash or size neutral counterparts. The proportion of profitable positions is again around 72% and the average pair beta is still very small.

To summarise, so far in this section three groups of portfolios of pairs were formed with varying levels of exposure to risk factors. Cash neutral portfolios portfolio were not optimised in any way, size neutral portfolios consisted of pairs that had zero exposure to size and risk neutral portfolios contained pairs whose systematic risk, as measured by the APT 20 factor model, was minimised. Each group consisted of three portfolios, P1 P2 and P3, whose pairs were formed by comparing each pair's current price ratio to its historic average measured over a period of 13, 26 and 52 weeks respectively. Portfolios P1 and P2 are characterised by large positive Sharpe ratios and in contrast to portfolio P3 that appears to be more volatile. All portfolios have statistically significant average portfolio as well as pair returns, negligible average pair betas and are neutral with respect to market risk. The performance of the risk neutral portfolios is not hampered by minimising the risk exposure of the constituent pairs and is comparable to the performance of the cash and the size neutral portfolios. When comparing the day to day total portfolio returns, P1 appears the best performing portfolio in all three groups. It yields the highest Sharpe ratio but the largest total number of pairs held over the simulation period. P1 also exhibits by far the smallest historical daily VAR number in all groups. However all portfolios have similar proportions of positive outcomes across all groups. P3 is the worst performing portfolio across all groups both at the portfolio and at the discrete position level. P3 comprises the smallest total number of pairs with larger on average total position returns which are also more volatile. So the portfolio performance appears to deteriorate as the length of the period over which historical averages are measured is increased.

3.3.3 Multifactor model, Johansen test implementation

So far the ADF test was used to identify pairs of securities whose price ratio is stationary over a period of time. The coefficient vector of the linear combination of the prices that was tested for stationarity was thus fixed to be [1 -1]. The Johansen test not only tests for co-integration between the stock prices but also provides estimates of the coefficient vector associated with the stationary linear combination of the prices. Table 45 presents portfolio results for the case where the strategy is implemented using the Johansen methodology to test for co-integration between a highly correlated pair of securities. The coefficient estimates produced by the Johansen test are used to calculate the actual value of the stationary linear combination of the log-prices every day over the next 3 months until the new factor set becomes available. The value of the linear combination thus calculated is compared with its 13, 26 and 52 week average and standard deviation in order to identify trading opportunities. When the new set of factor exposures arrives, the universe of highly correlated securities is refreshed and the Johansen test is applied again to identify new pairs of co-integrated securities and estimate their coefficient vectors. The results are remarkably similar to those of the ADF implementation, cash-neutral counterparts both at the portfolio and at the individual position level.

Table 45 Cash-Neutral Portfolios, Johansen Test			
	P1 (13 Weeks)	P2 (26 Weeks)	P3 (52 Weeks)
	Portfolio Return Statistics		
Normality Test	610	1,433	2,366
Critical Value	5.9910	5.9910	5.9910
Skewness	0.4780	0.7970	1.0140
Kurtosis	2.9240	4.4360	5.7070
Average Return	0.1680%	0.1210%	0.0580%
T-Statistic (5%)	8.76	6.06	2.92
Sharpe Ratio	3.6900	2.8200	1.4500
Average Profit/Loss	272,806	304,687	242,202
Total Profit/Loss	422,304,257	471,655,226	374,928,982
Average Portfolio Value	270,433,547	427,154,825	663,057,998
Historic Daily VAR @ 5%	-1,164,055	-1,875,412	-3,254,121
STD's Away From The Mean	1.365	1.3554	1.4112
	Position Return Statistics		
Normality Test	357,278	6,071,694	2,381,661
Skewness	3.5660	7.6350	6.5710
Kurtosis	27.5470	123.3420	85.2020
Sharpe Ratio	8.1600	7.0700	6.9400
Average Daily Return	0.7400%	0.6260%	0.4630%
T-Statistic (5%)	35.76	30.58	27.36
Average Total Return	3.9880%	5.0000%	4.8750%
Total Number of Pairs	10,590	9,434	7,691
Average Daily Holdings	136	215	335
Average Holding Period	19.8600	35.2400	67.4400
Systematic Risk	0.1801	0.1777	0.1763
Average Pair Beta	0.0089	0.0148	0.0160
Average MCap Difference	-17,874,659	-18,650,501	-43,875,837
P(Pair Return > 0)	73.9%	74.2%	72.7%
P(Pair Return < 0)	26.1%	25.8%	27.3%

Portfolio P3 is yet again the worst performer and it is still characterised by the smallest total number of pairs and the longest average holding period. The VAR numbers are only slightly smaller for P1 and P2 than those of their ADF counterparts leading to slightly improved Sharpe Ratios. The numbers of pairs held are almost identical to those of the ADF portfolios. The average pair systematic risk is still around 18% and the average pair beta is negligible. Finally the proportion of positive outcomes is still around 74%. The results therefore are not substantially affected when the restriction that the coefficient vector of the stationary linear combination of the prices is [1 -1] is relaxed. It appears that both the ADF and the Johansen tests identify very similar pools of stationary pairs of securities.

Table 46 Cash-Neutral Portfolios with Stop Loss and Profit Taking			
	P1 (13 Weeks)	P2 (26 Weeks)	P3 (52 Weeks)
	Portfolio Return Statistics		
Normality Test	944	493	941
Critical Value	5.9910	5.9910	5.9910
Skewness	0.2680	0.4870	0.6790
Kurtosis	3.7880	2.5870	3.5700
Average Return	0.2250%	0.1820%	0.1260%
T-Statistic (5%)	9.92	7.73	5.28
Sharpe Ratio	4.2400	3.6100	2.6000
Average Profit/Loss	218,751	227,417	196,529
Total Profit/Loss	338,627,157	352,040,999	304,226,673
Average Portfolio Value	176,746,780	224,712,944	267,080,027
Historic Daily VAR @ 5%	-750,724	-960,015	-1,253,220
STD's Away From The Mean	1.2693	1.2398	1.2735
	Position Return Statistics		
Normality Test	427,911	353,343	203,962
Skewness	-1.0030	-1.0140	-0.7140
Kurtosis	29.3800	26.4130	19.8120
Sharpe Ratio	5.2900	5.1400	4.8800
Average Daily Return	1.2470%	1.2540%	1.1890%
T-Statistic (5%)	25.51	24.48	24.35
Average Total Return	2.8600%	2.9130%	2.4520%
Total Number of Pairs	11,842	12,084	12,407
Average Daily Holdings	89	114	137
Average Holding Period	11.6900	14.6600	17.0400
Systematic Risk	0.1811	0.1793	0.1786
Average Pair Beta	0.2450	0.2424	0.2447
Average MCap Difference	-11,426,347	-28,260,089	-43,785,830
P(Pair Return > 0)	76.9%	78.4%	77.7%
P(Pair Return < 0)	23.1%	21.6%	22.34%

3.3.4 Cash-Neutral Portfolios with Stop Loss and Profit Taking

It was mentioned above that applying a stop loss rule combined with more aggressive profit taking could improve the strategy's performance. Table 46 displays the results when such a rule is imposed. Positions are now closed whenever one or more of the following conditions are met:

(a) the log price ratio of the two securities crosses it's mean

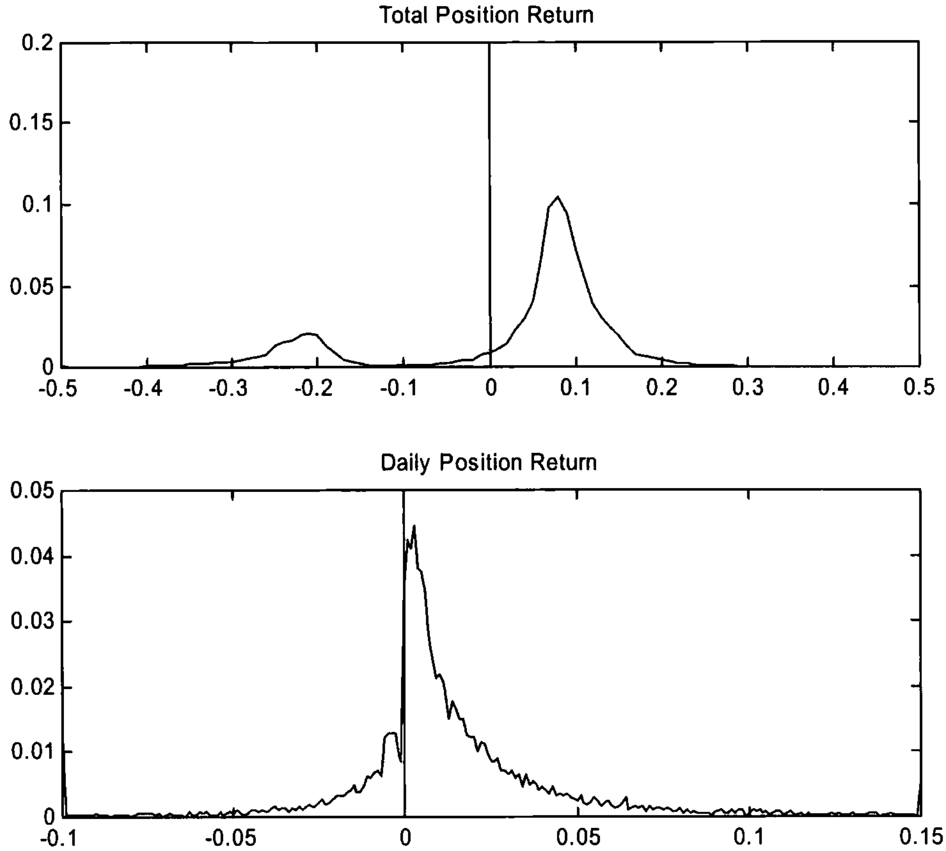
(b) the return of the position exceeds 7% (profit taking)

(c) the return of the position is less than -20% (stop loss limit)

As expected these rules increase the portfolio turnover. Indeed the average holding period for the three portfolios is reduced from 20, 35 and 66 days to 11, 14 and 17 days respectively. The total number of pairs on the other hand is increased from 10794, 9493 and 7724 to 11842, 12084 and 12407 respectively. The performance of all portfolios is improved significantly despite the increased turnover combined with the punitive transaction costs (0.4% roundtrip) imposed on the strategy. The average daily portfolio return is increased by 0.06% for all portfolios. The Sharpe ratio is also increased by around 1 across the board. Portfolio P3 is still performing poorly relative to P1 and P2, however its Sharpe ratio is now a respectable 2.6 compared with 1.45 before. The higher Sharpe ratios indicate that portfolio returns have become both larger in magnitude and less volatile. The lower volatility is also confirmed by the VAR numbers which are decreased by more than 50%. The distances of the lower VAR numbers from their respective mean returns are also shorter indicating that the portfolio returns are more concentrated around their mean value and hence less risky. All average portfolio and position returns are again significantly larger than zero and the average pair beta and systematic risk remain very low. Finally the proportions of positions with positive outcomes are slightly higher than before and close to 78%. Figure 5 displays the distributions of the total and daily position returns for portfolio P2. Both distributions appear now to be bimodal, reflecting the fact that a number of positions are closed when the stop loss criterion is met. Therefore there appears to be a relatively higher concentration of returns around the -20% and the 7.5% points. However the largest area under both curves is to the right of the zero return vertical line.

To conclude this section, it was shown that the performance of the pairs trading strategy was significantly improved by introducing a stop loss rule combined with more aggressive profit taking. This resulted in higher portfolio turnover but also higher portfolio returns characterised by lower volatility and hence higher Sharpe ratios. It must be noted that the trading rule is still fully automated and requires no human intervention. This leaves open the possibility that performance can be further improved by adjusting the decision making process to take account of information that is not yet impounded in the statistical model. For example a shift in the strategic objectives of a company will affect its correlation with its competitors. This shift will eventually be reflected in the share price but it will take several observations for the statistical model to detect it. An alert trader on the other hand will immediately consider the altered circumstances when making a trading decision.

Figure 5



3.3.5 The Sources of Profit and the Jegadeesh-Titman Decomposition

Jegadeesh and Titman (1995) provided an ingenious mechanism for identifying ex-ante the sources of the profit derived from a contrarian strategy. Their analysis will be used in this section to estimate the expected profit associated with a pairs trading rule as well as to attribute this profit to its various sources. Pairs trading is for all intents and purposes a contrarian strategy since it calls for selling short a security which is deemed to be overvalued relative to another highly correlated security which is held long.

Jegadeesh and Titman (1995) examine the profitability of short term horizon contrarian strategies and develop a generalised framework for identifying the different sources of contrarian profits based on how prices respond to information. They assume that stock returns are determined according to the following multifactor model:

$$r_{i,t} = \mu_i + \sum_{k=1}^{K}(b_{0,i,k}^t f_{t,k} + b_{1,i,k}^t f_{t-1,k}) + e_{i,t} \quad (3.3.5.1)$$

This model facilitates the separate examination of price reactions to common factors $f_{t,k}$, lagged realisations of common factors $f_{t-1,k}$ and firm specific information $e_{i,t}$, where $f_{t,k}$ denotes the unexpected factor realisation. The same model can be used to examine differences in the returns of two related securities as in the case of highly correlated pairs. The return of a pair of securities $r_{p,t}$, which consists of one share long in the first security and one share short in the second, is given by the difference of the two security returns, $r_{p,t} = r_{i,t} - r_{j,t}$. By substituting 3.3.5.1 for $r_{i,t}$ and $r_{j,t}$ we get:

$$r_{p,t} = \mu_p + \sum_{k=1}^{K}(b_{0,p,k}^t f_{t,k} + b_{1,p,k}^t f_{t-1,k}) + e_{p,t} \quad (3.3.5.2),$$

where $\mu_{p,t} = \mu_{i,t} - \mu_{j,t}$, $b_{p,k}^t = b_{i,k}^t - b_{j,k}^t$ and $e_{p,t} = e_{i,t} - e_{j,t}$. Equation 3.3.5.2 now describes how pair returns are affected by common factor realisations. Jegadeesh and Titman reasonably assume that:

(a) the factors are orthogonal and unrelated to their lagged values and

(b) cov($e_{i,t}, e_{j,t-1}$)=0 for all i $\neq$j.

It then follows that:

$$\operatorname{cov}(r_{i,t}, r_{j,t-1}) = \sum_{k=1}^{K} E(b_{1,i,k}^t b_{0,j,k}^{t-1}) \bullet \sigma_{f_k}^2 \quad (3.3.5.3)$$

However assumption (b) is not generally true in the case of pair returns since some pairs may contain the same security. The residual returns of those pairs will then be cross-serially correlated thus violating the assertion that cov($e_{i,t}, e_{j,t-1}$)=0 for all i $\neq$j. One way to get around this problem is to confine the analysis to distinct pairs of securities that do not share members. The residual returns of such pairs are then cross-serially uncorrelated and the cross-serial covariance between two pairs of securities is given by 3.3.5.3 where i and j now signify pairs rather than individual securities. Jegadeesh and Titman examine a strategy where the portfolio weight for stock i at time t is:

$$w_{i,t} = -\frac{1}{N}(r_{i,t-1} - \bar{r}_{t-1})$$

where $\bar{r}_{t-1}$ is the equally weighted index return and N is the number of stocks. The contrarian profit is then given by:

$$\pi_t = -\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - \bar{r}_{t-1}) \bullet r_{i,t} \quad \text{and}$$

$$E(\pi_t) = -E\left[\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - \bar{r}_{t-1}) \bullet r_{i,t}\right] = -\sigma_\mu^2 - \Omega - \sum_{k=1}^{K}\delta_k\sigma_{f_k}^2$$

where

$$\sigma_\mu^2 = \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \bar{\mu})^2$$

$$\Omega \equiv \frac{1}{N}\sum_{i=1}^{N}\operatorname{cov}(e_{i,t} - e_{i,t-1}) \text{ and}$$

$$\delta_k \equiv E\left(\frac{1}{N}\sum_{i=1}^{N}(b_{0,i,k}^{t-1} - \bar{b}_0^t) \bullet (b_{1,i,k}^t - \bar{b}_1^t)\right)$$

The same weights can be applied to a strategy where individual securities are now replaced by pairs of securities. The equally weighted market index is now an equally weighted index of pair returns. Individual pair returns are compared against this benchmark before long or short positions are taken.

The expected contrarian profit $E(\pi_t)$ is decomposed into three components:

The component, $-\sigma_\mu^2 \times 10^3$, measures the part of the return attributed to the cross-sectional variation of pair returns which is induced by the crossectional variation in stock returns. Stocks with higher than average expected returns tend to have higher than average realized returns and therefore reduce contrarian profits. The term $-\Omega \times 10^3$ measures the part of the return due to overreaction to firm specific information. Overreaction to firm specific information will lead to over-valuation of a certain security relative to the market and its peers. By taking a hedged position that holds this security short and a highly correlated security long, a riskless profit can be made when relative values adjust to their equilibrium levels. This profit will be entirely attributable to overreaction to firm specific news. Finally, the component $-\delta\sigma_{VWm}^2 \times 10^3$ is the contribution of delayed reaction of stock prices to common factor realizations. If prices overreact initially to firm specific news and subsequently adjust to equilibrium levels, Ω will be negative and will have a positive contribution to contrarian profits. The term δ_k measures the cross-sectional covariance of contemporaneous and delayed factor sensitivities and may be either positive or negative. Therefore, while overreaction to firm-specific information contributes to contrarian profits, overreaction to common factors can either increase or reduce them.

Table 47
Jegadeesh-Titman Decomposition - Stationary Pairs

Factor Date	$-\sigma_{\mu}^{2}\times10^{3}$	$-\Omega\times10^{3}$	$-\delta\sigma_{VWm}^{2}\times10^{3}$	Total
31/12/1995	-0.0009	0.1144	0.0014	0.012%
31/03/1996	-0.0009	0.1109	0.0020	0.011%
30/06/1996	-0.0010	0.1254	0.0018	0.013%
30/09/1996	-0.0009	0.0993	0.0018	0.010%
31/12/1996	-0.0008	0.1072	0.0021	0.011%
31/03/1997	-0.0007	0.0984	0.0025	0.010%
30/06/1997	-0.0010	0.0998	0.0024	0.010%
30/09/1997	-0.0018	0.1468	0.0020	0.015%
31/12/1997	-0.0012	0.1633	0.0024	0.017%
31/03/1998	-0.0012	0.2197	0.0048	0.022%
30/06/1998	-0.0016	0.2640	0.0038	0.027%
30/09/1998	-0.0019	0.3331	0.0060	0.034%
31/12/1998	-0.0021	0.3467	0.0055	0.035%
31/03/1999	-0.0021	0.3438	0.0049	0.035%
10/07/1999	-0.0039	0.4028	0.0031	0.040%
10/10/1999	-0.0027	0.4222	0.0062	0.043%
13/01/2000	-0.0035	0.4577	0.0039	0.046%
14/04/2000	-0.0022	0.4373	0.0031	0.044%
28/06/2000	-0.0030	0.4262	0.0027	0.043%
21/09/2000	-0.0025	0.3711	0.0023	0.037%
31/12/2000	-0.0023	0.3880	0.0025	0.039%
28/03/2001	-0.0021	0.3098	0.0021	0.031%
18/06/2001	-0.0022	0.3439	0.0028	0.035%
28/09/2001	-0.0022	0.3111	0.0019	0.031%
19/12/2001	-0.0098	0.1781	-0.0010	0.017%
27/03/2002	-0.0015	0.2603	0.0014	0.026%

Table 47 shows the components of the estimated contrarian profits for the largely overlapping sets of highly-correlated and stationary pairs of securities corresponding to the various factor dates. Pair returns are measured over a period starting 104 weeks prior to pair formation and ending 13 weeks after the pair formation date (i.e. the date the new factor exposures become available). 13 weeks is roughly the length of time between two consecutive pair formation dates. It is evident that the largest component of the expected profit by far is the one attributed to overreaction to firm specific news (101.68% on average). This is true for all sets of pairs. Furthermore all components retain their sign throughout the simulation period indicating that the contributions of the various sources of profit remain consistent over time

More specifically the cross-sectional variation of pair returns has a small negative contribution to the strategy's profits while a small part of the profits can be attributed to delayed reaction to factor realisations. Delayed reaction can contribute to the trading profit when for example the price of a sector leading stock A reacts instantaneously to a factor realisation while the price of its highly correlated peer stock B remains initially unaffected. However stock B has similar factor exposures to A and its price should sooner or later react to the unexpected factor realisation and adjust to a new equilibrium level. This adjustment can be profitably exploited since the price of B will at some point start moving faster toward equilibrium than that of A which is already adjusted to the new factor exposures. The average of the total profit estimate over the entire simulation period is 0.022% which coincidentally is almost equal to the average portfolio return of the cash neutral portfolio P1 when the stop loss rule is applied.

Table 48 presents the Jegadeesh-Titman Decomposition of highly-correlated sets of pairs regardless of whether they are stationary or not. At any given date these pairs are chosen as the top 5% of all possible pairs of securities when sorted in descending order of their systematic correlation. As is evident the total expected profit is positive during the entire period and almost all of it is attributed to overreaction. However the estimated profit is consistently lower than that of the stationary pairs indicating that highly correlated stationary pairs are on average more profitable than highly correlated pairs in general. Finally Table 49 presents the Jegadeesh-Titman Decomposition of sets of pairs that exhibit low correlation. At any given date these pairs are chosen as the bottom 5% of all possible pairs of securities when sorted in descending order of their systematic correlation. As anticipated the expected profit of the low correlation pairs is consistently lower than that of the high correlation pairs except for the last two sets that correspond to the period during which the expected performance of the high correlation pairs starts to deteriorate.

So far the Jegadeesh-Titman Decomposition suggests that almost all of the contrarian profit from pairs trading is attributed to overreaction to firm specific news. This appears to be in accord with the results in sections 3.3.1 to 3.3.3 which show that all pair positions have negligible betas and systematic risk on average.

Table 48
Jegadeesh-Titman Decomposition - High Correlation Pairs

Factor Date	$-\sigma_{\mu}^{2}\times10^{3}$	$-\Omega\times10^{3}$	$-\delta\sigma_{VWm}^{2}\times10^{3}$	Total
31/12/1995	-0.0012	0.0809	0.0008	0.008%
31/03/1996	-0.0020	0.0894	0.0014	0.009%
30/06/1996	-0.0054	0.0934	0.0022	0.009%
30/09/1996	-0.0014	0.0826	0.0015	0.008%
31/12/1996	-0.0020	0.1036	0.0020	0.010%
31/03/1997	-0.0019	0.0835	0.0010	0.008%
30/06/1997	-0.0019	0.1015	0.0009	0.010%
30/09/1997	-0.0033	0.0968	-0.0017	0.009%
31/12/1997	-0.0039	0.1388	-0.0019	0.013%
31/03/1998	-0.0018	0.1888	0.0022	0.019%
30/06/1998	-0.0066	0.2576	0.0061	0.026%
30/09/1998	-0.0029	0.2831	0.0038	0.028%
31/12/1998	-0.0026	0.2614	0.0025	0.026%
31/03/1999	-0.0036	0.3127	0.0020	0.031%
10/07/1999	-0.0046	0.3372	0.0022	0.034%
10/10/1999	-0.0041	0.3480	0.0029	0.035%
13/01/2000	-0.0044	0.3796	0.0022	0.038%
14/04/2000	-0.0039	0.3652	0.0010	0.036%
28/06/2000	-0.0034	0.2977	0.0020	0.030%
21/09/2000	-0.0046	0.3402	0.0012	0.034%
31/12/2000	-0.0042	0.3199	0.0003	0.032%
28/03/2001	-0.0027	0.2680	0.0005	0.027%
18/06/2001	-0.0030	0.2289	0.0016	0.023%
28/09/2001	-0.0081	0.2477	-0.0013	0.024%
19/12/2001	-0.0268	0.2605	0.0047	0.024%
27/03/2002	-0.0031	0.2645	0.0015	0.026%

Table 49 **Jegadeesh-Titman Decomposition - Low Correlation Pairs**				
Factor Date	$-\sigma_{\mu}^{2}\times10^{3}$	$-\Omega\times10^{3}$	$-\delta\sigma_{VWm}^{2}\times10^{3}$	Total
31/12/1995	-0.0059	0.0162	0.0022	0.001%
31/03/1996	-0.0074	0.0392	0.0035	0.004%
30/06/1996	-0.0077	0.0331	0.0053	0.003%
30/09/1996	-0.0037	0.0080	0.0030	0.001%
31/12/1996	-0.0042	0.0376	0.0046	0.004%
31/03/1997	-0.0037	0.0226	0.0019	0.002%
30/06/1997	-0.0040	0.0250	0.0044	0.003%
30/09/1997	-0.0060	0.0422	0.0011	0.004%
31/12/1997	-0.0045	0.0237	-0.0010	0.002%
31/03/1998	-0.0061	-0.0222	-0.0001	-0.003%
30/06/1998	-0.0065	0.0606	-0.0012	0.005%
30/09/1998	-0.0111	0.1075	0.0023	0.010%
31/12/1998	-0.0076	0.1786	0.0148	0.019%
31/03/1999	-0.0124	0.1578	0.0119	0.016%
10/07/1999	-0.0092	0.1458	0.0089	0.015%
10/10/1999	-0.0107	0.1121	0.0079	0.011%
13/01/2000	-0.0120	0.1714	0.0012	0.016%
14/04/2000	-0.0128	0.2360	-0.0051	0.022%
28/06/2000	-0.0087	0.2066	-0.0058	0.019%
21/09/2000	-0.0069	0.1862	-0.0115	0.017%
31/12/2000	-0.0071	0.0608	-0.0054	0.005%
28/03/2001	-0.0052	0.1610	-0.0147	0.014%
18/06/2001	-0.0052	0.2073	-0.0134	0.019%
28/09/2001	-0.0067	0.1997	-0.0107	0.018%
19/12/2001	-0.0055	0.2960	-0.0094	0.028%
27/03/2002	-0.0132	0.3010	-0.0085	0.028%

Table 50 Regressions of Portfolio Returns on the Value Weighted Market Return and its Lag				
	Constant	**Market**	**Lag Market**	**R-Square**
Cash-Neutral Portfolios ADF Test				
P1	0.002 (7.90)	-0.037 (-1.76)	0.001 (0.04)	0.004
P2	0.001 (5.30)	-0.041 (-1.92)	-0.000 (-0.00)	0.005
P3	0.001 (2.68)	-0.043 (-1.98)	-0.016 (-0.57)	0.008
Risk-Neutral Portfolios ADF Test				
P1	0.002 (7.90)	-0.031 (-1.48)	0.000 (0.00)	0.003
P2	0.001 (5.13)	-0.041 (-1.86)	0.004 (0.16)	0.006
P3	0.001 (2.50)	-0.041 (-1.89)	-0.013 (-0.45)	0.007
Size-Neutral Portfolios ADF Test				
P1	0.002 (8.44)	-0.047 (-2.22)	0.001 (0.02)	0.005
P2	0.001 (6.23)	-0.046 (-2.17)	-0.008 (-0.34)	0.007
P3	0.001 (3.25)	-0.044 (-2.08)	-0.025 (-0.96)	0.009
Cash-Neutral Portfolios Johansen Test				
P1	0.002 (8.51)	-0.017 (-0.91)	-0.004 (-0.20)	0.001
P2	0.001 (5.90)	-0.029 (-1.32)	0.013 (0.55)	0.003
P3	0.001 (2.77)	-0.031 (-1.52)	-0.003 (-0.13)	0.004
Cash-Neutral Portfolios with Stop Loss and Profit Taking				
P1	0.002 (9.93)	-0.009 (-0.41)	0.024 (1.06)	0.001
P2	0.002 (7.73)	-0.009 (-0.40)	0.031 (1.23)	0.003
P3	0.001 (5.22)	-0.026 (-1.28)	0.034 (1.24)	0.005

This should also translate into a small beta for the respective portfolio returns. Table 50 shows the results of the regressions of the returns of the various portfolios examined so far, on the market return and its first lag. The numbers in brackets are t-statistics corrected for serial correlation using the Newey-West formula.

As is evident the market beta for all portfolios is negative and negligible in size. The highest absolute value attained is 0.047. The associated T-statistics show that the market beta is not significant for the Johansen test, cash neutral portfolios and the cash-neutral portfolios with stop-loss and profit taking. All the ADF test portfolios appear to have statistically significant although very small betas. However the importance of statistically significant betas should not be over-stated. The explanatory power of the regression is very weak as shown by the R-Square value. The R-Square is an estimate of the proportion of the total variance of the portfolio return explained by the market return and its lag. In this case, the proportion is at best 0.9% and thus unimportant. The coefficient of the market lag is also negligible and not significant for all portfolios. Therefore all portfolio returns appear not to be correlated with state of the market.

In this section the Jegadeesh-Titman analysis of contrarian profits is applied on the returns of pairs of securities. It is shown that the overwhelming part of the profit from the pairs strategy is attributed to overreaction to stock specific news. This is in accordance with the results of previous sections which showed that pair positions have negligible betas and systematic risk. The expected profit remains positive during the entire simulation period and is higher for stationary pairs among the class of all highly correlated pairs. The expected profit is also higher for pairs that exhibit high rather than low correlation.

Conclusion

The efficient market hypothesis has been under intense scrutiny since its introduction in 1970 by Fama. A consequence of the efficient market hypothesis is the law of one price whereby equal future payoffs with identical risk profiles should carry the same price. Pairs trading is a trading strategy based on the law of one price. Practitioners have been engaging in trading pairs of highly correlated securities whose relative prices appear to diverge from their perceived equilibrium level in the belief that the law of one price will eventually drive the two prices back to a level justified by their risk profiles. The aim of this chapter is to develop a framework for analysing such pairs of securities, to examine whether pairs trading is profitable using Japanese stock market data and to examine the sources of these profits.

It has been shown that securities with similar risk profiles have highly correlated expected returns and therefore their respective prices move more or less in tandem. Cointegration techniques can be used to study this co-movement of prices and to deduce the value of one asset relative to the other. This leads to the estimation of a 'relative fair value' which lends it self to comparison with the actual relative value of the assets. Large deviations from the fair value may be profitably exploited by a pairs trading rule that calls for buying the relatively cheap and selling short the relatively expensive asset. The overall strategy portfolio consists of a number of pairs of securities which are formed on each day during the simulation period and have overlapping holding periods. The use of overlapping holding periods increases the confidence in the tests carried out on the strategy portfolio. Portfolio returns are measured using auction-determined open prices thus eliminating the bid ask bias inherent in high frequency data. The strategy is simulated entirely out of sample, meaning that no prior knowledge of future information is assumed at any point during the simulation. More specifically, three types of portfolios of pairs were examined with varying levels of exposure to risk. The cash neutral portfolio contained pairs that were not optimised in any way, the size neutral portfolio consisted of pairs that had zero exposure to size and finally the risk neutral portfolio contained pairs whose systematic risk, as measured by the APT 20 factor model, was minimised. The simulated portfolios were also distinguished by the length of the period used to estimate each pair's fair value. For example three cash neutral portfolios, P1 P2 and P3, were examined corresponding to an estimation period of 13, 26 and 52 weeks respectively.

Nine portfolios were examined in total, three for each risk profile. Portfolios P1 and P2 were characterised by large positive Sharpe ratios while portfolio P3 appeared to be more volatile. All portfolios had statistically significant average portfolio as well as pair returns, negligible average pair betas and were neutral with respect to market risk. The performance of the risk neutral portfolios was not hampered by minimising the risk exposure of the constituent pairs and was comparable to the performance of the cash and the size neutral portfolios. When comparing the day to day total portfolio returns, P1 appeared to be the best performing portfolio in all three groups. It was characterised by the highest Sharpe ratio as well as the largest total number of pairs held over the simulation period. P1 also exhibited by far the smallest historical daily VAR number in all groups. However all portfolios had similar proportions of positive outcomes. P3 was the worst performing portfolio both at the portfolio and at the discrete position level. P3 comprised the smallest total number of pairs with larger on average total position returns which were also more volatile. So the portfolio performance appeared to deteriorate as the length of the period over which historical averages were measured was increased.

The performance of the pairs trading strategy was significantly improved by the implementation of a stop loss rule combined with more aggressive profit taking. This resulted in higher portfolio turnover but also higher portfolio returns characterised by lower volatility and higher Sharpe ratios. All portfolios were subject to a trading rule that was fully automated and required no human intervention leaving open the possibility that performance could be further improved by taking into account information not yet impounded in the statistical model. For example a shift in the strategic objectives of a company would affect its correlation with its competitors. This shift would eventually be detected by the statistical model after several observations became available. An alert trader on the other hand would immediately consider the altered circumstances when making a trading decision.

By applying the Jegadeesh-Titman analysis of contrarian profits it was shown that the overwhelming part of the pairs strategy profit was attributed to overreaction to stock specific news. This was consistent with the negligible betas and systematic risk exhibited by pair positions. It was also shown that the expected profit remained positive during the entire simulation period and was higher for stationary pairs among the class of all highly correlated pairs. The expected profit was also higher for pairs that exhibited high rather than low correlation.

It appears therefore that the law of one price forces assets to be valued in accordance to their risk profile. In the short term though, relative asset valuations are not always consistent with their relative risk exposures. Such short term deviations from fair relative values can be profitably exploited by engaging in a form of riskless arbitrage namely pairs trading. When simulated using Japanese stock market data, this strategy appeared to generate economically significant profits despite the hefty transaction costs imposed and the realistic assumptions that were made regarding the prices at which trades occurred. Furthermore, practitioners have been engaging in such trading undeterred for years, which in itself is an indication that it is a profitable activity. This raises serious doubts about the efficiency of the Japanese stock market.

THESIS CONCLUSION

The emergence of asset pricing models in the late nineteen sixties has changed fundamentally the way financial markets operate. Asset pricing models provided a systematic link between risk and reward and thus a platform for assesing the efficiency of capital markets. The definition of efficient markets was formalised in the efficient market hypothesis. The weak form of the EMH stipulates that efficient markets are characterised by the absence of arbitrage opportunities. Very soon after the advent of the first asset pricing model, the CAPM, a multitude of studies attempted to either give support or disprove the EMH. To this day, researchers keep discovering 'anomalous' patterns in asset returns that cannot be explained by asset pricing models. The existence of such empirical anomalies suggests either that the empirical forms of asset pricing models are miss-specified and/or that capital markets are not efficient. The term 'and/or' in the previous statement epitomises the difficulties associated with testing for market efficiency. The EMH is a joint hypothesis and therefore the results of empirical efficiency tests are always open to debate. Nevertheless such tests can still be used to reveal the relative strengths and weaknesses of capital markets.

This thesis has endeavoured to examine various aspects of efficiency of the Japanese stock market by examining three different types of irregular return patterns. The first type is best represented by three related pricing anomalies which are associated with size, price and book value to market. The second type is the observed reversal in stock returns. The third irregular return pattern is typified by the oscillation of the relative prices of highly correlated assets around a mean value. We sought to improve the conventional methodology used to analyse these phenomena in various ways thus improving the robustness of our results. The three most significant improvements were the use of tradable, out of sample prices to assess the profitability of the simulated trading strategies, the imposition of realistic trading costs and finally the examination of optimised portfolios and individual positions. We focused on Japan because despite having the second largest capital market in the world it has received scant attention by the academic community and because of the accumulated personal experience as a professional participant of the Japanese stock market.

We started by examining the presence of the size effect, probably the most analyzed 'anomaly' to this date and historically one of the first to be identified, and found no evidence in support of it. This is in contrast to earlier studies on Japan.

However those studies used a much older sample than ours which ends in August 2003. The source of our data is also different compared to earlier studies. Our finding appears to lend support to Dimson & Marsh (1999) who argue that once an anomaly receives widespread publicity it attracts the interest of investors and eventually it disappears. We also examined the ability of price and book value to market to differentiate future stock returns and found both effects to be very strong and significant. We noticed that the higher observed returns of the small price portfolio are characterised by higher risk compared to the large price portfolio. However the average return of the large price portfolio is negative and thus smaller than the risk free rate which is positive. It would therefore appear that the return differential of the price portfolios cannot be entirely attributed to risk differences and, to a certain extent, price constitutes an anomaly. This is also true for the book value to market portfolios, where the small book value to market portfolio not only has a negative return on average but also appears to be slightly riskier than the P10 portfolio thereby negating the claim that return differences are accounted for by risk differences.

We found evidence of correlation between the state of the economy and the two effects and so concluded that price and book value to market are not pure anomalies. We showed that when conditioned on macroeconomic variables, the price premium and to a lesser extent the book value to market premium are indeed associated with the state of the underlying economy. Scenarios that are representative of expansionary periods in the economy are linked with larger premiums compared to recessionary periods. This finding is also in agreement to that of Kim and Burnie, (2002) who examined the relation of the small cap premium to the economic cycle using US data. The two effects therefore are linked to macroeconomic risk factors but are not entirely explained by them.

Both the book value to market and price effects were found to be seasonal. They were positive during the first half of the year and negative thereafter. The evidence suggested that the "January" effect which has been identified by a multitude of studies in the US market was also present in Japan. However the January effect in the US is linked to the financial year end which is in December. In contrast most Japanese companies report year end results in March and April. The price effect appeared strongest in February and May while the book value to market premium attains its largest values in February and May through July. The bimodal nature of the effect may be explained by the participation of international investors in the Japanese market who have a different year end to that of Japanese investors.

We found evidence of moderate correlation between the stock rankings according to price and book value to market implying that the respective portfolio returns were also correlated. In order to examine the net price and book value to market effects we used two established procedures to form price portfolios that were neutral in terms of their exposure to book value to market and vice versa. The net price effect appeared weaker but still statistically significant. The premium of the large book value to market portfolio on the other hand was unaffected by the elimination of large price differences in the constituents of the portfolios.

Having established the absence of a significant size effect and the presence of rather strong price and book value to market effects in the sample, we proceeded to examine another anomaly that has attracted renewed academic as well as investor interest in recent years. The anomaly in question is the observed reversals in stock returns which induce negative serial auto-correlation. This implies that past returns can predict future returns and thus runs contrary to the EMH. Despite being observed as early as the 1960's return reversals have attracted renewed interest due to DeBondt and Thaler (1985) who sought an alternative explanation to those given for the phenomenon up to that date. According to DeBondt and Thaler naive investors become overly enthusiastic about stocks that performed well in the past, buy them up and these stocks become overpriced. In a similar manner, they overreact to stocks that had a poor performance in the past and these stocks become under-priced. This behaviour is summed up in the over-reaction hypothesis. More sophisticated investors eventually step in and prices return to their equilibrium levels. A tacit admission of the over-reaction hypothesis is that agents do not behave rationally and so an important assumption of the EMH is violated. However the same return pattern results when investors react with delay to factor realisations. A distinction has to be made therefore between these two sources of *contrarian* profits. The term contrarian refers to action that is contrary to that taken by naïve investors. A multitude of studies over the last 20 years indicate that this phenomenon can be exploited economically with empirical estimates suggesting that contrarian strategies can consistently yield substantial profits. Inevitably this research attracted the attention of hedge funds and other investment professionals.

We sought to examine the existence of significant contrarian profits in the Japanese stock market by first implementing the analytical framework provided by Jegadeesh & Titman (1995). We presented evidence suggesting that the Jegadeesh & Titman strategy can lead to significant contrarian profits and that he main source of these profits is over-reaction to firm specific events. However their strategy maximised expected return with no regard for risk and so the strategy portfolio was not necessarily on the efficient frontier. Furthermore the assumptions made by Jegadeesh & Titman regarding trading costs and execution prices can lead to significant positive biases in the estimated profits. We then continued to examine our own implementation of a contrarian strategy that used portfolios on the efficient frontier. We also tested two different sets of execution prices which were net of trading costs. These were the open and volume weighted average prices of the trading day following the date on which the trading signal was generated thus ensuring that the strategy was simulated entirely out of sample. The portfolios were optimal with respect to their expected Sharpe Ratio thus maximising their expected return while at the same time minimizing their volatility. The first such portfolio employed a simple market model to generate the inputs to the optimisation process and had a much higher Sharpe ratio than the original Jegadeesh & Titman portfolio. The second portfolio used an APT type multifactor model to generate the optimisation inputs and resulted in an even higher Sharpe ratio, almost twice as large as that of the Jegadeesh & Titman portfolio. We therefore established that the Sharpe ratio of the strategy increased as the asset pricing model became more complex and the quality of the inputs to the optimisation process got better. A corollary of this finding is that the profitability of a contrarian strategy is strongly dependent on its implementation. As noted in the introduction to the thesis hedge funds performed rather badly on average in recent years. Our contention is that this does not necessarily imply more efficient markets. Weak average performance may also be due to the existence of a large number of badly managed funds. Our results showed that the main source of profits for all portfolios was over-reaction to firm specific events and that minimal amounts were attributed to lagged factor realisations. Ex-post attribution of profits to their various sources also showed that more than 98% of the portfolio returns were due to residual stock returns. Contrarian profits could not therefore be explained away by the assumption that higher systematic risk was associated with the strategy. Our evidence lent overwhelming support to the overreaction hypothesis instead.

We then proceeded to show that illiquid stocks are more prone to over-reaction than liquid stocks since their prices are more responsive to demand surges or supply squeezes. Illiquid stock prices are driven more by firm specific events rather than the market and thus have a smaller market beta on average than liquid stocks. Nevertheless liquid stocks still generate significant contrarian profits despite the imposition of realistic trading costs and prices. The existence of such profits raises questions about the short term efficiency of the Japanese stock market.

The final chapter examined the profitability of another contrarian strategy which is also popular with hedge funds, namely pairs trading. Pairs trading exploits perceived anomalies in the way assets are priced relative to each other. The strategy is based on the law of one price which was originally developed in options pricing theory and states that equal future payoffs with identical risk profiles should carry the same price. Violation of the law of one price is equivalent to violation of the no arbitrage condition of the EMH and so the examination of the pairs trading strategy provided us with an alternative aspect to the efficiency of the Japanese stock market. Pairs trading amounts to buying the relatively cheap and selling the relatively expensive, of a pair of highly correlated assets whose relative price appears to diverge from its equilibrium level. The expectation is that the law of one price will eventually drive the two prices back to a level justified by their risk profiles thus leaving the investor with an arbitrage profit that carries minimal risk.

We started by showing that securities with similar risk profiles have highly correlated expected returns. As a result the respective prices of such assets move more or less in tandem and so lend themselves to analysis by cointegration techniques. We simulated three different versions of the pairs trading strategy that were distinguished by the risk characteristics of the chosen pairs. The three types of pairs were cash, size and risk neutral pairs. For cash neutral pairs the yen amount of the long side of the pair was equal to the yen amount of the short side of the pair. Size and risk-neutral pairs in contrast were characterised by long and short amounts that were held in a proportion that entailed zero net pair exposure to size and systematic risk respectively. Systematic risk was calculated using the same APT type model used in the examination of the return reversal strategy. All portfolios had statistically significant average portfolio as well as pair returns, negligible average pair betas and were neutral with respect to market risk. The performance of the strategy was not affected by the risk characteristics of the individual pairs. All portfolios had similar success rates, as measured by the proportion of pairs that result in profit. The implementation of a stop loss rule and more aggressive profit taking affected the performance of the strategy significantly. It entailed higher portfolio turnover but also higher portfolio returns characterised by lower volatility and thus higher Sharpe ratio. By applying the Jegadeesh-Titman analysis of contrarian profits it was shown that the overwhelming part of the pair strategy profit was attributed to over-reaction to stock specific news. This was consistent with the negligible betas and systematic risk exhibited by pair positions. It was also shown that the expected profit remained positive during the entire simulation period. We demonstrated among all the highly correlated pairs, stationary pairs had the highest expected profit and that high correlation pairs had higher expected profit than low correlation pairs. This finding reinforced the conviction that our results are systematic rather than coincidental.

We tested the robustness of our results by applying two alternative cointegration techniques. We also used three alternative estimates of the equilibrium relative price of a pair. They were calculated over time periods of 13, 26 and 52 weeks respectively. We found that the choice of cointegration method had only a small but insignificant quantitative effect on the results which were otherwise unaltered. In contrast longer estimation periods for the relative pair price entailed more volatile strategy payouts and smaller turnover. However the total strategy profit and loss did not change significantly implying that the average payoff per pair became larger as the estimation period got longer. The success rate of the strategy also remained unaffected. Overall the strategy appeared to be fairly robust to the different implementations that were tested. The robustness of the results was also enhanced by the following facts: (a) individual positions had overlapping holding periods which increased the confidence in the tests carried out on the strategy portfolio, (b) portfolio returns were measured using auction-determined open prices thus eliminating the bid ask bias inherent in high frequency data, and (c) the strategy was simulated entirely out of sample.

In general, the apparent profitability of the strategy implied that the law of one price forced assets to be eventually valued in accordance to their risk profile. Pairs trading appeared to generate economically significant profits despite the hefty transaction costs imposed meaning that relative asset valuations were not always efficient in the short term. Our simulation results coupled with the fact that practitioners have been engaging in such trading undeterred for years, is in itself an indication that it is a profitable activity. This again raises doubts about the short term efficiency of the Japanese stock market.

The overall conclusion of the thesis is that as a developed stock market, Japan is both efficient and inefficient. It displays short term inefficiencies that can be profitably exploited by contrarian investors. However, as the investing public becomes more aware of them, such inefficiencies disappear in the long term thus affording the Japanese stock market a certain degree of efficiency. Market efficiency is therefore improved by wider investor participation and the faster dissemination of reliable information. This entails two important policy implications.

The first is that financial information should become available in a straightforward, timely and relatively inexpensive manner so that it reaches as wide a part of the investing public as fast as possible. Market efficiency is a multifaceted concept and defines an ideal state of affairs which is not always, if ever, attainable. Capital markets are operated by humans and as such are subject to behavioural biases. Despite thousands of years of evolution humans still engage in massive destruction of wealth as recent market failures demonstrated. The assumption that investors are rational is therefore clearly and repeatedly violated. The depth and breadth of such failures is mitigated by technological advances that make the dissemination and analysis of information ever faster. Consequently better informed participants make capital markets more efficient as attested by the fact that market failures in the early 1900's were far more catastrophic than recent incidents. In order for investors to be better informed, information should be straightforward so that non-experts can easily understand it and thus react to it appropriately. Recent scandals help highlight the catastrophic consequences of creative but otherwise legal accounting practices that purport to obfuscate the true financial position of a company. Information should also be inexpensive so that it becomes more symmetrically distributed. A market where wealthy investors are also better informed and benefit at the expense of ordinary investors, can not be efficient because it is not fair. Such a market is undermined by the fact that a large part of the investing public feels disadvantaged and so chooses not to participate. For the same reason, information should reach everyone more or less simultaneously.

A closely related second policy implication is that public participation to capital markets should be encouraged. This can be achieved by education and by strengthening the public's trust to the markets. Markets characterised by weak investor participation are susceptible to manipulation and pricing distortions. Education will help demystify the investing process and encourage people to assume a calculated risk in return for a reward. Trust to the markets is strengthened when markets are believed to be fair in the sense that they provide equal opportunities for wealth enhancement to everyone. As noted above, fairness is promoted when all investors have the opportunity to correctly asses the risk they undertake by ensuring access to reliable and intelligible information. This will help dispel the notion that investing is tantamount to gambling. It will also help undermine the perception that capital markets are the exclusive preserve of wealthy individuals. In a nutshell, wider participation of better informed individuals will result in more efficient markets in terms of resource allocation thus benefiting individuals in particular and society as a whole.

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