# The Size Anomaly in the London Stock Exchange. An Empirical Investigation.*

by

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# ABSTRACT

This study tests the size effect in the London Stock Exchange, using data for all non-financial listed firms from January 1985 to December 1995. The initial tests indicate that average stock returns are negatively related to firm size and that small firm portfolios earn returns in excess of the market risk.

Further, the study tests whether the size effect is a proxy for variables such as the Book-to-Market Value and the Borrowing Ratio, as well as the impact of the dividend and the Bid-Ask spread on the return of the extreme size portfolios.

The originality of this study is in the application of the Markov Chain Model to testing the Random Walk and Bubbles hypotheses, and the Vector Autoregression (VAR) framework for testing the relationship of macroeconomic variables with size portfolio returns.

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# Chapter I

# Introduction

Over the last ten to fifteen years articles documenting size, turn-of-the-year and earning/price ratio effects on stock returns have been of great interest to a broad group of financial economists. The so-called 'small firms' effect' has attracted the attention of both theoreticians and practitioners, and this is not incidental: Dimson and Marsh (1989) reported that over the last 33 years the Hoare Govett Smaller Companies Index (HGSC) had provided an annualised return six per cent larger than the All-Share Index.

The fact that the smaller companies' index earned higher returns than the All-Share (Market) Index is not bad news for the Market Efficiency Hypothesis. The latter is not falsified unless there are returns above the risk-adjusted returns. Under the risk-adjusted returns we perceive the amount of return an asset (portfolio) earns, which is proportional to the risk borne by this asset (portfolio).

Since investors can spread their wealth over a broadly diversified portfolio of securities, they should not be concerned with those elements of price volatility which are specific to each individual stock. Instead, the risk that matters to investors should be the element of volatility that cannot be diversified away even in a large portfolio. This undiversifiable element of risk, called beta-risk, reflects the extent to which the return on an asset moves together with the stock market. Therefore, if small firms' returns do not display excess returns after being adjusted for market risk (beta), this will not constitute any kind of puzzle.

During the 1980s an investor could consistently earn returns free of risk. More surprising was the fact that this could be done without special knowledge, intensive research, or use of inside information. All one had to do was to hold a well-diversified portfolio of small firms over a reasonable period of time.

The aim of this dissertation is to detect whether or not the size effect has been present in the London Stock Exchange over the last decade, to estimate its magnitude and eventually, to explain the causes.

There are several lines of thought about why small firms may provide higher returns to their shareholders. Firstly, small firms may be more efficient than large firms. Secondly, the risk estimated by conventional methods may be underpriced. Thirdly, the strategy of portfolio formation, used for testing the size effect, may capture turbulence in small firm prices better than large firms. Thus, the excess returns earned by small size firms may have nothing to do with their intrinsic efficiency. Small firm returns, therefore, may simply be due to trading strategy.

If we assume the first rationale, there are tempting reasons for investigating the size anomaly. Knight (1965) made an early reference to the firm size puzzle, which is as follows:

> 'The relation between efficiency and size of the firm is one of the most serious problems of theory, being, in contrast with the relation for a plant, largely a matter of personality and historical accident rather than of intelligible general principles. But the question is peculiarly vital, because the possibility of monopoly gain offers a powerful incentive to *continuous and unlimited* expansion of the firm, which force must be offset by some equally powerful one making for decreased efficiency' [1965, p. xxiii;]

Coase (1937, 1960) argued that, to some extend bureaucratic costs of running a firm are lower than the costs of co-ordination by market. It is not just costs of production that allow large firms to have a cost-advantage, but also costs of bargaining, implementing and enforcing the agreements, also called transaction costs.

However, if firms grow without limit, bureaucratic costs may outweigh the cost of co-ordinating the economic activities by market. Moreover, hierarchies abolish market incentives.[1]

Therefore, the possibility of different profitability based on the size of the firm is not ruled out by economic theory. The problem, though, is that this hypothesis is difficult to test.

The main line of interest, however, relates to specific stock price behaviour discriminated on the basis of firm size. In comparison to previous work which investigates the size effect in the LSE, this work has several distinctive features.

First of all, the data consist of all firms that have been listed in the LSE from 1982 to 1995, excluding the financial sector. Levis (1985) and Corhay *et al* (1987) are probably the first studies on the size effect in the LSE, confirming its existence during the seventies and the first half of the eighties. Since then, however, there have not been many studies on the size effect in the LSE. More importantly, the number of studies which attempt to explain this size effect is rather modest. Among these are Miles and Timmermann (1996) and Strong and Xu (1994), who both find that the book-to-market ratio explains some of the cross-sectional behaviour of expected returns.

Secondly, other papers (Fraser, 1995, 1996) investigate the size effect using the Hoare-Govett Smaller Companies Index, which comprises approximately 1200 companies, each with a maximum capitalisation of £100 m. The average market capitalisation of the smallest decile in this study appears to be £3 m. in 1985 and £39 m. in 1995. Therefore, using more aggregated data for small firms may not fully capture their behaviour.

In order to estimate risk, this study uses a fairly standard procedure, based on OLS, although introducing some improvements to cope with serial correlation of return series and infrequent trading of small size firms. The estimation of risk allows for assessment

[1]This is why, nowadays, many big companies try to mimic the market incentives introducing so called transfer prices. A nice example are holding companies, in which the subsidiary mimics a self-reliance company.

and comparison of the excess returns on both a yearly and monthly basis, therefore permitting examination of seasonal patterns.

While the existence of size effects in the LSE has not been questioned for the last decade or so, their explanation remains unanswered. Chapter 5 attempts to unravel this mystery. It would be a conundrum, indeed, if the constituent structure of extreme size portfolios did not change significantly, and yet they had a different return profile. Therefore, the composition and stability of extreme portfolios are examined, in addition to the test for book-to-market effects, in a manner similar to Fama and French (1992, 1995, 1996). The book-to-market factors are part of the so called 'proxy hypotheses'. It is possible for size simply to proxy for other factors that make more sense for the eventual difference in returns. A supplementary test for the ability of the borrowing ratio to subsume the size effect is carried out as well.

Many of the size effect explanation hypotheses, reviewed in Chapter 3, are examined too. The illiquidity hypothesis (Amihud and Mendelson (1989)) has been tested mostly in the US stock market. This study provides an estimation of the Bid-Ask spread for the two extreme size portfolios. In addition, the number of re-balancing sales and buys, and the average Bid-Ask spread for each year, are taken into account to obtain the 'net' after transaction cost returns.

Another point in criticising tests on size effects, is that return series typically do not include dividend payments. Again, the dividend yields for two extreme size portfolios are compared to examine a possible dividend impact on size effects.

A preliminary exploration of size portfolios' yearly returns shows certain differences in the intra-portfolio return distribution in terms of $t$-ratios. These findings, together with Knez and Ready (1997), inspire an exploration of the return distribution of the constituencies of size portfolios. The main question here is whether size portfolio average returns are the result of predominantly uniform returns within size portfolios, or whether there is a significant dispersion. Examination of intra-portfolio return distributions has not been reported before. It may be the case that a portfolio excess return may be due to a few exceptionally performing firms, while the rest of the firms perform modestly. It is worth examining the relationship between the sales turnover and the portfolio return for the two extreme portfolios, also carried out in Chapter 5.

However, if we are looking at genuinely original pieces of work, Chapters 6 and 7 come into play. Ever since the 1960s a reasonable number of studies have exploited the Markov Chain approach to test for predictability of various price and return series. To my knowledge, this has not been done so far for return series of portfolios formed on the basis of firms' market capitalisation. The Markov Chain approach allows for the testing of two hypotheses; one tests the weak form of efficiency, known as the Random Walk, and the other the so-called 'Bubble hypothesis'. Both tests allow us to detect possible inefficiencies based on different size portfolio returns.

While Chapter 6 deals with the possibility of predicting size portfolio returns on the basis of their previous values, Chapter 7 looks at the potential interaction between macro-economic indicators and size portfolio returns. Studies of the relationship between macroeconomic variables and stock returns, in general, confirm stock market returns as leading and macroeconomic variables as lagging indicators. Chapter 7 is unique in the sense that no investigation has been performed on the interaction between macroeconomic variables and stock returns, when the latter are discriminated on the basis of market capitalisation. Furthermore, Chapter 7 employs the comparatively contemporary framework of the Vector Autoregression model (VAR).

Chapter 2 looks at stock market efficiency, valuation and structure, with which most readers would be familiar. Chapter 3 reviews the papers that have made a contribution on size and other related anomalies.

# Chapter 2

# Stock Market Efficiency, Valuation and Structure

## 2.1. Efficiency of Capital markets

### 2.1.1. Introduction

'Efficiency' is probably the most multidimensional and controversial word in the economist's vocabulary. In a general context it refers to an organisation of society, which allows for maximisation of the total utility of the society's members. Pareto Efficiency is the state where nobody can be better off without making someone else worse off. Someone could be better off because he or she possesses information that a commodity can be bought at a lower and sold at a higher price. If such an opportunity exists it will imply an inefficient market.

The price mechanism, even though imperfect, has a unique role in organising society's economic activity and thereby promoting efficiency, since prices provide information about supply and demand.

Similar arguments can be applied to the efficiency of the stock market. The stock market, unlike the commodity market, deals with capital risk and provides stability to the rest of the markets.

A broader view on market efficiency is expressed by James Tobin, the winner of the 1981 Nobel Prize in Economics. Tobin (1984) suggests four meanings of market efficiency. First, a market is 'efficient' if it is, on average, impossible to gain from trading on the basis of generally available public information. That is, new information is quickly 'discounted', and arbitrage opportunities exploited. As a result, only insiders can beat the market consistently. Efficiency in this sense is called information-arbitrage efficiency.

Second, if the market in a financial asset accurately reflects the future payments to which the asset gives title, this market possesses fundamental-valuation efficiency.

The third meaning of efficiency stems from the nature of financial products. Nelson (1970) defines two types of goods – one whose quality can be ascertained at the point of purchase (search goods) and the other (experience goods) whose quality is ascertained after consumption. Financial products and services generally fall into the second category. Due to the uncertainty associated with the future, the efficiency of the financial system depends crucially on its ability to hedge against possible risks. Kenneth Arrow and Gerard Debreu show that a complete set of competitive markets dealing in contracts that cover specified future contingencies is necessary and, given some other conditions, sufficient to guarantee the existence of an optimal equilibrium. Thus, Tobin (1984) calls this type of efficiency in the Arrow-Debreu sense full-insurance efficiency.[1] Finally, functional efficiency refers to the functions performed by the financial industries and their cost effectiveness.

Information-arbitrage and fundamental-valuation efficiency are two forms of market efficiency which are closely related and will be subject of further investigation.

Capital markets are said to be efficient if security prices reflect the fundamental values of the securities. Research into the efficiency of capital markets has concentrated on the *information* content of prices. Efficiency refers to two aspects of price adjustment to new

[1] The dramatic growth in the number of financial derivative products in the 1980-s and the continuous financial innovation support the notion of full-insurance efficiency.

information, i.e., speed and accuracy. The main effect of efficiency should be that it precludes most, if not all, investors from being able to systematically outperform the market.

In Fama's (1970) survey on efficient capital markets, he defines an efficient capital market as one in which security prices fully reflect all available information. This definition is based on the 'fair game' model of price determination. A process is a fair game if it has an expected value of zero. In this way the best forecast of $X_{t+1}$ that can be constructed based on some information set in period $t$ is just $X_t$.

$$E(X_{t+1} / \Theta_t) = X_t \tag{2.1}$$

Therefore, for the fair game model to hold, there must be no way in which the information set $\Theta_t$ can be used to earn excess returns, i.e. a greater return than that inherent in this security. Thus the degree of market efficiency relates to the information set $\Theta_t$. Weak form tests of market efficiency are defined when $\Theta_t$ consists of the past history of the stock price. The market is weak form efficient if no one can use these past prices to earn excess returns.

For the semi-strong form of market efficiency to hold, prices have to reflect not only historical prices, but also all publicly available information. This form of market efficiency assumes that publicly available information, such as company reports, is costless to investors. The investors agree on the interpretation of this information, so their reaction to the news should be synchronous and instant.

For the purposes of this dissertation, an efficient capital market is one where it is impossible to earn consistent excess returns from a trading strategy based on the firm's market capitalisation level being publicly available information; that is, the so-called 'size-effect' should not exist.

## 2.2. Prehistory of Market Efficiency

Empirical work on capital market efficiency can be traced back to the 1960s, when many authors began a comprehensive investigation of this issue. The earliest cited test is a PhD dissertation written in 1900 by Louis Bachelier, a French mathematician.

### 2.2.1. The Random Walk Model

Bachelier suggested that share prices should have successive independent increments, i.e., today's price change should be independent of yesterday's. The test, performed against Government bond prices, concluded that the mathematical expectation of a speculator's return was zero. Therefore the Government bond market was a fair game, and efficient in the sense that speculators could not predict the future price from past price changes.

The model that tests this weak form of efficiency is known as the 'random walk' model, i.e., successive price movements are drawn from identical independent distributions. In 1934 Holbrook Working, an American statistician, noted that both commodity and stock prices followed a random walk.

The first systematic treatment of the random walk model was by Kendall (1953). He analysed the behaviour of weekly changes in the indices of shares on the London Stock Exchange and prices of cotton and wheat on American commodity markets. The conclusion that Kendall reached was that price series resemble random numbers drawn from a symmetrical population of fixed dispersion, added to the current price to define the next week's price.

Further research on the random walk efficient market was performed by Roberts (1959), who found that the weekly changes in the Dow Jones index resembled a time series generated from a sequence of random numbers. The implication was that price changes were independent of their past history. Osborne (1959) found that stock price movements were very similar to the random Brownian motion of physical particles.

A random walk is a very restrictive example of a stochastic process. It essentially assumes that the probability distribution of a process such as $\{x_t\}$ is independent and identically distributed such that the distribution must be the same for all time *t*. Equation (2.2) presents the random walk process as

$$f(x_{t+1}|\Phi_t) = f(x_{t+1}) \tag{2.2}$$

where $f(x_{t+1}|\Phi_t)$ is the probability distribution, conditional on $\Phi_t$, which is the information set available in time *t*, and $f(x_{t+1})$ is the unconditional distribution of $x_{t+1}$.
In the zero mean random walk, which is the simplest example of a random walk process, each successive change in $x_t$ is assumed to be drawn from an independent distribution with a zero mean, $x_t$ being defined by

$$x_t = x_{t-1} + \varepsilon_t \tag{2.3}$$

where $E(\varepsilon_t) = 0$, $E(\varepsilon_t^{\,2}) = \sigma^2$ and $E(\varepsilon_t \varepsilon_s) = 0 \quad t \neq s$, i.e. $\varepsilon_t$ is white noise.

If we knew the past history of $x_t$, the forecast of $x_{t+1}$ would be given by

$$x_{t+1} = E(x_{t+1}|x_t \ldots x_1) \tag{2.4}$$

which is the expected value of $x_{t+1}$ conditional on the previous values of $x_t$.

Since $x_{t+1} = x_t + \varepsilon_{t+1}$ is independent of $(x_t \ldots\ldots, x_1)$, the forecast one period ahead becomes

$$x_{t+1} = x_t + E(\varepsilon_{t+1}) = x_t \tag{2.5}$$

so that all information required to make a forecast of the future value of $x_t$ is contained in its most recent observation. Likewise, the forecast $n$ periods ahead is also $x_t$,

$$x_{t+n} = x_t + E(\varepsilon_{t+n}) = x_t \qquad n = 1,2,3....... \tag{2.6}$$

which can be translated as meaning that the optimal predictor of $x_{t+n}$ can be obtained as $x_t$.

If a stochastic process is a random walk, successive changes in $x_t$ must be uncorrelated since

$$(x_{t+1} - x_t) = \varepsilon_{t+1}$$
$$(x_t - x_{t-1}) = \varepsilon_t$$
$$Cov[(x_{t+1} - x_t),(x_t - x_{t-1})] = 0$$

This must be true not only for the successive changes in $x_t$, but for covariance between $x_t$ and $x_{t+i}$ taken at any interval.

The random walk model emerged as a favourite model for testing the random behaviour of stock prices. The assumption of independence inherent in the random walk model, however, requires that each $x_t$ is drawn from a probability distribution which repeats itself identically over time. This requires independence not only between the first moments, but also between the second moments of $x_t$ such as the conditional variance. Fama (1965) and Mandelbrot (1966) showed that the unconditional distribution of short-horizon returns was characterised by excess kurtosis. Thus, returns are distinguished by an excessive number of returns clustered around the expected returns or at the extreme ends of the tails (fat tails). This suggests that large returns are followed by large returns and small returns by small returns.[2]

According to LeRoy (1989) the random walk models seems flatly to contradict not only the received orthodoxy of fundamental analysis, but also the very idea of rational security pricing. If stock prices are patternless, as the random walk model implies, then these prices are exempt from the laws of supply and demand that determine other prices. By requiring probabilistic independence between successive price increments, the random walk model was too restrictive to make any reasonable economic sense.

### 2.2.2. Martingales and Sub-Martingales

A weaker restriction on asset prices that still captures the flavour of the random walk models is the martingale model. Paul Samuelson (1965) was the first to develop the link between capital market efficiency and martingales. A stochastic process is a martingale with respect to a sequence of information sets $\Phi_t$, if $x_t$ has the property:

$$E(x_{t+1} / \Phi_t) = x_t \tag{2.7}$$

and the stochastic process $y_t$ is a fair game if it has the attribute

$$E(y_{t+1} / \Phi_t) = 0 \tag{2.8}$$

where, $y_{t+1} = (x_{t+1} - x_t)$.

If $x_t$ is a martingale, the best forecast of $x_{t+1}$ based on currently available information $\Phi_t$ would be $x_t$. Similarly, if $y_t$ is a fair game[3] the forecast of $y_{t+1}$ would be zero for any value

[2] The Markov chain Model is applied in Chapter 6 to test for successive patterns in large and small returns of portfolios formed on size (market capitalisation).

of $\Phi_t$. The martingale model looks very similar to a random walk, but it is less restrictive. It does impose the restriction that successive changes in the value of $x_t$ be uncorrelated, but the distribution of $x_t$ is not assumed to be identical and independent.

The martingale model does not resolve all the puzzles attributed to random walk, but it does relieve many of them. Unlike the random walk model, the martingale model constitutes a real economic model of asset prices, in the sense that it can be linked with simple assumptions about preferences and returns.

The pure martingale model, however, assumes the expected value of $y_t$ to be equal to zero. Clearly, this is an unrealistic supposition in relation to stock prices. A model that descends from the martingale, and which treats stock market prices more pragmatically, is the sub-martingale model. It assumes that the stochastic variable $x_{t+1}$ has an expected value greater than or equal to $x_t$. The implication for $y_{t+1}$[4] is that it must have expected value greater than zero or zero at minimum. Thus, the sub-martingale model assumes that on average $x_t$ gets larger each period.

$$E(x_{t+1}|\Phi_t) \geq x_t \tag{2.9}$$

$$E(y_{t+1}|\Phi_t) \geq 0 \tag{2.10}$$

Thus, the sub-martingale model delineates a more authentic picture of stock prices and stock return behaviour, as it encompasses two concepts, both inherent in the stock market - the time value of money and risk.

[3] A fair game is one whose expected outcome is zero. The etymology of the term *Martingale* may come from the French town with the same name. In Martingale, during medieval times there was a popular game in which in every round players bet their cumulative losses in previous rounds. If players can play as long as they want to, that would imply a fair game.

[4] In respect to the Stock Market, $x_t$ represents a stochastic series of log share prices, while $y_t$ is the returns.

Returns on assets must be positive to compensate for the loss of liquidity and risk involved in a project. Therefore, asset prices must follow a sub-martingale.

$$E(r_{t+1}) = \frac{E(p_{t+1}|\Phi_t) - p_t}{p_t} \geq 0 \tag{2.11}$$

where $p_t$ is the price of an asset in time $t$, and $r_{t+1}$ is the return of the same asset in time $t+1$.

## 2.3. Fama's definitions and evidence

Fama's (1970) survey looks at the dividing line between the 'prehistory' of efficient capital markets, associated with the Random Walk model, and modern literature. Fama's definition of capital market efficiency became the industry standard, reproduced in innumerable subsequent papers. He distinguishes three types of test of the efficient market model, depending on the specification of the information set $\Phi_t$.

Capital markets are 'weak form efficient' if $\Phi_t$ comprises historical prices only. Weak form efficiency implies that no trading rule based on historical prices alone can earn excess returns. Market agents who seek to predict future price movements by looking at past price performance are known as *chartists*. Therefore, if the market is weak form efficient, there is little scope for chartists.

As has already been noted, weak efficiency tests, which began at the beginning of this century, were widely performed during the 1960's and are still on the analyst's agenda. The most important weak form test consists of measuring autocorrelation in the return series. Absence of autocorrelation would suggest weak form efficiency.

According to Fama (1970), serial correlation tests similar to Fama and MacBeth (1973) discovered no statistical dependence. However, contradictory results have been found more recently. For example, Fama and French (1988) tested for autocorrelation of both daily and weekly returns over 3, 5 and 10 year investment horizons and reported negative autocorrelation for holding periods between 1-6 years. The maximum autocorrelation was reached for holding periods between 3-5 years, where 25-40% of the variation in returns was explainable by past returns.

Capital markets are 'semi-strong' form efficient if $\Phi_t$ is widened to include all information that is publicly available. Analysts who study corporate financial reports and other relevant available information to try to gain an insight into the 'real worth' of shares are called *fundamental analysts.* If the market is semi-strong efficient the fundamental analyst cannot benefit from their studies.

The study of semi-strong efficiency most frequently cited is that of Fama, Fisher, Jensen and Roll (1969), further referred to as FFJR. These authors examined the NYSE reaction to stock splits. A number of prior studies had suggested that stock splits increased the value of the firm. This was seen to be an anomaly by many researches, because stock splits only involve changes in the number of shares per shareholder, without changing the percentage of ownership, the company's earning prospects, or the physical structure of assets. FFJR argued that stock splits were more likely to occur during abnormally good periods, when companies had performed well relative to the market. Their data comprised 940 splits between 1927 and 1959 and for each split they estimated the following Ordinary Least Square equation:

$$r_{it} = a_i + b_i r_{mt} + e_{it} \tag{2.12}$$

where $r_{it}$ is the return of the $i$th firm in month $t$, $a_i$ is the intercept term for firm $i$, $r_{mt}$ is the market return in month $t$, and $e_{it}$ is the residual error.

Two types of data were examined; Firstly, the excess returns 30 months before and 30 months after the splits, and secondly, the cumulative excess returns. FFJR showed that cumulative returns increased before the stock splits and this was most pronounced 10 months before a split took place. After the split, the stocks on average performance were without abnormal return. It was suggested that the market anticipated the better performance of the firms and FFJR interpreted the splits as being confirmation of this.

FFJR concluded that splits could not be used to generate trading profits by buying on announcement, because security prices would already reflect this information. Hence, FFJR's study provided evidence that the stock market is semi-strong form efficient.

Strong form tests of market efficiency are concerned with whether all information, private or public, is fully reflected in security prices. If market efficiency is strong, no *speculator* can gain. Neiderhoffer and Osborn (1966) showed that NYSE specialists used their monopolistic access to generate trading profits. In 1968, a study by Lorie and Neiderhoffer examined the possibilities of insider trading profits. In the US, potential insiders, such as top firms' managers, are required to declare any transaction in their firm's shares to the Securities and Exchange Commission (SEC). Lorie and Neiderhoffer studied the SEC's files of security transactions and found that excess returns could be made by trading on inside information. Fama's (1970) survey on efficient markets concluded that, in general, markets are efficient. Later works in this area showed that market returns might be predictable. In a second study, Fama (1991) found predictability of long horizon stock returns, in contrast to the conclusion drawn in Fama (1970). In the 1991 paper he acknowledged strong negative autocorrelation in 2- to 10-year returns due to large, slowly declining temporary (stationary) components of prices. There was also evidence on return predictability from other variables, such as dividend yields and E/P ratios, which favoured market inefficiency. Other works, which test market efficiency, such as De Bondt and Thaler's (1985, 1987) overreaction hypothesis are reviewed in Chapter 3 since they relate to the size effect. Various other anomalies are considered in the next section.

## 2.4. Evidence against market efficiency

Le Roy and Richard Porter's 1975 paper (published 1981) suggested that if returns were unpredictable this would imply that asset prices should have lower volatility relative to dividend volatility. The so-called volatility test performed by LeRoy and Porter ascertained that the more information agents have, the greater the variance of price and the lower the variance of discounted returns.

These facts implied that hypothetical variation in agents' information induces a negative relation between the variance of prices and the variance of returns. Thus, if agents have very little information, stock prices will not be much different from the discounted sum of unconditional expected dividends. Therefore stock prices have low volatility. In this case the realisation of actual dividends comes as a near-complete surprise, inducing high volatility in actual returns. However, if the agent has a great deal of information about future dividends, stock prices will have almost as much volatility as discounted actual dividends, the two being highly correlated. Hence, significant surprises occur very seldom, implying that returns will usually be nearly equal to their unconditional expectation.

Given that price and return volatility depend monotonically on how much information agents have, it follows that, if bounds were placed on agents' information, these would induce bounds on the variances of price and return. Having in mind Fama's definition of weak-form efficiency, the obvious choice of a lower bound on agents' information means that agents know past returns but nothing else.

Le Roy and Porter's (1981) volatility test confirmed that stock price volatility was higher than could be predicted by dividend volatility, thus providing evidence against efficiency. Shiller (1979, 1981) found similar results.

## 2.5. Ordinary Share Valuation Models

The main ordinary share valuation models are reviewed in this section. Most of these models include a single-security valuation, rather than portfolio combination approaches.

Another feature of these models is the lack of variables that price the risk of an asset and, therefore, the asset's return variability has no impact on firm's value. None the less, such models as the Dividend Discount Model (DDM) and the Price/Earnings ratio model (P/E) are powerful tools for the assessment of individual assets, due mainly to the direct relation of the market value to the return generating process. It is likely, however, for one to argue that the accounting indicators are not precise due to creative accounting and accounting standards incompatibility (see section 2.5.4).

The practical use of conventional ordinary share pricing models requires a time-series estimation of past performance indicators. In this instance, they resemble the Market Model approach relating past share price behaviour to the current price and expected future return.

The Dividend Discount Model and P/E ratio model are often referred to as share price fundamental models as they attempt to derive the share value from the discounted income flow, reflected in firms' accounting reports. If the accounting reports represent a true and fair picture of firms' activities, DDM and P/E ratio models are natural models for assessing share value, as they stem from fixed interest security models of valuation. For both fixed interest securities and ordinary share valuation models there are two unknowns in the general Present Value equation, i.e., the income stream and the discount factor.

### 2.5.1. The Dividend Discount Model

Owners of a company have a legal claim on the company's net assets, i.e., assets minus liabilities. The net assets, however, due to a number of factors, are a rather elusive category. A more realistic outcome for an investor's claim is the market value of their shares. As the market value of a share is subject to frequent movements, investors cannot be sure that they will get a good deal when selling their shares. That is why one may estimate share value by taking the present value of all future expected dividends:

$$V = \sum_{t=1}^{T} \frac{E(d_t)}{(1+i_t)^t} \tag{2.13}$$

where $E(d_t)$ is the expected dividend to be received in period $t$, and $T$ is the number of periods before the last expected liquidation dividend from the stock.

Equation (2.13) is identical to the Present Value model, the only difference being that the cash flow is now replaced by the dividend payment stream. Future dividends can be projected with the aid of proforma balance sheets and income statements. However, as dividends cannot be estimated infinitely far into the future, equity valuation models typically make the simplifying assumption that the dividend stream becomes constant at some future period. Because the constant dividend stream represents perpetuity, the value of the stock at time $t$ will equal the expected constant dividend at this time divided by the required return.

$$V = \frac{E(d)}{i} \tag{2.14}$$

### 2.5.2. The Constant Growth Model

If dividends are expected to grow at a constant rate $g$ and the term structure of interest rates is flat, equation (2.14) converts to

$$V = \frac{d_0(1+g)}{i-g} \tag{2.15}$$

where $d_0$ represents the nominal dividend on a share at the time $t_0$. Equation (2.15) shows that equity value is a positive function of dividend growth rates and a negative function of the required return. However, the model muddies the relationship between equity values (prices) and inflation. Thus, during periods of inflation, when both $i$ and $g$ increase, the final effect on $V$ is unclear. Research on the relationship between inflation and stock returns provides evidence of suppressed stock prices during inflation.

The constant growth model provides some insight as to why stock prices, respectively returns, are highly volatile. Assume that $d_0$ and $i$ in equation (2.15) are held constant, while the dividend growth $g$ changes. Table 2.1 shows the impact of the changes in $g$ on the value of stock $V$.

**Table 2.1**
Impact from the changes in $g$ on $V$

| $V$ | $d_0$ | $g$ | $i$ |
|---|---|---|---|
| 100.00 | 1.82 | 0.1 | 0.12 |
| 66.06 | 1.82 | 0.09 | 0.12 |
| 49.09 | 1.82 | 0.08 | 0.12 |
| 38.91 | 1.82 | 0.07 | 0.12 |
| 32.12 | 1.82 | 0.06 | 0.12 |
| 27.27 | 1.82 | 0.05 | 0.12 |

This constant-growth formula makes it easy to see why quite small changes in the views of investors can lead to large variations in the stock price. For example, imagine that stock A is expected to pay a dividend next year of £1.82 and that the dividend is expected to grow indefinitely at an annual rate of 10 percent. If investors require a return on the stock of 12 percent, the current price will be £100. If, however, the growth rate was overestimated, or markets readjust their view and perceive 8 percent dividend growth, then stock value plummets to £49.09.

Thus, the high sensitivity to small changes in the estimate of $g$ is a major problem with the constant growth model, which sometimes may lead to ridiculous valuations. For most companies the constant growth model is not particularly applicable, except as a very rough valuation of very stable companies or the stock market as a whole. Besides, dividend growth may not always indicate growth in the company's value: it may imply scarcity of investment opportunity and decline. Empirical evidence in Benartzi *et al* (1997) even suggests a lack of support for the hypotheses that dividends have information content about future earnings changes.

### 2.5.3. The P/E Ratio Model

Price/earnings ratios, which are often called P/e ratios, measure the price paid per pound of earnings. Throughout substitution, equation (2.15) can be converted into a model in which the company's value is a function of earnings $e$. The numerator in equation 2.15 equals the expected dividend in the next period, i.e., $d_0(1+g)=d_1$, since $g$ represents the periodic constant growth in dividends and earnings. The expected dividend $d_1$, the numerator, is equal to the expected earnings times the dividend payout ratio, where the dividend payout ratio is the percentage of earnings paid out in dividends, i.e., $d/e$. Thus, the numerator in equation (2.15) can be re-written as $d_1 = e_1(d/e)$. Dividing both sides by $e_1$ yields

$$\frac{V}{e_1} = \frac{\frac{d}{e}}{i - g}. \tag{2.16}$$

Equation (2.16) suggests the amount an investor would be inclined to pay for a pound of the company's earnings in the next period. The model indicates that investors are willing to pay more for a pound earnings if the earnings and dividends of the company are expected to grow fast, and if the discount rate is low.

Introducing the operational ratios into the P/E ratio model, and assuming a constant return on equity ($ROE = const.$) and a constant earnings retention ratio $(1 - d/e)$, yields

$$g = r\left(1 - \frac{d}{e}\right)^{5} \tag{2.17}$$

where $r$ denotes the company's expected $ROE$.

Substituting 2.17 into 2.16 produces

$$\frac{V}{e_1} = \frac{\frac{d}{e}}{i - r\left(1 - \frac{d}{e}\right)} \tag{2.18}$$

Equation (2.18) casts a further insight on the investors' behaviour. The higher the expected ROE $(r)$, the higher the amount that can be paid for a pound of future earnings, and vice-versa. However, equation (2.18) also shows that high ROEs alone are not sufficient to justify high P/e $(V/e_1)$ ratios. A significant amount of earnings must be reinvested at this high ROE in order for a very high P/e to be justified. The discount rate, on the other hand, relates negatively to the value of the stock $(V)$. The discount rates for different companies should be different, reflecting variation in beta risk and transaction cost premiums. A simple ROE ratio says nothing about the risk incurred. ROEs can often be magnified by increasing the gearing ratio (Debt to Assets ratio).

[5] See Appendix 2.1 for mathematical proof of equation 2.17.

### 2.5.4. The fallacy of models based on accountancy figures

The previous ordinary share valuation models rely heavily on accounting information. Except in the simplest cash-based businesses it is impossible, even with the best will in the world, to produce accounts which are anything other than an approximation which has its basis in the transactions and events of the year under review. The biggest difficulty is that companies are required to report annually. As a period of accountability there is a lot to be said for the twelve month cycle. Unfortunately, it has no relevance at all to the natural business cycle of any company one cares to mention. A baked-bean manufacturer would have a cycle measured in weeks. A construction company would, however, have a cycle measured in years. Yet both are obliged to report their results on an annual basis and to report them using the same accounting standards.

In addition, there exists a natural craving from both the City and the companies' management to see a rather smooth and uninterrupted growth of companies' earnings, or as Griffiths (1995) puts it:

> 'The biggest problem it faces is the unwitting conspiracy between the City and industry which ensures that the black and white which so much appear to demand will be condemned always to a murky grey. While much is made of the tension between companies and their investors there is a remarkable overlap in their interests. Both would like to see a steady increase in a business's earning growth profile. In reality it is rarely achievable. However, that does nothing to diminish the zealous pursuit of this elusive Holy Grail.' (p. xi)

There are many possibilities a company can employ in order to alter the 'true and fair picture' of its performance, such as taking the costs up front and below the line, as well as varying its income and expenses, fixed assets and deferred taxation.

In some cases companies are incurring significant costs relating to rationalisation and restructuring of business which are treated as extraordinary. The nature of these programmes means that they could be quite often carried out over a number of accounting periods. However, by taking the costs up front and below the line a company is able to ringfence its profit and loss account and earnings per share from the otherwise negative implications. It is not just in year 1 that the earnings per share figure is protected. The actual cash to pay for the rationalisation is paid out in later years. The charge is made not against profits for the year but against the provisions which have been set up at the outset and treated as extraordinary.

The degree of flexibility of income and expenses is influenced considerably by the nature of the business. It is much more difficult, for instance, to manipulate the sales of a supermarket chain, which is essentially a cash business, than it is to tinker with the turnover attributed to a leasing company where there is usually a much more tenuous relationship between the cash handed over by the customer and the provisions of goods or services.

The warranty payments are themselves an area which offers some creative accounting opportunities. The way in which a company chooses to deal with them can have a marked impact on the declared income for the year. There is a debate about whether the warranties should be seen as a reduction in sales or an expense of the business. The financial effect ultimately is the same but the way it is presented can give a rather different impression of the same situation.

Take companies A and B. Both sell exactly the same numbers of the same product at the same price. Both incur warranty claims amounting to half of their sales, and the other cost of sales equates to 25 percent of the gross selling price. Assume sales are £24 million but that Company A treats warranties as a cost of sale while Company B shows sales net of warranties.

**Table 2.2.**

| | Company A | Company B |
|---|---|---|
| | (£m) | (£m) |
| Sales | 24 | 12 |
| Cost of sales | 18 | 6 |
| Gross profit | 6 | 6 |

The gross profit figure is the same, but company A is making an apparent margin of 25 percent on sales while company B is making a 50 percent margin. Company A looks like a high volume low-margin business where as company B appears to be operating in high-value-added territory. That could have quite an impact on the perceptions which outside investors have of the two companies.

The great thing about fixed assets is that their values are completely mobile. The purchase price sets the benchmark from which the creative accounting process begins. The justification for this creativity is actually embodied in company law, which permits three different bases for the valuation of fixed assets to be adopted. Alongside the old favourite of historical cost, which is simply the price paid for an asset, the legislation also allows market valuation to be used. Companies can also state their fixed assets at current cost although the law gives no indication of what it means by this rather vague term. Given this overt approval of a variety of valuation methods, it is not surprising that most businesses are more than happy to take advantage of them.

It is both difficult and dangerous to attempt to manipulate the actual tax bill artificially. The flexibility arises from the mismatch between the Revenue's attitude to a company's tax liability and that adopted by the accounting standard setters.

At the heart of the mismatch are the differences between the tax treatment of some items of income and expenditure and their accounting treatment. These differences may be permanent or temporary, and are a function of what are known as timing differences, so called because they reflect the fact that a tax liability will arise at some later point in time.

It follows that the analysis based on accountancy figures may lead to deceptive estimates of companies' value. Furthermore, the accountancy reports come into the public domain well after the events they describe. Although accountancy reports convey highly sensitive price information, if one believes in stock market efficiency, this information is grossly incorporated into prices, before reports are published. An equilibrium model which makes use of the information embodied in market prices is the Capital Asset Pricing Model (CAPM).

### 2.5.5. The Capital Asset Pricing Model (CAPM)

The CAPM was introduced into the theory of equilibrium asset pricing by Sharpe (1964) and Lintner (1965) from the ideas put forward by Markovitz (1959). Markovitz (1959) developed a model that prices individual assets based on the variance-covariance matrix of these assets' returns. Although ingenious, Markovitz's model is not applicable in practice, due to the large number of covariances required for optimising the portfolio structure.

The CAPM is an elegant and attractive model that offers the prospect of being able to ignore investor preferences when pricing assets. Each asset price depends only on the asset's covariance with the market, which simplifies the estimation procedure exceedingly. Sharpe and Lintner showed that if investors have homogeneous expectations and optimally hold mean-variance portfolios then, in the absence of market frictions, the portfolio of all invested wealth, or the market portfolio, will itself be a mean-variance efficient portfolio.

The Sharpe and Lintner derivations of the CAPM assume the existence of lending and borrowing at a riskfree rate of interest. The expected return of asset $i$, for this version of the CAPM, is:

$$E(R_i) = r_f + \frac{E(R_m) - r_f}{\sigma^2(R_m)} \sigma(R_i, R_m) \tag{2.19}$$

$$E(R_i) = r_f + \beta_{im}\left[E(R_m) - r_f\right] \tag{2.20}$$

where,

$E(R_i)$- the expected return of security $i$,

$E(R_m)$- the expected return of the market,

$r_f$ - the risk free rate of return which compensates for the time value of money,

$\beta_{im} = \dfrac{\sigma(R_i R_m)}{\sigma^2(R_m)}$.

Equations (2.19) and (2.20) state that the required equilibrium ex-ante return on asset $i$ is equal to the return $r_f$ on a risk free asset and a risk premium, $\beta_i\left[E(R_m) - r_f\right]$. The risk premium for asset $i$ is proportional to the systematic risk, beta, where $E(R_m) - r_f$ is the market risk premium. The unsystematic risk $\varepsilon_i$ is the specific risk associated with $i$, which can be diversified away by investing in a portfolio. Therefore, the market does not remunerate investors for their specific risk exposure.

In the absence of a riskfree asset, Black (1972) derived a more general version of the CAPM, known as the Black version. The Black CAPM uses the return on a portfolio that has the minimum variance of all portfolios uncorrelated with the return of the market portfolio, or the *zero-beta portfolio*. Specifically, for the expected return of asset *i*, $E(R_i)$, we have

$$E(R_i) = E(R_{0m}) + \beta_{im}\left[E(R_m) - E(R_{0m})\right] \tag{2.21}$$

$R_m$ is the return on the market portfolio, and $R_{0m}$ is the return on the *zero-beta portfolio* associated with *m*. Any other uncorrelated portfolio would have the same expected return, but a higher variance. Since it is wealth in real terms that is relevant for the Black model, returns are generally stated on an inflation-adjusted basis and $\beta_{im}$ is defined in terms of real returns. Econometric analysis of the Black version of the CAPM treats the zero-beta portfolio return as an unobserved quantity, making the analysis more complicated than that of the Sharpe-Lintner version.

The CAPM can be presented in terms of fair game as follows

$$y_{i,t} = R_{i,t} - E\left(R_{i,t} / \hat{\beta}_{i,t}\right),$$
$$E\left(R_{i,t} / \hat{\beta}_{i,t}\right) = r_f + \left[E\left(R_{m,t}\right) - r_{f,t}\right]\hat{\beta}_{i,t},$$
$$E\left(y_{i,t} / \beta_{it}\right) = 0.$$

where $\hat{\beta}_{i,t}$ is the estimated market risk.

The CAPM tests the joint hypothesis that the CAPM is the appropriate equilibrium model and that markets are efficient. If this is the case, then $E\left(y_{i,t}\right)$ must be a fair game. There is evidence that the difference between the actual return and the expected return is either non-zero, or exhibits predictable components. An extensive review of this evidence, in relation to the size anomaly, is presented in Chapter 3.

The following section (2.6) considers stock market microstructure issues and the possibility that stock prices exhibit different behaviour under different trading rules. As the model applied for testing the size anomaly (CAPM) employs stock prices, any failures to reflect information may weaken the performance of the model.

## 2.6. Stock Market Mechanism and Price Discovery

It is a common view that the stock market is a place where trade between market agents takes place. As such, the stock exchange has been covered in mystique. Commentators have been fond of using the analogy of the club to describe the system of self-regulation which operated in the City. The City relied on light self-regulation with occasional intervention from the Department of Trade and Industry and the Bank of England. The Stock Exchange formed its own rules, and takeovers and mergers were regulated by a code, which had no legal force.

Hilaire Belloc's famous rhyme epitomises it:

'In the City they sell and buy
and nobody ever asks them why.
But since it contents them to buy and sell
God forgive them, they might as well.'

People do not know what goes on in the City. They doubt if it is very valuable, but so long as it does not interfere too much with what is going on in the rest of the economy, they are content to let it go on happening.

### 2.6.1. Trading Mechanism in Securities Markets.

The crucial function of a trading mechanism is to transform the latent demand of investors into realised transactions. Recent empirical research suggests[6] that the trading mechanism, as a part of market structure, has an important effect on the properties of asset prices. The key to this transformation is the process of finding market clearing prices, known also as price discovery.

Stock prices in world stock markets are formed under two major mechanisms: a continuous quote-driven system where dealers post prices before order submission and an order-driven system where traders submit orders before prices are determined. The order driven system can either be a continuous auction with immediate execution, or a periodic auction where orders are stored for simultaneous execution.

[6]See for example, Amihud and Mendelson (1987), Stoll and Whaley (1990), Amihud and Mendelson (1991) and Draper and Paudyal (1997).

The London Stock Exchange (LSE) uses a quote-driven system, where a trader can acquire price quotations before trading and order execution. Contrarily, in many other European stock markets, orders must irrevocably be submitted before prices are determined.

Pure forms of the quote-driven (continuous) and order-driven systems are not present in practice. Every stock market adopts different features of both systems in different degrees. Continental European markets are traditionally order-driven (e.g., the Paris CAC system) and as such depend primarily on *limit orders* of public participants to 'drive' the market. The London Stock Exchange (LSE) is, on the other hand, historically a quote-driven system, relying on the market-makers' commitment of substantial capital to provide a deep market, standing ready to trade very large blocks of stock.

Madhavan (1992) shows that equilibrium may not exist in continuous mechanisms (i.e., the quote-driven system and the continuous auction) unless there is a minimum amount of noninformation trading. It is not, therefore, by chance that there is a relatively high degree of transparency of the CAC system compared with the LSE. The full breakdown of the central order book is visible to all Bourse members, including the codes identifying the number of firms which have placed each order. However, this 'pre-trade transparency' is diminished by the use of 'hidden orders', i.e., the undisclosed portions of orders which only become visible as the disclosed portions are executed.

Due to secular competitive pressures during the eighties, many of the European Stock markets underwent changes. The LSE was the first in Europe to launch a full-scale restructuring[7], albeit not without blustering resistance from many of its members. The reforms in the LSE involved scrapping the traditional distinction between jobbers and brokers, opening dealership to banks and other financial institutions, liberalising commissions, introducing a screen-based system, halving the stamp duty on UK equity and exempting non-UK equity from duty.

[7] Known by the name 'The Big Bang'.

However, London retained one basic feature of its former trading system – i.e., its dealership structure. Although there were suggestions for a possible introduction of an automated order-matching system, it was feared that, for most stocks, the order flow on the LSE would be insufficient to sustain it. Few stocks were actually traded, and therefore the 'private liquidity' of dealers was thought necessary to provide price continuity and timely execution.[8]

Another important issue for stock market functioning is the type of order an investor can put. There are essentially two types of order – market order and limit order.

### 2.6.2. Types of Orders

The market order is probably the most common. When investors place an order at the market, they are telling the broker to buy or sell stock at the best possible price at that time. A market order will always be filled. The drawback is that it may not be filled at the price an investor expected or wanted. For instance, an investor wants to buy Imperial Chemical Industries (ICI). He or she calls their broker and tells them that ICI is currently trading at 760 bid, 765 ask. The bid is the price the market-maker is willing to buy the stock at. The ask is the price the market-maker is willing to sell the stock at. When the broker gets back to the investor, he tells him that he bought, say, 100 shares of ICI at 770. What happened? Between the time the investor gave the broker the order and the order was filled by the market maker, the price went up. One should keep in mind that the price of ICI could have easily been filled at 755 had more people been selling rather than buying at that time.

A 'Limit Order' is a request to the broker to buy or sell a specific amount of stock only if a certain price specified by the investor or better can be obtained. If the specified price is not within the current market quote, it is said to be 'away from the market' and will be entered into the market-maker's book beneath any other orders. This means that there is no guarantee that a limit order will ever be filled.

[8] See Kregel (1990).

When deciding whether to place a limit order or a market order, the investor needs to evaluate the tradeoff between a guaranteed fill, which might be different from what he expects, and getting the price he wants but perhaps not getting filled. It all depends on his analysis and needs.

A stop order represents a conditional market order that is triggered by a transaction at a certain price specified by the investor. A stop buy order immediately becomes a market order to buy if other investors conduct a transaction at the specified stop price or higher. A stop sell order becomes an immediate market order to sell if other investors conduct a transaction at the specified price or lower.

There is also a stop limit order. A buy stop limit means that as soon as trading occurs at the target price, the order becomes a limit order to buy. A sell stop limit order means that as soon as the stock hits a target price, the order becomes a limit order to sell.

There are also three types of orders which can be placed with respect to the duration of time the order stays open. The first is called a 'Day Order'. A day order is just as the name implies: for the day only. At the end of the day if the order is not filled, it is cancelled. The second type of order is called 'Good Till Cancelled' (GTC). An order which is Good Till Cancelled, GTC, means that until the investor tells his broker to cancel the order, the order remains open on the market-maker's book and can be filled at any time.

The last type of order is most frequently used in options and futures trading on a day trading basis. However, it may also be used in stock trading although not all firms will accept it. It's called a 'Fill or Kill' order. Usually, it is placed with a time limit. For instance, a '10 minute fill or kill' means that if the order is not filled in the next ten minutes, kill the order.

Thus, investors can either choose to trade via limit order and supply liquidity to the market or choose to trade via market order and demand liquidity from the market. On this basis, Glosten's (1994) framework has two types of investors: patient traders, who supply liquidity to the market, and other traders, who wish to trade immediately. Handa and Schwartz (1996) find that the viability of an order driven market depends on limit order trading being profitable for a sufficient number of public participants.

### 2.6.3. Transaction costs and Market structure

One of the most consistent empirical findings regarding the relative efficiency of the auction and dealer market is that auction markets offer lower transaction costs. However, auction markets are unable to provide immediate execution of large orders without substantial 'price erosion', or market impact. In other words, auction markets offer cheap execution, but can provide immediacy for retail-sized orders; a trader who wishes for immediate execution of a large order can only obtain it cost-effectively in a dealer market.

There are differences in the pre- and post-trade transparency of the order and quote-driven markets. In a dealer market (LSE), the maximum level of pre-trade transparency is achieved with publicly visible two-way quotes. However, no one can see the consolidated order flow, which has an impact on the market at each moment, and can at best try to infer some information on the orders received by other dealers by observing their quote revisions and by trading with them. Post-trade transparency in dealer markets is, again, much lower than the post-trade transparency in the order-driven markets, where participants know immediately about volumes and prices of the deals. In the LSE, on the other hand, trades must be manually reported to the exchange within a set time limit, after which they may be published, perhaps with a time delay, according to the rules of the exchange. These rules underwent three changes from 1986 to 1996.[9] From October 1986 to February 1989, prices were published immediately. From February 1989 to January 1991, the prices of trades which exceeded £100,000 were subject to a 24-hour delay. From January 1991 to January 1996, there was a 90-minute delay in publication for trades which exceeded three times normal market size (NMS)[10].

[9] See Gemmill (1996).
[10] Each share is allocated to one of twelve NMS bands, based upon customer turnover in the last 12 months.

The rationale[11] behind the delayed publication is that market-makers commit capital to provide immediate 'private liquidity' for investors looking to buy or sell at a specific point in time, regardless of whether there happens to be a natural counterpart at that point of time[12].

## 2.7. Conclusion

In respect to the size anomaly, it is expected that the Bid-Ask spread should decrease as size increases. Therefore, the Bid-Ask spread should be taken into account when estimating the magnitude of the size anomaly.

Another interesting point is the variation in the rules of price publishing: in particular the period from February 1989 to January 1991, when prices of trades which exceeded £100,000 were subject to a 24-hour delay. This threshold did not take into consideration the fact that the average market values of the lowest and highest decile were £14m and £5330m respectively in 1990. Both deciles faced the same publication rules, but it was much easier to buy-out or sell-off in the smallest market decile, and still enjoy non-publication for 24 hours.

[11] A report by the Office of Fair Trading (1994) argues that delayed publication confers unfair competitive advantage on large market-makers.

[12] Market-makers are also exclusively entitled to gather inside information about the firms they are dealing in. Large conglomerates, on the other hand, are compelled by law to prevent inside information leakage across different divisions within the conglomerates. (See McVea (1993)).

## Appendix 2.1

### Dividend Growth Rates and the Return on Equity

Assuming a constant return on equity (ROE), $r$, a company's expected earnings[13] in period 1 could be presented as

$$e_1 = E_0 r \tag{A.1}$$

where $E_0$ is the equity capital in period 0, and $ROE = r = e / E$.
In period 2, the earnings are equal to

$$e_2 = E_1 r \tag{A.2}$$

where

$$E_1 = E_0 + [e_1(1 - d / e)], \tag{A.3}$$

or in other words, the Equity in period 1 are equal to the Equity in period 0 plus the earnings in period 1, times the constant earnings retention ratio.
Replacing $e_1$ in A.3 with the right-hand side of A.1 yields

$$E_1 = E_0 + [E_0 r(1 - d / e)] = E_0 [1 + \{r(1 - d / e)\}] \tag{A.4}$$

Inserting A.4 into A.2 for $E_1$, we get

$$e_2 = E_0 [1 + \{r(1 - d / e)\}] r \tag{A.5}$$

Dividing $e_2$ in A.5 by $e_1$ in A.1, results in

$$e_2 / e_1 = 1 + [r(1 - d / e)] \tag{A.6}$$

which in turn implies an earnings growth rate equal to

$$g = r(1 - d / e) \tag{A.7}$$

[13] Expected earnings are net after paying taxes and interest.

# Chapter 3

# Anomalies' Literature Review

## 3.1. Introduction

Market anomalies can be defined as phenomena where share price behaviour does not comply with investors' rationality or where there are no plausible ways of explaining the anomalous price movements within a set paradigm. Most anomalies have been documented as recurring events which imply either investors' failure to take them into account, or some factors not specified by the Capital Asset Pricing Model (CAPM), which affect the pricing of assets. If the latter case is true, then the benchmark CAPM must be misspecified. In the former case the CAPM is undermined, as it would imply non-rational behaviour of investors.

The Stock Market Equilibrium, as defined by the CAPM, assumes two kinds of risk: systematic, or market risk, and non-systematic, or diversifiable risk. An investor should only be remunerated for suffering systematic risk. As the non-systematic risk can easily be diversified by investing in a portfolio rather than in a single asset, no refund should be given for this type of risk. Therefore, if a group of assets, selected on a basis different to their market risk, i.e. beta, earns returns higher than its overall beta suggests, it would constitute digression from the Efficient Market Hypothesis (EMH) and equally from the CAPM.

Market anomalies in general relate to the EMH. One group of market anomalies relates to the CAPM directly. This group of anomalies, such as P/E, size, and Book to Market anomalies, challenges the CAPM by assuming other risk factors in addition to beta.

The other group of anomalies undermines the weak-form of the EMH test, known also as the random walk test. According to the weak EMH test, publicly available information can not be used to predict future prices. If markets are efficient in their weak form, they should quickly incorporate publicly available information, so that no one would be able to earn excess returns by using some sort of public information, including share prices. Within this second group fall several anomalies, known as calendar anomalies, as well as stock market overreaction and the reversal of large stock price decreases.

When some obvious indicator is used to foresee the future movement in a share price and there is regular success in predicting it, an anomaly is present. Indicators predicting the likely price behaviour, which are also publicly available information with very low cost of collection, can be referred to, such as:

I. Stock Market Statistics.
II. Firms' Balance Sheet and Statements.
III. The Calendar.
IV. A combination of I. and II.

Some of the anomalies which have been documented since the late 70s and early 80s and attract greater interest can be summarised by the sources of data:

I. Stock Market Statistics.
1. Small Firm Anomaly.
2. Initial Public Offering (IPO) Anomaly.
3. Long Run Stock Market overreaction, e.g. Mean Reversion.
4. Reversal of Large Stock-Price Decreases.

II. Calendar
1. The Day of the Week Effect.
a. Friday Effects.

b. Weekend anomaly (Monday effect).

2. Holiday Effect.

3. Turn-of-the-month Effect.

4. January Effect.

III. A combination of Stock market statistics and Firm's Balance Sheet and Statements.

1. Price/Earnings ratio Anomaly.

2. Book-to-market Anomaly.

This chapter is organised as follow: The next section (3.2) reports on evidence of the size anomaly and the likely explanations of it, such as size effect reversals, stock market overreaction, transaction costs, marginal firms and neglected firms. The last sub-section (3.2.7.) looks at some recent advances in the relationship between the Book-to-market and other factors associated with the size anomaly. Other anomalies' associated with the size anomaly, i.e., the Initial Public Offering (IPO) and the Calendar anomalies, are considered in the subsequent sections.

## 3.2. Small Firm Anomaly

### 3.2.1. Evidence

The 'firm size' effect was documented by Banz (1981) and Reinganum (1981). According to their studies, small firms have higher average returns than larger firms, even after adjusting for market risk beta.

Banz (1981) examines the linearity of the CAPM relationship by forming market value (MV) portfolios and then including the ratio of portfolios' MV to the total market value as an additional variable to the market risk (beta) factor in the cross-section return relationship. He finds a negative and persistent relationship between returns and market value of equity for a sample of all common stocks listed on the NYSE for at least 5 years between 1926 and 1976 throughout all sub periods.

The final results of the study show that, in the period 1936-1975, the common stock of small firms earns *on average*, higher risk adjusted returns than the common stock of large firms. Banz notes that his study is not based on a particular theoretical model, and therefore it is not possible to determine whether market value *per se* matters or whether it is only a proxy for unknown factors correlated with market value.

Banz's model relied essentially on Black's (1972) zero-beta CAPM, incorporating size as an additional variable,

$$E(R_i) = \gamma_0 + \gamma_1 \beta_i + \gamma_2 [(\phi_i - \phi_m)/\phi_m] \tag{3.1}$$

$E(R_i)$ = expected return on security *I*,

$\gamma_0$ = expected return on a zero beta portfolio,

$\gamma_1$ = expected market risk premium,

$\phi_i$ = market value of security *i*,

$\phi_m$ = average market value of all securities in the market,

$\gamma_2$ = constant measuring the contribution of $\phi_i$ to the return of a security.

If there is no relationship between $\phi_i$ and expected return, i.e. $\gamma_2 = 0$, then (3.1) reduces to the Black (1972) version of the CAPM. In respect to the errors-in-variables problem, Banz concludes that it should not be a factor as long as the portfolios contain a reasonable number of securities, so that the extreme high and low beta error-in-variables would cancel out.

The major empirical result is a significantly negative estimate for $\gamma_2$ for the overall time period. Thus, shares of large firms appeared to have smaller returns, on average, than small firms with similar risk.

This result, however, should be considered with caution, as Banz reports that:

> 'The correlation between the mean market values of the twenty-five portfolios and their betas is significantly negative, which might have introduced a multicollinearity problem.' (Banz 1981, p.11)

This multicollinearity is regarded as a major problem in testing the size and other anomalies, and subsequent papers suggest ways of tackling it.

Reinganum (1981), whose paper was published simultaneously with Banz (1981), challenges Ball's (1978) E/P effect by providing evidence of the superiority of the 'size effect' over the E/P effect. The E/P effect, also called price/earnings ratio anomaly, states that stocks trading on a high E/P ratio (low price/earnings ratio) outperform the market averages. To answer the question as to whether the E/P and market value of a firm are related or independent, Reinganum classifies firms by both the market values of the common stock and E/P ratios. Twenty-five portfolios are formed, in ascending order, from the lowest MV and E/P to the highest. Then mean excess returns and betas for these portfolios are estimated.

All E/P portfolios within the lowest MV quintile have positive excess returns. However, not all of the MV portfolios within the lowest E/P quintile have positive excess returns. Thus, portfolios formed on MV are more powerful in explaining excess returns, compared to those formed on the basis of E/P ratios. Therefore Reinganum classifies the CAPM as misspecified and defines the size, rather than E/P ratio, as more closely related to equilibrium pricing.

Possible explanations emerged as soon as the size anomaly was documented. Roll (1981) claimed that small firms' thin trade was a possible cause of beta underestimation. Roll expresses a doubt that small capitalisation firms are able to earn excess return when adjusted for risk. Although it is a common belief that small firms are riskier, he still maintains that risk measurements are incomplete. In order to prove this incomplete measurement hypothesis, Roll estimates the return variance of the Equally Weighted Index and Standard & Poor's 500

Index (value weighted) for different time intervals. Then the ratios of the variances between the two indices are calculated for the corresponding time intervals.

The result is puzzling. The variance ratio ($\sigma_e/\sigma_{s\&p}$) gradually increases from 1.05 for daily intervals to 3.166 for semi-annual intervals in the period 1962-1977. As is well known, the equally weighted return index is more populated by small firms, the S&P-500 by large firms. Hence, the relationship between equally weighted and S&P-500 indices could be treated as a relationship between the returns of small and large firms. As the ratio of the equally weighted and S&P-500 return variances changes, when measured for different intervals, movement in the risk measurement should be expected.

On the basis of this evidence, no rational investor whose preferences are to hold his portfolio for more than a day would regard a well-diversified small firm portfolio as equal in risk to a similar well diversified large firm portfolio.

The reason for this measurement bias originates in infrequent trading, inherent in small firm assets. As small firms' assets are not traded for days or even months, their prices do not fluctuate like the prices of large firms. Therefore, the traditional way of estimating return variances and beta underestimates the true risk of holding small firm assets for longer investment horizons.

To solve the problem of incomplete risk measurement, Roll uses both an ordinary method and Dimson's (1979) method, regressing the Equally Weighted Index against the S&P 500 Index. As a result, Dimson's beta is always higher than the ordinary beta estimated for the 1963- 1977 period. The actual beta is obtained by summing the lagged, contemporary and lead beta estimates, a technique, which according to Dimson (1979), allows for infrequent trading of small firms' shares. The inclusion of lead and lagged independent variables aims to deal with the thin-trading problem. Thin-trading is a common feature of smaller size firms, in which the number of shareholders is significantly lower than the number of shareholders in larger companies. As a result, small companies' shares are not traded for long intervals and thus their prices may remain unchanged, especially when the observation frequency is short. In OLS terms, beta would be biased, if estimated only from the contemporary market index.

Thus Roll rejects the existence of size effects and challenges the significance of the previous works. Roll states as a major conclusion:

> 'Trading infrequency seems to be a powerful cause of bias in risk assessments with short interval data.' (Roll, R., 1981, p.887)

Reinganum (1982) reacts to Roll's (1981) conjecture on the firm size effect. The results from his investigation reveal that average returns of small firms exceed those of large firms by more than 30 percent on an annual basis. Even if Dimson's (1979) estimator is employed, beta could not explain more than a 30 percent difference in the average portfolio returns.
At the end of each calendar year all common stocks listed on NYSE-AMEX are placed into one of ten portfolios, based upon the stocks' relative position in the value ranking. The ten market value portfolios are updated annually, in order to account for the changes in the assets' market capitalisation. The number of firms that satisfy the data requirements ranges from 1457 in 1963 to over 2500 in the mid 1970s.

The portfolio betas are estimated using OLS and Dimson's (1979) aggregated coefficient method. The following regression is run to test for the magnitude of the size effect in each of the 180 months from 1964 through to 1978.

$$R_{pt} = \gamma_{0t} + \gamma_{1t}\beta_{py} + \gamma_{2t}S_{py} + \varepsilon_{pt} \tag{3.2}$$

$R_{pt}$ = return in month $t$ on market value portfolio $p$,

$\beta_{py}$ = estimated Dimson's beta for portfolio $p$ during year $y$,

$S_{py}$ = logarithm of median firm size in portfolio $p$ at the end of year $y$-$1$,

$\varepsilon_{pt}$ = disturbance term.

**Table 3.1.**

Average size effect and Standard Error for selected periods

| Period/Subperiod | $y_{2t}$ | Standard Error |
|---|---|---|
| 01.64/12.78 | -0.911 | 0.22 |
| 01.64/12.68 | -1.420 | 0.30 |
| 01.69/12.73 | 0.024 | 0.35 |
| 01.74/12.78 | -1.337 | 0.43 |

Reproduced from Reinganum, (1982)

Table 3.1 shows the significance of the size effect for the investigated period and selected sub periods. It is evident that the size effect is unstable and insignificant for the sub period 01.69/12.73.

Further analysis reveals that small firm portfolios have *higher beta* than larger firm portfolios, which raises the question whether it is a small firm effect or high beta effect. The separate assessment of beta and size is, apparently, exacerbated by the negative correlation between size and beta. A similar dilemma exists when the significance of several factors, such as beta, size, market-to-book value, E/P ratio, etc. are to be tested in one multivariate cross-sectional return relationship.

Jegadeesh (1992) suggests an approach that alleviates the multicollinearity problems. First he forms 10 size portfolios, in a manner similar to the previous studies, and then each size portfolio is split into 2 portfolios, one with high beta and the other with low beta. The target high beta is 1.25 and for low beta, 0.75. Thus, the correlation between size and beta is close to zero, as beta remains constant owing to the design of the portfolios.

Jegadeesh finds negative and statistically more significant size coefficients than beta coefficients in both high and low beta cross-sectional regressions. Furthermore, beta coefficients are negative.

Another approach to tackle the multucollinearity problem is applied by Fama and French (1992). Their method consists of forming a number of portfolios sorted by a given criterion, then each of these portfolios is ranked according to a second criterion. An example is forming, say, 5 size portfolios first, and then sorting each size portfolio into 5 portfolios ranked by beta.

If there is a rate of return pattern across size portfolios and no pattern across beta ranked portfolios, the size rather than the beta should be considered as a determinant of the cross section return differences.

Fama & French (1992) aim to evaluate the joint roles of market beta, size, E/P, leverage and book-to-market equity in the cross section of the average returns on NYSE, AMEX and NASDAQ stocks.

Fama & French confirm the previous findings, i.e., the relation between betas and average returns disappears during the most recent 1963-1990 period, even when betas are used alone to explain average returns. When common stock portfolios are formed on size alone, Fama & French find that average return is positively related to beta. However, size portfolios' betas are almost perfectly correlated with the size, so that the test is unable to distinguish between beta and size influence on returns. Hence, Fama & French need to apply more sophisticated techniques to eradicate the high correlation.

After assigning firms to size-beta portfolios in June, Fama & French calculate the equally weighted monthly returns on these portfolios for the next 12 months. In this manner, they obtain post-ranked monthly returns from July 1963 to December 1990 on 100 portfolios formed on size and pre-ranking beta. Betas of every size-beta portfolio are estimated, using the full sample (330 months) of post ranking returns on each portfolio.

Beta is estimated as the sum of the slopes in the regression of a portfolio return on the current and previous months' market returns. According to Fama & French, additional leads and lags of the market have little effect on these beta estimations.

When Fama & French investigate portfolios based on pre-ranking betas, they find a strong relationship between average returns and size, but no relationship between average return and beta. When portfolios are formed on size alone, Fama & French observe a strong negative relationship between average return and beta. Average returns fall from 1.64 percent per month, for the smallest capitalisation portfolios, to 0.90% for the largest. Post-ranking betas also decline from 1.44 percent for the smallest portfolio to 0.90 for the largest.

Like the size portfolios, the beta sorted portfolios do not support the Sharpe (1964), Lintner (1965) and Black (1972) (SLB) model. There is a little spread in average returns across the beta portfolios, and there is no obvious relationship between beta and average returns. Therefore Fama & French's final verdict is:

> 'The proper inference seems to be that there is a relationship between size and average return, but controlling for size, there is no relationship between beta and average return.' (Fama and French, 1992, p.433)

Because Fama and French (1992) were initially interested in analysing the impact of leverage on security returns, they excluded from their analysis all financial firms[1]. Barber and Lyon (1997) examine a large holdout sample of financial firms, which they test for the robustness

[1] This study defines financial firms as those belonging to retail and merchant banks, insurance and life assurance companies, other financial, property and investment trusts, in line with the *DATASTREAM* definition for financial firms. These firms are excluded from the study because of the differences in their capital structure from the rest of the firms and to allow a comparison with other studies, most of which are based on samples excluding the financial firms.

of the relationship between the firm size, book-to-market ratios and security returns. Barber and Lyon's analysis is restricted to NYSE, AMEX and Nasdaq firms with available return data from July 1973 through to December 1994. The comparison between the percentage mean monthly returns for both nonfinancial and financial firms by size decile shows similar patterns of diminishing portfolios' returns as the size increases. In addition, the t-statistic for the difference between returns of the corresponding size deciles of the nonfinancial and financial firms is insignificant for all 10 size portfolios. A similar relationship is established between the returns of portfolios sorted by firms' book-to-market ratio. Firms with high book-to-market ratios earn on average higher returns, no matter whether they belong to the financial or nonfinancial sector.

Dimson and Marsh (1986) and (1989) report evidence on the size effect in the London International Stock Exchange. They conclude that the size effect has an important role as small firms have consistently earned at least 6 percent greater return than that of the market on an annual basis.

More recent papers of Fraser (1995) and (1996) look at the UK companies traded on the London Stock Exchange. Fraser (1995) runs the standard CAPM for the Hoare-Govett Smaller Companies Index[2] over the period May 1970 to October 1991. If the market is efficient, the intercept term should be zero. Fraser (1995) finds that smaller companies consistently outperformed the market over the period May 1970 to July 1989, but since then, abnormal returns have disappeared.

Fraser (1996) uses UK data comprising the market portfolio and the smaller companies' portfolio. The family of GARCH-type models are applied to examine whether the expected excess returns[3] of companies with a low market capitalisation display similar characteristics to those of the market as whole.

[2]The Hoare-Govett Smaller Companies Index comprises approximately 1200 companies, each with maximum market capitalisation of £100m.

[3] The return on shares less the return from a relatively risk-free bond.

The summary statistics for the UK monthly mean excess returns shows excess returns for the FT-All Share Index of 0.006 and 0.013 for the small company index[4], or a 0.007 gross return on size. Overall, the smaller companies index and the market as whole have similar characteristics. The differences in the risk-return behaviour may be because information on smaller companies has tended not to be available to all traders simultaneously and is also less likely to be acted upon immediately.

### 3.2.2. Size Effect Reversals

Brown, Kleidon and Marsh (BKM) (1983) use data on the same 566 firms studied by Reinganum (1981) in which the size-related anomaly is reported. Of the 566 existent firms in December 1975, 535 survived through December 1977 and 496 through December 1979. Brown *et al* emphasise that, for the investigation period from 1975 to 1979, 45 of the 62 mergers and acquisitions have resulted in the disappearance of firms smaller than the median firm size. BKM run an OLS regression in an excess return form of the market model:

$$\left(R_{it}-R_{ft}\right)=\alpha_{it}+\beta_{im}\left(R_{mt}-R_{ft}\right)+\varepsilon_{it} \tag{3.3}$$

They find that excess returns obtained by ranking firms according to market value of equity are not stable. In some years the distribution of ex-ante returns for the small firms has a positive value, while in other years the effect is reversed. They also find that the risk-adjusted excess returns $\alpha_{it}$ exhibit reversion across the 10 sized portfolios, i.e., for some periods the excess returns are earned by small firms and for others by large firms.

To explain the risk-adjusted excess returns by the size anomaly, BKM run a cross-section regression where the size is an independent and the excess returns a dependent variable:

$$\alpha_{it}=\gamma_0+\gamma_1 S_i+\eta_i,\ i=1,\ldots\ldots,N \tag{3.4}$$

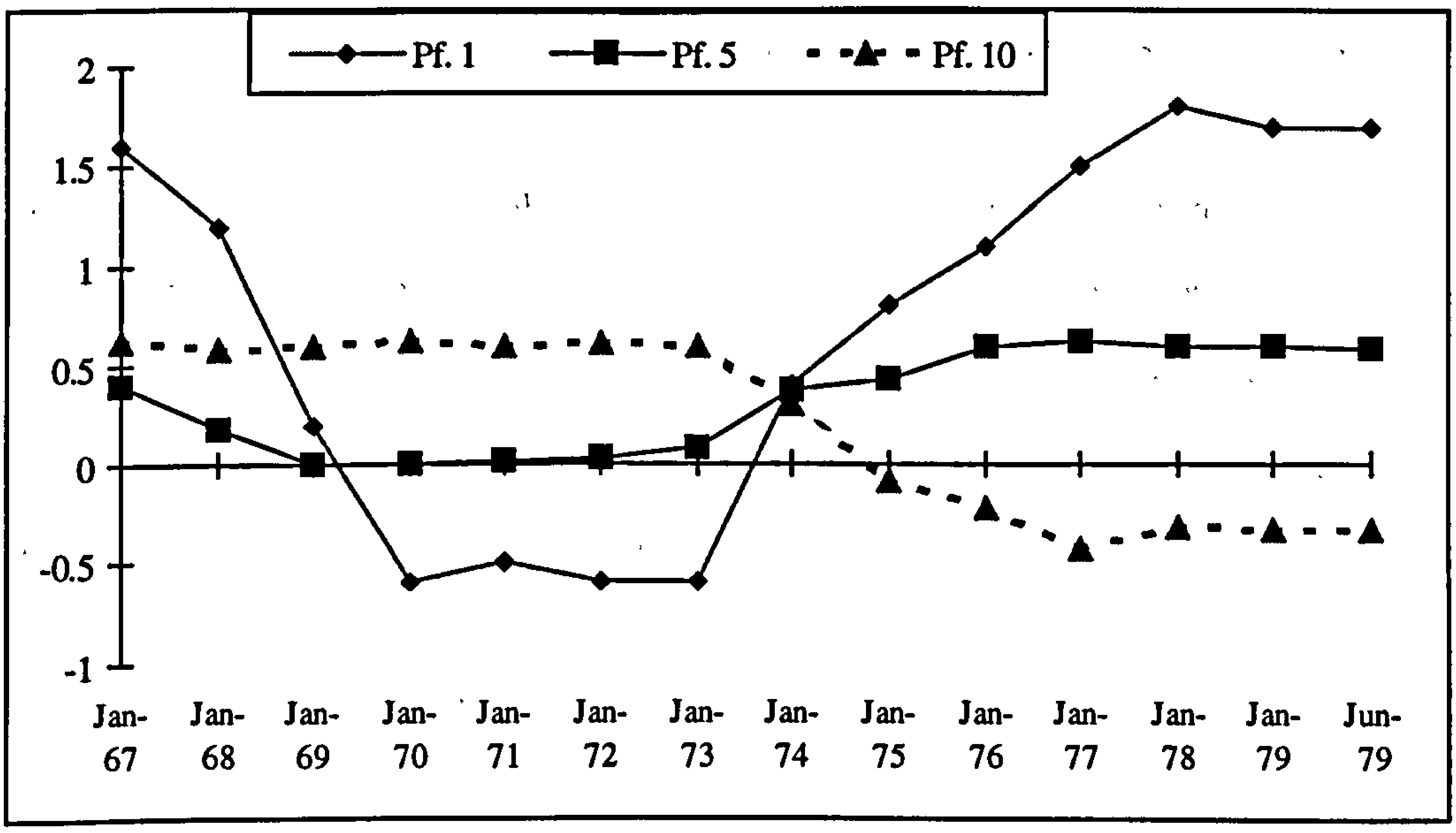
[4] i.e., the Hoare-Govett Smaller Companies Index.

where $\gamma_1$ represents the magnitude of the size effect.

Overall, for the whole period 1967-79, the size effect is negative. However, for the subperiod 1/67-12/76 the size effect is positive, implying that larger firms earn higher risk adjusted excess returns. Part of the results are illustrated in Figure 3.1.

**Figure 3.1**

Time series of risk adjusted excess returns ($a_{it}$) for selected portfolios 1, 5 and 10.




Reproduced from Brown, Kleidon and March, (1983).

BKM fail to explain the reasons behind the reversals of the size effect. Further investigation of the reversals of the size effect is carried out by Reinganum (1992), who forms ten size portfolios assuming dividend reinvestment for the period from January 1926 through December 1989. On average, the small capitalisation stocks outperform the large ones, although this is not a universal result.

To examine the reversals in size portfolios' performance, Reinganum considers an investment horizon of five years. Was the size effect over the period 1926-30 related, for example, to the size effect of 1931-1935?

For each small firm portfolio, the autocorrelation of the excess returns is computed for investment horizons ranging from one to seven years and the correlation of fifty-six pairs of two adjoining five-year periods are computed. The autocorrelation for the small size portfolios is negative when a three-year horizon is reached. It becomes more negative and statistically significant at investment horizons from five to six years. Therefore, the excess returns on size portfolios exhibit a tendency to reverse themselves. That is, periods when the size effect is negative tend to be followed by periods when the size effect is positive.

In a similar study, Fama and French (1988) assign 17 industry and 10 size portfolios for the period 1926-85. In order to estimate $\beta$ - the first order autocorrelation - they run a time series regression $r(t,t+T)=\alpha(T)+\beta(T)r(t-T,t)+\varepsilon(t,t+T)$ where $T$ is an investment horizon varying from 1 to 10 years. Their analysis shows that $\beta$ increases after lag 2, and decreases after lag 6 in both industry and size assigned portfolios.

### 3.2.3. Stock Market overreaction

Stock Market overreaction is based on the notion that many investors overweight recent information and underweight prior data. The overreaction hypothesis is developed by De Bondt and Thaler (1985). They use monthly returns to form portfolios of winner and loser shares. The selection procedure includes the calculating of cumulative excess over the market returns for each share for the various periods from 5, 3 and 1 years before the portfolio formation for even and odd years. Then the extreme winners and losers form the winner and loser portfolios for a given date. After this date, Cumulative Average (Market Adjusted) Residual returns (CAR) of winner and loser portfolios are calculated for 36 months ahead. The estimated difference between the winner and loser portfolios CAR 1, 12, 13, 18, 24, 25, 36 and 60 months into the test period is positive and highly significant, showing a tendency for growth. This difference is mostly pronounced for winner and loser portfolios based on a 5-year formation period.

In a subsequent study, De Bondt and Thaler (1987) develop the overreaction hypothesis further, now examining its association with anomalies such as the January anomaly, the small size anomaly, etc. For the period under investigation they find seasonal patterns and relationships between the winner-loser effect and the small size anomaly. Thus, the winner portfolio earns the highest excess return in January, whereas the loser portfolio has the highest negative excess return in the same month of January during the portfolio formation period. This state is reversed for the winner and loser portfolios when CAR is calculated in the test period. Now, the winner portfolio underperforms mostly in January, whilst the loser outperforms in January.

As many authors world-wide document, the January anomaly is mainly due to small capitalisation firms, as the small firms may have a stronger overreaction pattern. Further, De Bondt and Thaler compare the Size and Winner-Loser Effects by forming 5 size portfolios and calculating their CAR in the formation and test periods. The results show that smaller size portfolios are formation period losers (-0.258 CAR for smallest MV portfolio), whereas bigger size portfolios are basically winners (0.762 CAR for biggest MV portfolio (see p.572)).

Winner-loser reversals for 16 countries' national stock market indices are investigated by Richards (1997). The interesting evidence found by Richards is that small markets are subject to larger reversals than large markets, implying greater imperfections in the small markets.

### 3.2.4. Transaction Costs

Soon after Banz (1981) and Reinganum (1981), Stoll & Whaley (1983) argue that their studies are based on gross returns, not accounting for transaction costs. The market-maker's spread on a proportional basis is generally higher for small firms, they claim, because of their infrequent trading activity and risk, while the broker's commission rate is an inverse function of the total value of a stock. In addition there are other less explicit costs such as the cost of investigating and monitoring a firm, which might be higher for small firms.

Stoll & Whaley's test on the size effect involves forming 10 size portfolios for the period 1960-1979. Then, they measure market risk ( $\beta$ ) using monthly returns of the NYSE stocks and applying Dimson's approach. For the entire period of 240 months the smallest firms outperform the largest ones by more than 13 percent annually. Further, they apply excess return series in the manner of Black (1972):

$$R_{at} = \alpha_a + \beta_a (R_{mt} - R_{ft}) + \alpha'_{at} \qquad (3.5)$$

or the so-called zero-beta model, where the subscript *'a'* refers to arbitrage. The intercept term $\alpha_a$ of these regressions estimates the abnormal returns realised by engaging in arbitrage activity.

The relative spreads for each of the stocks within every size portfolio is estimated as an average of the beginning and end-of-year values of the bid-ask spread. The commission rate on each stock is computed from the minimum commission schedule.

The mean abnormal return of the lowest market value portfolio is estimated for various investment horizons, before and after transaction costs. After accounting for transaction costs, the abnormal return of small firms is dramatically reduced, as the transaction costs for small capitalisation assets are 2-3 times higher than these of large firms (Table 5, p.72). Small capitalisation firms still earn excess returns, but only for investment horizons greater than 4 months. For investment horizons less than 4 months, small firm excess returns are negative.

Amihud and Mendelson (1989) suggest an illiquidity model to explain the excess returns. The illiquidity is measured by the bid-ask spread integrated into an asset-pricing model. According to their theory, the shares have bid-ask spreads which reflect their transaction (or illiquidity) costs and investors have heterogeneous liquidation plans or holding periods.

Their test procedure consists of forming portfolios, calculating beta, residual standard deviation, size and bid-ask spread, for each portfolio, and then testing the cross-sectional relation between the average returns and these portfolio characteristics over the period 1961-1980.

Amihud and Mendelson find that beta and the bid-ask spread are the only variables with significant coefficients. These results are consistent with the hypothesis that the principal factors affecting asset returns are beta-risk and illiquidity, measured by the bid-ask spread. Therefore the size effect hypothesis is not supported. However, their results seem to be ambiguous due to the relatively high correlation (always above 0.4) between market size and bid-ask spread.

Aitken and Ferris (1991) provide additional evidence of the small firm anomaly using Australian data. They implement a CAPM adjusted for transaction costs. The findings confirm an overall difference between the large firm and small firm portfolio transaction costs over the period January 1965 to December 1985 of 7.33 percent. These include differences in brokerage (2.4%) and the bid-ask spread (4.93%).

To test for the clientele effect[5], Atkins and Dyl (1997) investigate the relationship between the average holding periods and the Bid-Ask spread, market value and return variance on the NYSE from 1975 to 1989 and Nasdaq from 1984 to 1991. The regression results for the Nasdaq firms show that the coefficient on the bid-ask spread is positive and significant at the 0.01 level, with t-statistic of 89.85. This finding provides strong support for the hypothesis that investors' holding periods for common stocks are related to the level of transaction

[5]See Amihud and Mendelson (1986, 1989) and Constantinides (1986).

costs. The regression coefficients on firm size and on the return variance also have the expected signs and are highly significant. Longer periods are associated with larger firms, and shorter holding periods are associated with more volatile firms.

For the NYSE firms the coefficient on the bid-ask spread variable is again positive and significant at the 0.01 level. The coefficients on firm size and return variance are also significant and have the expected sign.

Eleswarapu (1997) examines the possible biases in the empirical findings of Amihud and Mendelson (1986) due to the restrictive data selection criterion and methodology revealed in Chen and Kan (1989) and Eleswarapu and Reinganum (1993). Eleswarapu (1997) forms 49 portfolios (7x7) on the basis of the bid-ask spread and beta, and reports the spread, beta, market value (MV) and price per share (PPS) for each portfolio from 1976-1990. The profile of the lowest spread and lowest beta portfolio (LL) and the highest spread and highest beta portfolio (HH) are shown Table 3.2.

**Table 3.2.**

| Portfolio / Variable | LL | HH |
|---|---|---|
| Bid-Ask Spread | 1.827 | 30.675 |
| Beta | 0.533 | 1.271 |
| MV | 1287 | 4 |
| PPS | 36.40 | 1.49 |

It is apparent that the bid-ask spread, beta, MV and PPS exhibit a relationship across the portfolios formed on the beta and the bid-ask spread. While the patterns of the beta and the bid-ask spread are obtained by construction, the MV and PPS patterns, however, emerge without controlling them.

After applying Fama and MacBeth (1973) type cross-sectional regressions and Seemingly Unrelated Regressions (SUR), Eleswarapu finds the bid-ask spread to be the only variable that consistently explains the cross-section differences in portfolio returns, beta and size being marginally significant. Thus, Eleswarapu concludes that there is a liquidity premium in Nasdaq, contrary to the findings in the NYSE.

### 3.2.5. Marginal Firms

Other papers emphasise the difference in the structural characteristics between small and large firms. Chan and Chen (1991) assume that small firms are 'marginal firms'. They suggest that small firms have lost market value because of poor performance, they are inefficient producers and they are likely to have high financial, leverage and cash flow problems. The share prices of marginal firms tend to be more sensitive to changes in the economy and these firms are less likely to survive adverse conditions. Since many small firms are marginal firms, as a group they tend to behave like marginal firms.

Chan and Chen (1991) distinguish the structural characteristics of small and large firms from 1956 to 1985, in order to prove that the small firms are generally marginal firms. All NYSE firms are classified by how they enter the top (largest) and bottom (smallest) market value quintile. The most revealing statistic from the bottom quintile is that 66 percent of the firms have fallen from the higher quintile, and only about 14 percent have been listed directly into that quintile over the previous 10 years. In contrast, about 51 percent of the firms in the top size quintile have been there for over 10 years. Of the remaining 49 percent about 41 percent have gone up from the lower quintiles and 8 percent remain listed into the top quintile over the previous 10 years.

Chan and Chen calculate the averages of the annual median return on asset and the interest expense coverage for 19 industries in the lowest and highest quintiles, using data from 1966 to 1984. The results show, that those industries in the smallest size quintile have a lower return on assets and a higher interest coverage ratio, compared to the same industries in the largest size quintile.

Chan and Chen search for additional characteristics that discriminate *ex ante* 'marginal' from non-marginal firms. They suggest that leverage (Gearing) and dividend changes could indicate a marginal firm and therefore relate to the firm size. In order to explain the logic behind firm's size effect and dividend changes, Chan & Chen stated:

> 'It is well known that firms are reluctant to cut their dividends. Consequently, firms that cut their dividends drastically are likely to have done poorly and face a very uncertain future' (Chan and Chen, 1991, p.1472)

Chan & Chen discover patterns in the relation between firm size, leverage and dividend changes. For instance, among the firms that have cut their dividends in half (or more) the year before size portfolio formation, over 50 percent are in the bottom size quintile. In respect to the relationship between firm size and leverage, 33 percent of the bottom size and only 8.5 percent of the top size firms are highly leveraged. This relationship is reversed in the low leverage band; 9.8 percent of the bottom size and 36 percent of the top size firms have low leverage for the period from 1956 to 1985. Thus, Chan & Chen deduce, that the relationship patterns between firm size, dividend change and leverage are consistent with their hypothesis of why a small firm portfolio is riskier.

A controversy with Chan & Chen's argument is that it does not explain why the incremental risk born by small capitalisation firms is not captured by the systematic market risk, i.e., beta. On the other hand, if small firms bear a risk that is not accounted for by beta, then the rational investor should perceive it. Therefore, the arbitrage process should incorporate this risk into prices.

### 3.2.6. Neglected Firms

The 'neglected' firm explanation of the size effect appeared soon after the size effect was discovered. According to the CAPM, high risk shares sell at a lower price because the investors do not like risk. Many practitioners use very similar reasons in arguing that prices of smaller firms' shares are lower (recall that small firm portfolios are high beta as well) because this is a 'neglected' sector of the market. Merton's (1987) investment theory, for example, predicts that fund managers tend to invest in securities they know about and avoid those they do not have information about.

Arbel and Strebel (1983) use two separate indicators as benchmarks to divide neglected from non-neglected firms: the number of analysts regularly following a firm security and the number of analysts reporting earning forecasts which comply with those in Standard and Poor's *Earning Forecaster*. In order to reduce measurement problems, three broad research concentration ranking groups (RCR) are formed, where RCR1 comprises the most intensively followed stocks and RCR3 represents the least followed, or neglected firms.

Arbel and Strebel find that for the period 1970-1979 (except for 1971) the average annual return of the neglected stocks is 16 percent compared to 9 percent for the highly followed companies.

In respect to the relationship between neglected companies and small companies, Arbel and Strebel report that the neglected firm effect dominates over the small firm effect. They find excess return attached to neglected firms, rather than small firms, when controlling for size.

### 3.2.7. Small Size, Book-to-Market, or other factors?

Fama and French (1995) underline that book-to-market equity plays a consistently stronger role in average returns, although the size effect has attracted more attention. They suggest a theoretical model that explains the contribution of Book-to-market ratio to excess returns, which goes as follows:

Consider an all equity firm that finances its investments entirely with retained earnings. Dividends paid by the firm in any year *t*, *(D (t))* are equal to equity income plus depreciation *(DP (t))*, minus investment outlays *(I (t))*.

$$D(t) = EI(t) + DP(t) - I(t)$$

Suppose that at time *t* expected depreciation and investment for any year *t+i* are proportional to expected future equity income, that is,

$$E_t D_{(t+i)} = E_t \left[ EI_{(t+i)} + DP_{(t+i)} - I_{(t+i)} \right] \quad (3.5a)$$

$$= E_{(t)} EI_{(t+i)} (1 + k_1 - k_2) \quad (3.5b)$$

$k_1$[6] and $k_2$ are the proportionality factors, defined as $k_1 = DP_t / EI_t$ and $k_2 = I_t / EI_t$.

If the discount rate *r* is constant, then the value of the market equity at *t* is:

$$ME_{(t)} = (1 + k_1 - k_2) \sum_{i=1}^{\infty} \frac{E_t EI_{(t+i)}}{(1+r)^i} \quad (3.5c)$$

and the ratio of market-to-book equity is:

$$\frac{ME_{(t)}}{BE_{(t)}} = (1 + k_1 - k_2) \sum_{i=1}^{\infty} \frac{E_t EI_{(t+i)} / BE_{(t)}}{(1+r)^i} \quad (3.6)$$

[6] As notation follows closely Fama and French (1995), the time (*t*) subscripts for proportionality factors are not applied, although they are time varying. This detail is important, though, as it may turn out that identity in 3.5c and 3.6 is not obeyed, if proportionality factors change.

This simple model predicts that firms with higher required equity returns, *r*, will have higher book to market ratios. Thus, Fama and French (1995) make a further contribution to the three factor asset-pricing model that includes a market factor and risk factors related to size and BE/ME. Fama and French admit that size and BE/ME remain arbitrary indicator variables that, for some unexplained economic reasons, are related to risk factors in returns. The goal they specify is 'to begin to fill this economic void' (p.131). The theoretical model they offer relates a firm's Equity Income to the same firm's Market Equity to Book Equity ratio. Using the ratio of Equity Income to Book Equity as a proxy for a firm's profitability, Fama and French allot NYSE, AMEX and NASDAQ into four portfolios, i.e., B/L, B/H, S/L and S/H where B and S stand for big and small firms. For each year from 1963 to 1991 the whole sample is split by the median Market Value into Small (S) and Big (B) firms. Stocks in the bottom 30 percent or top 30 percent of the values of the Book-to-market equity are assigned to Low (L) and High (H) Book-to-Market value. The four portfolios (B/L, B/H, S/L and S/H) are the intersection of the four groups, i.e., B, S, L and H. Then, Fama and French (see Figure 1, p.136) produce the 11-year evolution of earnings on book equity for size-BE/ME portfolios formed in June of year *t*. Figure 1 shows that in year 0 relative to the ranking year, B/L performs best, (equity income/book equity, apx. 0.18) followed by S/L, B/H and S/H. This result supports the model offered by Fama and French (1995, p.135), and establishes the superiority of the Book-to-Market value over the Size Effect. Although low-BE/ME equities tend to be highly profitable long before and after they are sorted into portfolios, Figure 1 (Fama & French (1995)) shows that their profitability improves prior to portfolio formation, and deteriorates a bit thereafter. The reverse pattern of decay and then improvement in EI/BE is observed for high-BE/ME stocks. Further Fama and French (1995) exploit the return differences of portfolios sorted on a large variety of variables (ratios), to finally affirm size and book-to-market (BE/ME) as factors that capture 'strong common variation' in stock returns.

Fama and French's results are challenged by Kothari, Shanken, and Sloan (1995), who examine a cross-section of expected returns, and find an economically and statistically significant compensation (about 6 to 9 percent per annum) for beta risk when betas are estimated from time-series regressions of annual portfolio returns on the annual return on the equally weighted market index. The relation between book-to-market equity and returns is weaker and less consistent than that in Fama and French (1992).

According to KSS, there are at least three reasons for re-examining the risk-return relationship using longer measurement interval returns. First, the CAPM does not provide explicit guidance on the choice of horizon in assessing whether beta explains the cross-section variation in average returns. Secondly, beta estimates are biased due to trading frictions and non-synchronous trading[7] (Ball (1977), Scholes and Williams (1977) and Cohen *et al.* (1983)) or other phenomena including systematic cross-temporal covariance in short-interval returns (e.g. Lo and MacKinlay (1990) and Mech (1993)). These biases can be mitigated using Dimsons' (1979) approach to estimating betas. Thirdly, there appears to be a significant seasonal component in monthly returns (see, for example, Rozeff and Kinney (1976) and Keim (1983)).

In addition, Handa, Kothari and Wasley (1989) show empirically that the betas of small firms increase and those of large firms decrease with the return measurement interval, substantially reducing the size effect when annual returns are employed. Moreover, the annual estimates of beta are strongly correlated with both monthly and annual average returns.

Each month KSS estimate the following cross-sectional regression of portfolio returns on beta, size or beta and size.

$$R_{pt} = \gamma_{0t} + \gamma_{1t}\beta_p + \gamma_{2t}Size_{pt-1} + \varepsilon_{pt} \qquad (3.7)$$

[7] The term 'non-synchronous trading' is another way of addressing thin-trading or infrequent trading. Non-synchronous trading describes another aspect of small size firms trading, i.e., the irregular arrival of buy and sell orders for small size firms.

$R_{pt}$ -equally-weighted buy-and-hold return on portfolio *p* for month *t*,

$\beta_p$ - full period postranking beta on portfolio *p*,

$Size_{pt-1}$ - natural log of the average market capitalisation on June 30 of year *t* of the stocks in portfolio *p*,

$\gamma_{0t}, \gamma_{1t}, \gamma_{2t}$ - regression parameters,

$\varepsilon_{pt}$ - regression error.

KSS find economically and statistically significant compensation for beta risk, when yearly intervals and an equally weighted market return are applied. The results also indicate that the incremental contribution of size, while not unimportant, is not large either.

Further, KSS employ a three-factor model, similar to that in Fama and French (1993), including the market index as one of the factors. They estimate it for *CRSP*, *COMPUSTAT* and *CRSP-COMPUSTAT* samples, in order to examine for possible selection biases in *COMPUSTAT* data.

In order to construct size and B/M equity factors, all stocks are ranked and assigned to five size portfolios and five B/M portfolios each year. Then they calculate so-called excess returns on a factor.

The size factor is the difference, each year, between the sample average return on the five portfolios within the smallest market capitalisation quintile (i.e., the smallest firm quintile that is split into five portfolios on the basis of low and high B/M) minus the sample average return on the five portfolios within the largest market capitalisation quintile. The B/M factor is constructed similarly as the difference between the average return on the five portfolios within the highest B/M quintile minus the average return on the five portfolios within the lowest B/M quintile. As in Fama and French (1993), the B/M and size factors are only weakly correlated (correlation -0.20). The size factor has a correlation coefficient of 0.69

with the equally weighted market, whereas the B/M factor has a correlation of -0.26 with the market.

The estimated time-series regression, in an excess-return form, with annual data from 1963 to 1989 is:

$$R_{pt} = \alpha_0 + \beta_1 R_{mt} + \beta_2 R_{B/Mt} + \beta_3 R_{Sizet} + \varepsilon_{pt} \quad (3.8)$$

$R_{pt}$ -equally-weighted excess-return on size portfolio *p*, calculated from July of year *t* to June of year *t+1* where size is measured as of June-end of year *t* and returns are in excess of the T-bill rate.

$R_m$ -annual excess return on the equally weighted market portfolio,

$R_{B/Mt}$ - the B/M factor, derived from an independent portfolio ranking,

$R_{Sizet}$ -the Size factor, derived from an independent portfolio ranking.

The intercept terms for the *COMPUSTAT* size portfolios are small and not significantly different from zero, consistent with the hypothesis that the size and B/M factors capture the relevant components of systematic risk as in Fama and French (1993). The extremely small firms have nontrivial coefficients on the B/M factor and the size factor in the *CRSP* and *COMPUSTAT* samples. Apart from this, the B/M factor betas are small and generally statistically insignificant. Thus, KSS conclude that the strong Book-to-Market effect in Fama and French is likely to be influenced by a survivorship bias in the *COMPUSTAT* data.

Fama and French (1996b) react to Kothari, Shanken, and Sloan (1995) and strongly reject the ability of the size and the Book-to-Market ratio (BE/ME) to explain the average differences in returns.

Fama and French (1996a) subsequent to Fama and French (1995), develop a conditional three factor model, including the excess return on a broad market portfolio $(R_M - R_f)$, the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB), and the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks (HML). The HML factor is classified as a distress factor.

$$R(t) - RF(t) = a + b[RM(t) - RF(t)] + sSMB(t) + hHML(t) + e(t)$$

Since the average HML return is *strongly* positive, low Book-to-Market (BE/ME) load negatively on the HML, implying lower excess returns. The Book-to-Market effect, however, can be related to DeBondt and Thaler's (1985) reversals, as stocks with low long-term past returns (losers) tend to have positive SMB and HML slopes and higher future average returns.

Daniel and Titman (1997) address the question of whether there really are pervasive factors that are directly associated with the size and book-to-market returns, and whether there are risk premia associated with these factors. After examining the 25 size/book-to-market portfolios from Fama and French (1993) over the period 63:07 to 93:12, they find different return patterns for January and non-January months. The size effect is almost exclusively a January phenomenon, while the book-to-market phenomenon occurs mainly in January for larger firms.

In addition, Daniel and Titman (1997) perform a factor analysis on the possibility of relating the returns of portfolios formed on size and book-to-market with factors, such as the trading volume and returns over the 12 pre-formation months, following liquidity (Amihud and Mendelson (1986)) and momentum (Jagadeesh and Titman (1993)) hypotheses. Their findings, however, lack support for the factor model load on either momentum or liquidity.

Jaganathan and Wang (1996) assume that the CAPM holds in a conditional sense, i.e., it holds at every point in time, based on whatever information is available at that instant. Instead of the Sharpe-Lintner-Black (static) CAPM $E[R_i]=\gamma_0+\gamma_1\beta_i$, where $\beta_i$ is defined as $\beta_i = Cor(R_i, R_m)/Var[R_m]$, they propose a conditional CAPM $E[R_{it}|I_{t-1}]=\gamma_{0,t-1}+\gamma_{1,t-1}\beta_{i,t-1}$ with beta defined as $\beta_i = Cor(R_i, R_m|I_{t-1})/Var[R_m|I_{t-1}]$.

Jaganathan and Wang form 100 portfolios (10x10) on size and beta, exploring monthly returns of a sample listed on NYSE and AMEX non-financial stocks from 1963 to 1990. They run various static and conditional CAPM specifications. The standard variables in the CAPM models are beta and logarithms of market equity (size) and two additional variables- the spread between BAA- and AAA-rated bonds as a proxy for the market risk premium[8] and the growth rate of labour income[9], estimated as the difference between total personal income and dividend income. A parallel examination of the static and conditional forms of the CAPM leads Jaganathan and Wang to support the conditional form of the CAPM. When betas and expected returns are allowed to vary over time by assuming that the CAPM holds period by period, the size effect and the statistical rejections of the model specifications become much weaker. When a proxy for the return on human capital is also included in measuring the return on aggregate wealth, the pricing errors of the model are not significant at conventional levels. More importantly, firm size does not have any additional explanatory power.

Kim (1995) claims that the Fama and French (1992) findings are subject to errors-in-variable (EIV) of the traditional two-pass estimation methodology. In the first pass, beta estimates are obtained from separate time-series regressions for each asset, and in the second pass, gammas are estimated cross-sectionally by regressing asset returns on the estimated betas. Therefore, the explanatory variable in the cross-sectional regression is measured with error.

[8]See Stock and Watson (1989) and Bernanke (1990) for the applicability of interest-rate variables as a forecaster of the business cycle.

[9] The Roll (1977) critique emphasises that the market portfolio is not observable and do not include all assets in the economy, human capital *intra alia* and Mayers (1972) denotes that human capital forms a substantial part of the total capital in the economy.

The EIV problem results in an underestimation of the price of beta risk and an overestimation of the other coefficients associated with variables observed without error, such as firm size and book-to-market equity ratio.

Kim provides a mathematical proof of the gamma bias, when an OLS estimator is used, and proves that the cross-sectional dependence between residuals from the market model decreases as the number of size portfolios increases.

In summary, the market beta has an economically and statistically significant effect after correcting for the EIV problem for the whole period from July 1936 to December 1991. It is worthwhile, however, to note that the residuals are sensitive to the choice of testing period. For the subperiod from July 1963 to December 1990, for example, when the size variable is included in the model, the explanatory power of the market beta is weaker than that obtained for the whole period.

Hasbrouck (1985) shows that Tobin's $q$ and firm size are important variables in identifying potential takeover target firms. Specifically, he finds that targets of takeovers are typically low $q$ and small size firms. Lang, Stulz and Walking (1989) find that gains to the bidder, the target, as well as the combined gains are largest when a high $q$ bidder acquires a low $q$ target. Both Hasbrouck (1985) and Lang, Stulz, and Walking (1989) also acknowledge a disequilibrium explanation, in that the gains from a takeover can be the consequence of systematic underpricing of the target. They further argue that the takeovers that create the most wealth are made by high P/E bidders for low P/E targets. Since $q$ is positively correlated with the P/E ratio, this argument implies that takeovers that create the most wealth are those by high $q$ bidders for low $q$ targets.

Tobin's $q$ is defined as the ratio of the market value of the firm to the replacement cost of its assets, and was first introduced into macroanalysis by Tobin (1969) in order to explain the causal relationship between $q$ and investment. He argues that if, at the margin, $q$ exceeds unity, then the firms have an incentive to invest, since the cost is less than the new capital investment. If such investment opportunities are widely exploited, the marginal value of $q$ should tend towards unity. Since then Tobin's $q$ has been widely used in the takeover literature.

Badrinath and Kini (1994) find that the magnitude of the size effect does not change after controlling for $q$, but the E/P effect becomes much smaller. Furthermore, the size effect is extremely robust, even when controlling for $q$ and E/P variables. After controlling for both size and $q$, the E/P effect becomes small in magnitude and perhaps economically insignificant. The examination of the January seasonality effect, for each of the three effects, (size, E/P and $q$), each time exercising experimental control over the other two variables, confirms the size effect as solely a January phenomenon, while the E/P effect does not result from excess January returns.

Badrinath and Kini (1994) compute the firm size, the E/P ratio and Tobin's $q$ ratio for each firm for each year in the period 1967-1981. For each year, firms are ranked in ascending order on the basis of the relevant choice variable (firm size, E/P ratio or Tobin's $q$) and grouped into five portfolios. Portfolio performance is estimated relative to systematic risk using both the single factor and the two factor CAPM. The estimated equations are:

$$R_{pt} - R_{ft} = a_p + b_p(R_{mt} - R_{ft}), t = 1,...,180 \tag{3.9a}$$

$$R_{pt} - R_{0t} = a_p + b_p(R_{mt} - R_{0t}), t = 1,...,180 \tag{3.9b}$$

where $R_{pt}$ -return on portfolio $p$ in month $t$, $p$= 1,2,.....5,

$R_{mt}$ -return on market portfolio for month $t$,

$R_{ft}$ - return on riskfree asset for month $t$,

$R_{0t}$ - return on a "zero-beta" portfolio for month $t$,

$a_p$ - estimated abnormal return for portfolio $p$,

$b_p$ - estimated systematic risk for portfolio $p$.

The results are also replicated using Dimson's beta to adjust for infrequent trading biases but the conclusions are essentially the same. Of some interest, however, is the fact that as we move from the low to the high size portfolios, the median E/P ratio seems fairly stable while the median $q$ increases. It is quite possible that the size effect is merely proxying for a $q$ effect or vice versa.

Badrinath and Kini utilise Basu's (1983) randomisation technique to distinguish between several concurrent effects. The size effect, after controlling for E/P, then shows an abnormal return between the extreme size portfolios of 0.741 percent per month (8.892 percent per year). The E/P effect on the two extreme E/P portfolios, after controlling for firm size, is 0.623 percent per month (7.467 percent per year). Finally, for the interactions between size and E/P effects, small firms with high E/P ratios earn 1.28 percent per month (15.36 percent per year) on a risk-adjusted basis. The size effect does not subsume nor is it subsumed by the E/P effect. However, significant interactions between size and E/P are evident.

If Tobin's $q$ is controlled for, however, the differential E/P return is substantially smaller, whilst the size effect is not altered. In addition, the differential returns between the extreme size portfolios are almost entirely due to the January effect.

## 3.3. The IPO Anomaly

The Initial Public Offer (IPO) anomaly encompasses low return performance of IPOs in a period of 3 to 5 years after going public. Ritter (1991) performs an investigation of the IPOs anomaly from 1975 to 1984 on the NYSE and finds a 34.4 percent average holding period return of IPOs common stock in the 3 years after going public. The holding period return is measured from the closing market price on the first day of public trading to the market price on the 3 year anniversary. The control sample, matched by industry and market value, produces an average total return of 61.86 percent over the same 3 year holding period. This is what Ritter calls long-run underperformance. In addition to this anomaly, numerous studies have documented the so called short-run underpricing phenomenon, where, measured from the offering price to the market price at the end of the first day of trading, IPOs produce an average initial return of 16.4 percent. Why IPOs are priced in a manner that results in such large positive initial returns has always been a mystery. According to Ritter, the offering price is not too low; it is the first after-market price which is too high. Further, Loughran and Ritter (1995) found that the average annual return during the five years after an initial public offering is only 5 percent for a sample of 4753 operating companies going public in the United States during 1970 to 1990 and listed within the next three years.

## 3.4. Reversal of Large Stock-Price Decreases

The reversal of large stock-price decreases consists of a slow recovery of the large stock-price decreases. The biggest average excess returns are observed on Day 1 after the event of the decrease (Bremer and Sweeney, (1991)), still existing on Day 2 and 3 and decaying slowly. Such a phenomenon of long and slow recovery is inconsistent with the assumption that market prices fully and quickly reflect relevant information.

## 3.5. Calendar Anomalies

The investigation into calendar anomalies concerns two issues; firstly, to detect the possible existence of these anomalies and, secondly, to relate them to other anomalies.

Calendar anomalies have been widely investigated in the US Stock Market. This, however, does not categorise them as just a US phenomenon. Calendar anomalies are reported on other stock markets as well.

### 3.5.1. Day-of-the-week anomaly

In the early 1980's various papers reported on the weekend anomaly. It was found that Friday returns were generally larger than that for other days and these returns tended to be negative from close of trading on Friday to close of trading on Monday. French (1980) finds that if an investor purchases a portfolio at the close on Monday, sells it at the close on Friday, and holds cash over the weekend, it generates an above average annual return of 13.4 percent. Gibbons and Hess (1981) examine the 17 years' period 1962-1978 and discover that Monday's return is negative, -33.5 percent on an annualised basis. Harris (1986) confirms a large negative Monday return between 1981-1983, which occurs within the first 45 minutes of trading.

Despite the existence of this anomaly, the presence of transaction costs does not permit the operation of a profitable trading system based on the weekend effect. Nonetheless, the mere existence of the day-of-the week anomaly may offer an explanation for other anomalies.

Athanassakos and Robinson (1994) find that the Monday negative return is due mostly to large firms' negative returns, whereas Tuesday's negative return is due mostly to small firms' negative returns. They suggest two reasons for the day-of-the-week anomaly; the dividend effect and information flows. The dividend effect is supported by the fact that the ex-dividend day is not evenly spread across the days of the week. Canadian firms tend to go *ex-dividend* more often on Mondays than on any other day of the week. However, after adjusting returns for dividend payments, the day of the week anomaly is only partially explained.

Thus, Athanassakos and Robinson suggest an "information flows" explanation for the day-of-the-week anomaly. This explanation rests on the tendency for unexpected "bad news" to be systematically released late on Friday or over the weekend. Evidence in favour of this tendency has been previously reported in Dyl and Maberly (1988), Patell and Wolfson (1982) and Penman (1987).

Athanassakos and Robinson examine the relationship between information flows and the day-of-the-week effect by testing for (i) a relationship between Friday and Monday returns, (ii) a pattern of negative Monday returns throughout the month, and (iii) a comparison of day-of-the-week returns for large and small stocks.

Solnik (1990) examines how specific settlement procedures affect the distribution of daily stock returns on the Paris Bourse. Settlement procedures vary considerably across national stock markets. In many countries settlements take place a fixed number of business days after the transaction. These countries are referred to as countries with a *fixed settlement lag*. In other countries settlements take place periodically on a fixed date and all transactions performed before this date are settled then. These countries are referred to as countries with a *fixed settlement date*.

The expected influence of the settlement procedure on the distribution of daily returns is usually much larger for countries with fixed settlement dates such as the U.K., France or Italy. In the U.K. the trading year is divided into *account settlement periods* of two weeks.[10] This is a forward market with a new account period starting every other Monday. The financial advantage brought by a new account period should imply a positive return on these Mondays; the extra return should be in the order of two weeks of interest. In theory, the forward stock price should converge to the implicit spot price on the last day of the account period and move up from the spot price on the first day of the account period by an amount equal to the bias (cost of carry). In the absence of dividend payments and transaction costs, arbitrage requires that the forward price be equal to the spot price plus the financing cost of the position to maturity of the forward contract.

[10]There are only 24 or 25 account periods in a year because of vacations, so the length of this account settlement period is sometimes greater than two weeks. All the trades during an account period are settled on the second Monday following the last Friday of the period.

In France, Italy, and, to some extent, Switzerland and Belgium, as well as some developing countries, the settlement of all transactions takes place once a month on a fixed date. This system was instituted by Napoleon, the French emperor. The last day of trading on which all trades are settled is called the *liquidation*. The liquidation takes place on the seventh business day preceding the end of the calendar month. The cash transfers take place on the last business day of the month. The liquidation day is set a week before the end of the month. All transactions before the liquidation day will be settled at the end of the month. The magnitude of the effect ought to be one month of interest and hence much larger than in London.

Solnik explores the daily CAC 240 index from January 2, 1978 to November 3, 1989. In a continuous market maintained during the day by specialists or market makers, the difference between opening and closing prices can be significant and can affect the result of empirical studies of the behaviour of daily returns. In a fixing market, where shares are only traded for a few minutes during the day, there exists a single price for the day.

The equality of mean (forward) returns and the monthly settlement effect is tested by running the regression:

$$R_t = \alpha_0 d_{0,t} + \sum_k \alpha_{T+k} d_{T+k,t} + u_t \qquad (3.10)$$

where:

$R_t$-is the return for day $t$ (from day $t$-$1$ to day $t$),

$d_{0,t}$- dummy variable, that takes the value of one if day $t$ falls on any day not included in the interval $T$-$5$ to $T$+$7$ and zero otherwise,

$d_{T+k,t}$- a dummy variable taking the value of one if day $t$ falls on a day $T$+$k$ surrounding the liquidation date $T$ and zero otherwise. $k$ ranges from five days prior to liquidation to seven days after the liquidation; hence, the last day ($k$=$7$) is the first business day of the new calendar month.

The mean daily return over the period January 1978 - November 1989 is 0.074%. The mean daily return on the opening day of a new settlement month, 0.698%, is large and significantly different from the mean daily return at the 99% confidence level. The difference, 0.624%, is in the order of magnitude of one month's interest but is somewhat smaller than the average one-month risk-free rate over the period (around 0.9%).

Solnik tests the effect of dividend payments on daily returns. French companies pay their dividends only once a year, and payments are mostly made in the months of June and July. If a stock pays a dividend during a given settlement month, any purchaser of the stock during that month will receive the shares ex-dividend at the settlement taking place at the end of the month. Hence, the forward price should drop, ceteris paribus, on the first day of the monthly settlement period by an amount related to the scheduled dividend payment during the month. If the impact on the firm's value is exactly equal to the dividend paid out, then the forward price on the first day of the settlement period should drop by an amount equal to that discounted dividend. Given the higher dividend payments in June and July, settlement months should be roughly 1.7% below that of other months since index return calculations do not include the dividend paid.

Mean daily returns are estimated separately for June-July and for other months of the year. The price appreciation (for the days *T, T+1, T+2*) due to the new settlement month is indeed smaller on the first day of June and July (0.571%), than non-dividend months (1.216%). While this difference (0.645%) is statistically significant, it is less than the average difference in the monthly dividend yield between June-July and the other months (1.7%), consistent with a drop in the stock price on the ex-day being less than the dividend.

The final question is whether this settlement procedure could explain the pattern of daily returns, observed in previous studies of the Paris Bourse[11].
The standard methodology is replicated by running the regression:

[11] See Condoyanni, O'Hanlon, and Ward, (1987), Solnik and Bousquet, (1990).

$$R_t = \alpha_1 d_{1,t} + \alpha_2 d_{2,t} + ..... + \alpha_5 d_{5,t} + u_t \qquad (3.11)$$

$R_t$ - the rate of return on day $t$,

$d_{i,t}$ - a dummy variable taking the value of one on the respective day of the week and zero otherwise.

If daily returns are drawn from an identical distribution, we would expect the regression coefficients to be equal. The hypothesis of equality of the regression coefficients is rejected at the 5% confidence level. As in the countries with other types of settlement procedures, the monthly settlement cannot explain the day-of-the-week effect observed on the Paris Bourse because there is no concentration of liquidation dates on Tuesdays.

Recent research on calendar effects in the FT-SE indices by Mills and Coutts (1995) finds statistical evidence supporting calendar anomalies. The day-of-the week anomaly is unveiled by high average returns on Wednesday and Friday for FT-SE 100, 250 and 350 indices and negative mean returns on Monday for the Mid 250 and 350 indices. These results are consistent with previous findings for the UK by Board and Sutcliffe (1988).

Splitting Mondays into account and non-account days leads to the result predicted by the 'account day' hypothesis[12]-Monday non-account days have significant negative returns for all three indices, whereas account days on Mondays have positive returns for the 100, although essentially zero returns for the Mid 250, perhaps reflecting the size effect.

### 3.5.2. Holiday Effect

Fields (1934) finds a disproportionate frequency of advances on trading days preceding long holiday weekends. Roll (1983) reports high returns accruing to small firms on the trading day prior to New Year's Day. Lakonishok and Smidt (1984) remark that "prices also rise in

[12]See Lakonishok, J and Levi, M. (1982) and Board and Sutcliffe (1988).

all deciles (of market capitalisation) on the last trading day before Christmas" and conclude that ' the Christmas returns of large companies might be considered (another) ..... mystery.'. Merrill (1966) finds a disproportionate frequency of Dow Jones Industrial Average advances on the days preceding holidays during the 1897 to 1965 period. Fosback (1976) has noted high pre-holiday returns in S&P 500 index returns.

Ariel (1990) uses value and equally weighted daily indices from 1963 to 1982. He divides 5020 trading days into two subsets; the trading days prior to the holidays in this period (160 days), and the rest (4860 days). The 160 pre-holidays are the trading days prior to the holidays.

For the period under investigation Ariel reports means for the 160 pre-holiday returns of 0.528% on the equally weighted and 0.364% on the value weighted index respectively. Means of 4860 other daily returns are 0.059% and 0.026% for the equally and value weighted indices. Both equally and value weighted indices have a highly significant t-statistic for the difference of the means.

Ariel tests the hypothesis of equal positive return frequencies in the two groups of days for the two indices. The test rejects this hypothesis in favour of the alternative hypothesis of more frequent pre-holiday advances. The actual figures are 0.856 for the pre-holiday days equally-weighted index, and 0.750 for the value weighted index, whereas the other days' positive advances are 0.558 and 0.538 respectively. Ariel tests whether the high pre-holiday returns persisted during the entire sample period by splitting the 20-year interval into two sub-periods. The results reported for the two 10 year sub-periods are only trivially different: 0.503% and 0.556% for the equally weighted index, and 0.343% and 0.386% for the value weighted index.

Another important assertion is that despite the much higher returns, the pre-holiday return variance is no larger than the return variance for all other days. Ariel states:

> 'Rather, it seems an extra component of return is added to regular trading days.' (p.1614).

Therefore, the conclusion is:

> 'This fact serves to emphasise that the high pre-holiday return is not a reward for bearing extra risk.' (p.1614).

Ariel examines whether the pre-holiday returns are a materialisation of other calendar anomalies, such as the January effect, the weekend effect and the small firm effect. As the last day and beginning of the months are seasonally strong periods (Ariel, 1987, Rozeff and Kinney, 1976, Reinganum, 1983, Roll, 1983) and this is especially true for January, Ariel applies pre-holidays and pre-New Year holiday dummy variables. Despite this, the pre-holiday dummy for both equally and value weighted indices is still significant. The New-Year's dummy though, is only significant for the equally weighted index. While the equally weighted index is largely populated by small firm returns, this implies that the New Year's Holiday excess returns are due to the small firms.

Ariel uses dummy variables for the days-of-the-week returns, plus an added pre-holiday dummy variable. The magnitude of the pre-holiday dummy represents the incremental returns earned on pre-holidays after correcting for the differing means across different days of the week. For both value and equally weighted indices the magnitude of the pre-holiday dummy is large and statistically significant. This confirms that the high return frequency of Friday and low return frequency of Monday pre-holidays is not responsible for the observed pre-holiday strength. Further, Ariel shows that the pre-holiday effect is not a small firm effect.

### 3.5.3. Turn-of-the-month (January) effect

Another calendar anomaly is the turn-of-the year effect. There is evidence (Reinganum, 1983; Roll, 1983) that securities yield high excess returns in the month of January. Recently this phenomenon was tied in with the small firm effect by Roll (1983) and Pettengill and Jordan (1990).

Ogden (1990) tests the hypothesis that monthly and January effects are due, at least in part, to a standardisation in the payment system in the United States, specifically a concentration of cash flows at the turn of each month.

Ogden argues that the end of each month is a preferred habitat (in the Modigliani and Sutch (1966) sense) for paying off accrued wages, dividends, interest and principal payments and other liabilities. As a result, economic entities would prefer to invest their short-term investable funds in securities that mature at the end of the calendar month, rather than before or well after that date. If securities are to be rolled over (sold prematurely) to provide necessary liquidity, it would involve greater interest rate risk and transaction costs.

The intra-month returns on the stock market can be partially explained by assuming that the bulk of expected monthly cash income for the representative investor is received at the turn of the month, while expected cash expenditures are distributed uniformly throughout the month.

As for the representative investor, Ogden makes several behavioural assumptions, i.e., commensurate holding of investable wealth (cash), liquid securities (Treasury notes) and relatively illiquid stocks. As a consequence, investors will be more committed to invest in relatively illiquid stocks at the end of the month, when economy-wide profits are large. When aggregate liquid profits are small, investors would be less willing to buy stocks.[13]

[13]Individual investors may have no compulsion to invest immediately. However, many firms provide reinvestment plans (Kinoshita, 1989)), indicating that investors have a substantial interest in reinvesting their income.

Ogden suggests FED's[14] monetary policy as a measure of stock market liquidity (illiquidity). The monetary policy affects the expected liquid profits, which in turn will affect turn-of-the month stock returns.[15]

Ogden links the turn-of-the month liquidity hypothesis with the January effect. The arguments for this are: (i) the evidence, that the positive January returns are concentrated in the first few trading days of January, (ii) that it is reasonable to assume that liquid profits are greater in December than in other months, (iii) that the January turn-of-the month profits are greater for small firm stocks, and evidence on the ownership of stocks in the U.S. indicates that individual investors hold proportionately more small firm stocks, while institutional investors hold proportionately more stocks of large firms (Ritter, 1988).

Ogden uses daily equally- and value-weighted stock indices from January 1969 to December 1986 and the FED fund spread for the measure of a stringent (easy) monetary policy. For various sub periods and for the whole period, easy-money months have positive and high turn-of-the month returns. These returns however, are even higher for the equally weighted index, which in turn implies that the turn-of-the-month effect is more pronounced for small firms' stocks.

January returns are higher for easy-money than stringent-money Januarys. In spite of this, stringent-money Januarys have positive abnormal returns, implying that other factors apart from monetary policy may contribute to the high January turn-of-the month returns.

Bhardwaj and Brooks (1992) provide evidence that the share price (High/Low share price stock) may dominate the firm size in explaining the January anomaly. They claim that many of the small size firms' characteristics that are used in explaining the size anomaly, such as transaction costs, degree of neglect, misassessment of risk, and infrequent trading, are

[14] The US Central Bank, The Federal Reserve System, often abbreviated as FED from the first three letters.
[15] Note that monetary policy is likely to affect real economic activity, and thus investors' liquid profits, with a lag (Laurent, 1988). However, a positive association between contemporaneous changes in the money supply and stock returns is well documented (Sorenson, 1982).

equally, if not more, applicable to low price stock. To test this hypothesis, Bhardwaj and Brooks form 25 portfolios, 5 sorted by market value and 5 by share price, and estimate January returns over a 20-year period. The conclusion is that there is a stronger relationship between share price and the January anomaly than between firms' size and the January anomaly.

Jegadeesh (1991) claims that past return predictability, reported in Fama and French (1988), is mostly due to seasonal price mean reversion. He finds that the stock price mean reversion is entirely concentrated in the month of January and the estimates of long-term serial correlation outside January are indistinguishable from zero. Further, Jegadeesh examines an LSE return sample and finds that the seasonality in stock price mean-reversion in the U.K. is similar to that in the U.S.

Jones, Lee and Apernbrink (1991) examine the returns of stocks in the Cowles Industrial Index before and after the introduction of personal income taxes in 1917. They find that excess returns at the turn-of-the-year and for the month of January were not significant until after 1917. Thus their results provide support for the tax-loss selling hypothesis as an explanation for the January seasonal excess return of small firms.

## 3.6. Conclusion

The extensive work carried out on the size anomaly shows the interest in this phenomenon. Overall, the existence of the size anomaly has been well documented. The remaining problem is its logical explanation. Once the size anomaly was documented, attention has shifted towards its explanation. Most contemporary papers on the size effect have an introductory section which confirms its existence, and the rest is dedicated to the explanations of the size effect.

It seems that any rationale for the size effect is multidimensional. It looks perfectly logical, bearing in mind the stock market mechanism (Chapter 2), to expect higher transactions costs in terms of bid-ask spread pertaining to small firms. The overreaction patterns may also contribute to the explanation of the size anomaly, especially when they are coupled with analysis of size portfolios' stability after rebalancing. The papers on the size anomaly seem to avoid this issue, so that Chan and Chen's (1991) paper is of great significance. The question is whether there would be excess return on size, if size portfolios were not rebalanced.

Of course, explanations that embrace the so called 'proxy hypothesis' are of great interest too. First, though, we need to know whether a size effect existed in the LSE between 1985-1995, which is dealt with in the next Chapter.

# Chapter 4

# The Existence of Size Effects: Empirical Evidence From the UK Stock Market 1985 to 1995

## 4.1. Introduction

The aim of this chapter is to detect whether or not the size effect has existed in the London Stock Exchange over the period 1985-1995, and to estimate its magnitude. In brief the procedure involves:

1. Forming ten portfolios, each consisting of an equal number of commercial firms listed on the London Stock Exchange, on the basis of the firms' market capitalisation every year for the period 1985-1995.
2. Rebalancing these size-portfolios every year over the sample period.
3. Estimating portfolio market risk (beta) using the Market Model and regressing monthly size-portfolio returns against the return of an Equally Weighted Market index.
4. Measuring the significance of beta and size in explaining the cross-sectional differences of the size portfolio returns.
5. Checking for seasonal patterns in the behaviour of the size portfolio returns.

## 4.2 Formation and Rebalancing of Size Portfolios

The stock market data for this research are derived from *DATASTREAM* Database on-line and cover the period from 1982 to 1995 inclusive. The sample contains the constituents of the FTSE Actuaries Share Indices except Financials and Investment Trusts, i.e., General Industrials, Consumer Goods, Services, Mineral Extraction and Utilities[1]. The sample is restricted to those shares available at the end of 1995, as *DATASTREAM* does not provide on-line data for those firms that have ceased trading. The number of firms is further restricted to those with available and positive Market-to-Book (MTB) value and borrowing ratios (BR).

The market value[2] (MV) for every sample firm is collected at the end of each year from 1982 to 1995. Then, shares are sorted into 10 size-portfolios by market value at the end of the year and by industry. For a share to be included in a size-portfolio, it should be listed for at least 3 years. Therefore, the first set of 10 size-portfolios was formed using firms' market value at the end of 1984. Similarly, 10 size-portfolios of firms ranked by their market value at the end of the year were formed for each year up to 1994.

To be eligible for inclusion in one of the 1985 size-portfolios, an asset should be listed and traded from the end of 1982 to the end of 1984. At the end of 1984 325 assets are eligible for inclusion, and their number grows gradually to 534 at the end of 1994. However, after discarding those shares for which MTB and BR are either unavailable or meaningless, these numbers are slightly reduced to 304 at the end of 1984 and 500 at the end of 1994.

For each size portfolio (portfolio 1 being the lowest market capitalisation, portfolio 10 the highest), one calendar year following portfolio formation is considered and monthly share prices for this year are extracted from *DATASTREAM*. Hence, for size portfolios formed at

[1]The corresponding *DATASTREAM* codes are *LFTAGENM, LFTACGDS, LFTASERV, LFTAMEXT, LFTAUTIL.*
[2] The market value or firm's size is defined as firm market capitalisation, i.e., the number of firm ordinary shares multiplied by their current market price.

the end of a given year falling into the 1984-1994 period, monthly prices are derived for the following year, e.g., the end of 1984 market value portfolios have equally weighted monthly returns, calculated from individual asset prices for 1985. Thus, size portfolio returns are estimated as:

$$R_{pt} = \sum_{1}^{n} \frac{(p_{it} - p_{it-1}) / p_{it-1}}{n} \tag{4.1}$$

$R_{pt}$ - return for size portfolio $p$ ($p$=1 .....10) for month $t$,

$p_{it}$ - price for a share $i$, constituent of portfolio $p$ for month $t$,

$p_{it-1}$ - price for a share $i$, constituent of portfolio $p$ for month $t$-$1$,

$n$ - total number of portfolio $p$ constituencies for a given year.

Table 4.1 shows the gross size portfolio returns, calculated from monthly asset prices and then aggregated on a yearly basis.

**Table 4.1.**

**Size Portfolios' Average Monthly Return from 1985 to 1995**

| Period Portf.# | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.0419 | 0.0524 | 0.0353 | 0.0262 | 0.0065 | -0.0059 | 0.0403 | 0.0179 | 0.0731 | 0.0300 | 0.0227 |
| 2 | 0.0325 | 0.0248 | 0.0310 | 0.0204 | -0.0033 | -0.0079 | 0.0353 | 0.0043 | 0.0546 | 0.0101 | 0.0173 |
| 3 | 0.0270 | 0.0314 | 0.0312 | 0.0190 | 0.0034 | -0.0179 | 0.0299 | -0.0068 | 0.0365 | 0.0036 | 0.0137 |
| 4 | 0.0251 | 0.0197 | 0.0138 | 0.0190 | 0.0002 | -0.0100 | 0.0308 | 0.0028 | 0.0285 | 0.0053 | 0.0068 |
| 5 | 0.0336 | 0.0232 | 0.0147 | 0.0185 | -0.0016 | -0.0102 | 0.0238 | -0.0033 | 0.0318 | -0.0007 | 0.0100 |
| 6 | 0.0203 | 0.0209 | 0.0164 | 0.0178 | 0.0026 | -0.0165 | 0.0224 | -0.0009 | 0.0245 | 0.0014 | 0.0038 |
| 7 | 0.0205 | 0.0202 | 0.0181 | 0.0163 | 0.0132 | -0.0124 | 0.0144 | 0.0091 | 0.0241 | -0.0031 | 0.0062 |
| 8 | 0.0162 | 0.0222 | 0.0005 | 0.0201 | 0.0100 | -0.0101 | 0.0067 | 0.0070 | 0.0199 | 0.0033 | 0.0091 |
| 9 | 0.0239 | 0.0191 | 0.0047 | 0.0182 | 0.0102 | -0.0106 | 0.0094 | 0.0109 | 0.0169 | 0.0008 | 0.0082 |
| 10 | 0.0163 | 0.0148 | 0.0030 | 0.0099 | 0.0245 | -0.0029 | 0.0086 | 0.0149 | 0.0102 | -0.0023 | 0.0079 |

Table 4.1 indicates that the smallest MV portfolio 1 average return is superior to the remaining 9 portfolios. Only for two years out of eleven does the portfolio 1 average return

rank below first, 1989 and 1990. The largest MV portfolio 10's average return ranks 10th in three out of the eleven years, and 9th in four. In addition, there is a tendency for average returns to diminish as portfolio size increases. To allow for an easier interpretation of the results of Table 4.1, Table 4.2 reports the portfolio rank order for each year. It also reveals a rather surprising result for the overall 1985-95 ranking of the 10 MV portfolios; on average, MV portfolios are almost perfectly arrayed from portfolio 1 ranking first to portfolio 10 ranking last. The only disharmony consists of portfolios 6 and 7 and portfolios 8 and 9 swapping places. This does not reduce the significance of the relation shown on Table 4.2, as the swaps take place between neighbouring size portfolios.

**Table 4.2.**

**Ranked Portfolios' Return**

| Period | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 85-95 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Portf. #** | Size Portfolios' Rank for different years | | | | | | | | | | | |
| **1** | 1 | 1 | 1 | 1 | 5 | 2 | 1 | 1 | 1 | 1 | 1 | 1 |
| **2** | 3 | 3 | 3 | 2 | 10 | 3 | 2 | 6 | 2 | 2 | 2 | 2 |
| **3** | 4 | 2 | 2 | 5 | 6 | 10 | 4 | 10 | 3 | 4 | 3 | 3 |
| **4** | 5 | 8 | 7 | 4 | 8 | 4 | 3 | 7 | 5 | 3 | 8 | 4 |
| **5** | 2 | 4 | 6 | 6 | 9 | 6 | 5 | 9 | 4 | 8 | 4 | 5 |
| **6** | 8 | 6 | 5 | 8 | 7 | 9 | 6 | 8 | 6 | 6 | 10 | 7 |
| **7** | 7 | 7 | 4 | 9 | 2 | 8 | 7 | 4 | 7 | 10 | 9 | 6 |
| **8** | 10 | 5 | 10 | 3 | 4 | 5 | 10 | 5 | 8 | 5 | 5 | 9 |
| **9** | 6 | 9 | 8 | 7 | 3 | 7 | 8 | 3 | 9 | 7 | 6 | 8 |
| **10** | 9 | 10 | 9 | 10 | 1 | 1 | 9 | 2 | 10 | 9 | 7 | 10 |

It seems that 1989 and 1990 break the pattern which appears for the whole period. Therefore this behaviour can be classified as anomalous. A plausible speculation for the exceptionally low market returns for both years might include high interest rates and growth stagnation caused by Britain's joining the ERM. This, however, is not sufficient to clarify why there is a reversion in the rank order.

In the research conducted for the Wilson Committee (Wilson 1979) at the end of 1970s it was observed that 'small' and 'intermediate' size firms (of up to £4m total assets in 1975) were characterised by high ratios of bank borrowing and of higher current liabilities in general than was the typical large firm. This disadvantage, as the Wilson Committee to Review the Functioning of Financial Institutions (1980) concluded, although it cannot be properly called discrimination, constitutes a barrier to small firm growth. During the 1970s it appears to be a major barrier to the growth of the small independent British business. Thus, one might hypothesise that:

I. In a state of relatively high costs of borrowing, poor performance of the small capitalisation stocks is to be expected. II. In a state of cheap credit and high market returns, an excellent small capitalisation stocks' performance is to be expected. The econometric model, therefore, should embrace the gearing behaviour of firms, as well as interest rate movements, compared with the average market return. Testing of the above hypothesis is beyond the scope of this chapter.

Table 4.3 supplies the size portfolios' descriptive statistics, which are estimated for the whole period. The important characteristics of the size portfolios' return are their normalised third and fourth moments, skewness and kurtosis, which in turn serve as a test for the normality of these returns.

**Table 4.3.**

**Descriptive Statistics for the ten size portfolios' return from 1985 to 1995.**

| Portfolio # Statistics | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.0309 | 0.0199 | 0.0155 | 0.0129 | 0.0127 | 0.0103 | 0.0116 | 0.0096 | 0.0099 | 0.0095 |
| St. Error | 0.0057 | 0.0048 | 0.0049 | 0.0048 | 0.0051 | 0.0052 | 0.0054 | 0.0054 | 0.0051 | 0.0046 |
| Median | 0.0278 | 0.0237 | 0.0131 | 0.0143 | 0.0156 | 0.0134 | 0.0174 | 0.0163 | 0.0112 | 0.0142 |
| St. Dev. | 0.0651 | 0.0548 | 0.0567 | 0.0547 | 0.0584 | 0.0603 | 0.0622 | 0.0616 | 0.0590 | 0.0526 |
| Variance | 0.0042 | 0.0030 | 0.0032 | 0.0030 | 0.0034 | 0.0036 | 0.0039 | 0.0038 | 0.0035 | 0.0028 |
| Kurtosis | 2.6462 | 2.4948 | 2.7569 | 3.3396 | 1.6513 | 2.2606 | 2.5166 | 4.1461 | 3.0944 | 5.5692 |
| Skewness | -0.4224 | -0.3451 | -0.6004 | -0.7777 | -0.6016 | -0.3679 | -0.5100 | -0.8716 | -0.6590 | -0.9163 |
| Range | 0.4514 | 0.3775 | 0.3834 | 0.3927 | 0.3926 | 0.4469 | 0.4591 | 0.4605 | 0.4324 | 0.4203 |
| Minimum | -0.2365 | -0.2113 | -0.2114 | -0.2306 | -0.2210 | -0.2439 | -0.2639 | -0.2984 | -0.2691 | -0.2717 |
| Maximum | 0.2149 | 0.1662 | 0.1720 | 0.1621 | 0.1716 | 0.2030 | 0.1952 | 0.1620 | 0.1632 | 0.1486 |

The sample standard deviation is $s=\sqrt{\frac{\sum\left(x_i-\bar{x}\right)^2}{n-1}}$, whereas the standard error of the mean is $\sigma_{\bar{x}}=\frac{\sigma}{\sqrt{n}}$.[3]

The skewness, or normalised third moment, of a random variable $X_i$ with mean $\overline{X}$ and variance $\sigma_x$ is defined by[4]:

$$S[X_i]=\frac{1}{n}\times\frac{\sum_{i=1}^{n}\left(X_i-\overline{X}\right)^3}{\sigma_x^{\ 3}}$$

The kurtosis, or normalised fourth moment of $X_i$, is defined by:

$$K[X_i]=\frac{1}{n}\times\frac{\sum_{i=1}^{n}\left(X_i-\overline{X}\right)^4}{\sigma_x^{\ 4}}$$

The normal distribution has skewness equal to zero, as do all other symmetric distributions. Positive skewness will result if the distribution is skewed to the right, since the average cubed deviations would be positive. Skewness will be negative for distributions skewed to the left. For the size portfolios the skewness values are negative for all ten, i.e., all are skewed to the left.

The normal distribution has kurtosis value of 3, but fat-tailed distributions with supplementary probability mass in the tail area have higher or even infinite kurtosis. Monthly return series tend to be thinner-tailed compared to daily or even weekly return series, but portfolios 8 and 10 are still distinguished by their high kurtosis. Mills (1995a), using daily

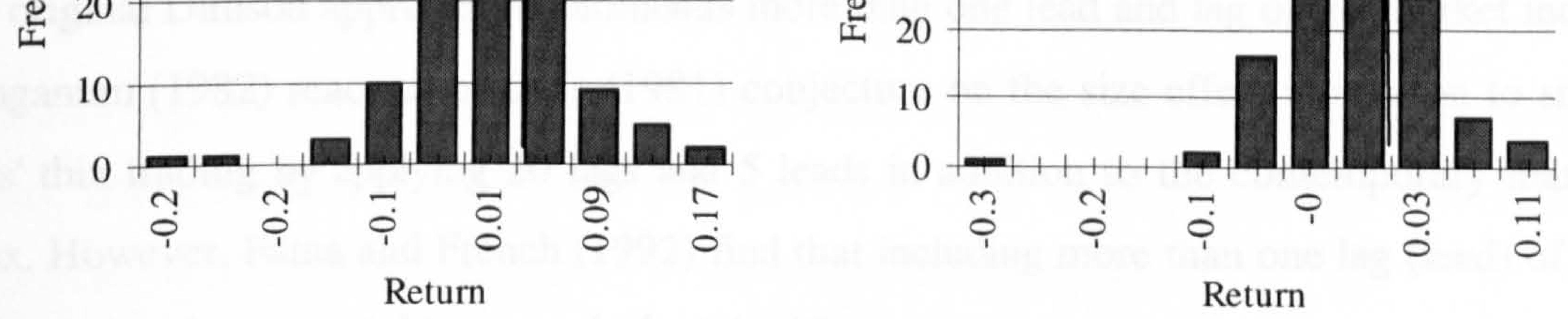
[3] See M. Fleming *et al,* (1994).
[4] See Newbold, P., (1991).

return series on different FT-SE indices over the period 1986-1992, finds that empirical return distributions are often *elongated*, having tails heavier than those of the Gaussian distribution.

The mean, median and mode must coincide for a normal distribution. As it is impossible for the mode to be determined in non-discrete series, we report two indicators of the central tendency: the mean and median. If the mean and the median of the size portfolios are compared, it becomes obvious that the median of portfolio 1 is less than the mean, i.e., the median is situated on the left. As the portfolios' market capitalisation increases, the median moves to the right, which is particularly pronounced for the largest market value portfolios 9 and 10. Again, mean returns follow the same pattern as rank order, but median returns do not.

Figure 4.1 displays histograms of the returns of the two extreme portfolios 1 and 10. The arrows in the middle show the approximate position of the mean. An apparent difference is that the portfolio 1 distribution is rather flat, while the portfolio 10 distribution is spindly.

**Figure 4.1.**



These departures of the size portfolios' return distribution from normality, however, are not to be exaggerated. It is another story when daily return series are used, and as shown in Mills (1995), the departure of these series from normality is far greater that that of the series used in this study.

## 4.3. Size Portfolios Systematic Risk

The size portfolios' betas are estimated by the Market Model:

$$R_{p,t} = \alpha + \beta_{p,t-1} R_{m,t-1} + \beta_{p,t} R_{m,t} + \beta_{p,t+1} R_{m,t+1} + \varepsilon \qquad (4.2)$$

$R_{p,t}$ - is size portfolio $p$ ($p$=1...10) monthly returns, from month -36 to month 0,

$\alpha$ - intercept,

$R_{m,t}$ - equally weighted market return,

$\beta_{p,t-1}, \beta_{p,t}, \beta_{p,t+1}$ - beta measured as lagged, contemporary and lead coefficient.

The actual beta is obtained by summing the lagged, contemporary and lead beta estimates, a technique, which according to Dimson (1979), allows for infrequent trading of small firms' shares. The inclusion of lead and lagged independent variables aims to deal with the thin-trading problem. Thin-trading is a common feature of smaller size firms, in which the number of shareholders is significantly lower than the number of shareholders in larger companies. As a result, small companies' shares are not traded for long intervals and thus their prices may remain unchanged, especially when the observation frequency is short. In OLS terms, beta would be biased, if estimated only from the contemporary market index. The original Dimson approach recommends more than one lead and lag of the market index. Reinganum (1982) reacted to Roll's (1981) conjecture on the size effect in relation to small firms' thin trading by applying 20 lags and 5 leads in addition to the contemporary market index. However, Fama and French (1992) find that including more than one lag (lead) of the market index does not yield a great deal of significance.

Thin-trading is a severe problem when daily return series are used to estimate beta. The problem of thin trading, although alleviated, still exists within the smallest 2-3 deciles when monthly average prices and returns are used. Due to lack of information, this study does not recognise whether and when the zero return is due to lack of trading or other reasons such as trade suspension.

Yet another way of mitigating the thin-trading problem is by combining single assets into portfolios. Fortunately, this study's methodology requires share bundling into size portfolios. Nonetheless, in addition to the contemporary market index, lagged and lead market indices are included in the market model. However, if either lagged or lead market index or both are not statistically significant at the 5% level, they are dropped from the equation. Information on how the final portfolio beta is arrived at, i.e., as a sum of contemporary, lead and lagged beta estimates and whether the lagged and lead coefficients are insignificant, is provided in Appendix 4.1. In summary, the estimated lead beta coefficient almost always turns out to be insignificant, being included only twice out of 110 regressions. These are portfolios 8 for 1992 and 9 for 1995, respectively. On the other hand, the lagged market index coefficient is significant in a considerable number of cases, and also contributes a fair amount to the total beta estimate. For instance, the lagged market coefficient contributes 0.189 of the contemporary market index value to the total portfolio 1 beta. The lagged market coefficient share, however, diminishes gradually at the middle MV portfolios. Portfolio 5 has an average contribution of the lagged index of 0.015 for the whole period 1985-1995. From portfolio 6 onwards the lagged market index contribution magnifies in absolute value but reverses its sign, i.e., it is a negative contribution that reaches the peak value of -0.23 at portfolio 10.

It follows that the returns of the low and high MV portfolios relate to the lagged market returns, but in a different way. Small MV portfolios' (1-3) relate positively, whereas large MV portfolios (8-10) relate negatively to the lagged market return.

An important procedure in portfolio beta estimation is the restriction on the intercept. According to the theory, the intercept of the market model should represent the fraction of the total asset return which is unrelated to market risk, i.e., beta. Portfolio theory claims that no return should be paid for idiosyncratic risk, hence the intercept should be zero. The Present Value Theory, however, admits a proportion of the total return which is free of risk as compensation for the Time Value of Money. Thus, the intercept of the Market Model is between:

-A lower bound, i.e., zero.

It is true that the CAPM in its analytical form of the Market Model implies $\alpha = (1-\beta)R_m$. However, the Market Model estimates $\alpha$ and $\beta$ simultaneously, when estimated by OLS. The primary criterion in this case is the minimisation of the least squares. Thus, the process of minimisation of the least squares may lead to a wide variety of estimated values of the intercept ($\alpha$) across size portfolios' Market Model. The intercept ($\alpha$) should represent the significance of all factors other than the market index in explaining size portfolio returns. These factors are grossly embodied in the time value of money discount rate and it is normally positive. On the other hand, if we allow $\alpha$ to move freely, fulfilling the minimisation of the least squares criterion only, then a negative estimate of $\alpha$ would require an unjustifiable increase in $\beta$ for the sample period so as to offset the negative $\alpha$ and keep the identity $\alpha = (1-\beta)R_m$.

- An upper bound, i.e., the monthly risk free rate of return. In this study the three month UK treasury bill rate is used as a proxy for the risk free rate of return. In terms of regression technicalities, the upper bound is calculated as an average of the monthly risk free rate for all months included in the regression period.

The market model regression is re-run without an intercept, either when the intercept is outside the upper and lower bounds, or when the intercept is within the bounds, but statistically insignificant.

There are two major problems with beta estimation. One problem is non-normality of the regression residuals. An inspection of the residuals shows that non-normality is usually caused by one, or sometimes by two, outliers. To tackle the non-normality problem, a dummy variable is assigned for the month(s) in which outliers are observed. An 'outlier' assigned a dummy variable is defined as the highest absolute value residual, which lies outside of the Standard Deviation band. It is, however, fair to say that in most occasions the outliers are around or above two Standard Deviations of the dependant variable.[5]

Another problem is autocorrelation in the residuals. Whenever autocorrelation is detected, the market model regression is run with the lagged dependent variable added as a regressor. The estimated lagged dependent variable coefficient ρ is then used to correct the beta coefficient, as shown below

$$\beta_c = \frac{\beta_m + \beta_{m-1} + \beta_{m+1}}{(1-\rho)} \qquad (4.3)$$

The market index return ($R_{m,t}$) is calculated as equally weighted assets' returns for each month from 02.1982 to 12.1995. Then, every size portfolio return is regressed on the contemporary, lead and lagged market index return, for a rolling sample of 36 months. Thus, to estimate portfolio 1 beta for 1986, portfolio 1's monthly return is regressed on the equally weighted market index for the period from 01/1983 to 12/1985. The corresponding beta values are shown in Table 4.4.[6]

[5]Dummy variables for outliers are used in 14 regressions, out of 110. In all regressions a dummy variable for one observation (outlier) is assigned except for portfolio 1 for 1993 where two dummies are required to achieve normality. Dummy variables are included in the following incidents, where the figures in the brackets indicate the ratio of the outlier's value and the Standard Deviation: 1987, pf.6 May '86 (1.83), pf.8 July '84 (-2.17); 1988, pf.8, Jan.'85 (-1.87) ; 1990 pf.1 August '87 (2.53), pf.4 April '87 (1.14), pf.9 August '87 (-1.53); 1992 pf.1 Oct. '91 (3.32); 1993 pf.1 Oct. '91 (2.96), June '92 (1.64), pf.3 Oct. '92 (-2.39); 1994, pf.1 Oct.'91 (3.02), pf.3 Oct. '92 (-2.49), pf.9 Nov. '92 (2.41); 1995 pf.3, Oct. '92, (-2.40), pf.9, Nov. '92, (2.47).

[6]Table 4.4 provides normalized beta estimates. Due to the approach used in estimation of the size portfolios' betas, they do not add up to one, although being very close to it. This can be compared to the raw estimates in Appendix 4.1. The normalisation procedure thus provides consistency of the beta estimates throughout the period.

**Table 4.4.**

**Size Portfolios Beta**

| Period / Portfolio | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| pf1 | 1.134 | 1.260 | 1.198 | 1.413 | 1.381 | 1.267 | 1.176 | 1.270 | 1.169 | 1.563 | 1.696 |
| pf2 | 0.818 | 0.962 | 0.807 | 0.914 | 0.922 | 1.018 | 0.912 | 1.113 | 1.180 | 1.378 | 1.255 |
| pf3 | 1.014 | 1.002 | 1.066 | 1.218 | 1.206 | 1.263 | 1.023 | 1.133 | 1.110 | 1.129 | 1.068 |
| pf4 | 1.113 | 1.026 | 1.009 | 1.051 | 1.068 | 1.071 | 1.041 | 1.134 | 1.121 | 1.080 | 0.972 |
| pf5 | 1.143 | 1.151 | 1.085 | 1.015 | 0.991 | 0.990 | 0.955 | 1.010 | 1.038 | 1.038 | 1.024 |
| pf6 | 0.940 | 0.923 | 0.869 | 0.898 | 0.946 | 0.938 | 1.150 | 1.092 | 1.129 | 1.057 | 1.004 |
| pf7 | 0.984 | 0.959 | 0.987 | 1.051 | 1.026 | 1.006 | 1.010 | 0.977 | 1.051 | 0.969 | 0.951 |
| pf8 | 0.945 | 0.845 | 1.044 | 0.865 | 0.875 | 0.849 | 1.052 | 0.774 | 0.754 | 0.679 | 0.951 |
| pf9 | 0.927 | 1.081 | 1.035 | 0.821 | 0.824 | 0.846 | 0.920 | 0.883 | 0.844 | 0.664 | 0.649 |
| pf10 | 0.982 | 0.791 | 0.901 | 0.754 | 0.763 | 0.751 | 0.761 | 0.615 | 0.604 | 0.444 | 0.430 |

Table 4.4 confirms the widespread belief that smaller capitalisation firms have higher risk as measured by beta. Despite the equally weighted market index used for beta estimation, smaller size portfolios have higher risk than larger size portfolios throughout all years from 1985 to 1995. In addition, beta displays an almost perfect subordination from small to large size portfolios. The only major exceptions are the low beta of portfolio 2 from 1985 to 1991 and the high beta of portfolio 6 from 1991 to 1993. Considering beta stability for the period under investigation, it is obvious that size portfolios' betas are not invariant. The most stable beta estimates are from portfolio 4 to portfolio 8, despite portfolio 6's beta leap in 1991-1993. Portfolios' 1-3 betas increase gradually from 1985 to 1995, whereas the opposite behaviour characterises portfolios' 9 and 10.

Betas were also estimated using the standard approach, rather than Dimson's estimator. If the two approaches are compared, the conclusion is that Dimson's estimator increases small firms' betas and decreases large firms' betas.[7]

[7] Standard approach results are not provided.

Regression statistics are provided in Appendix 4.1. Appendix 4.1 exhibits values and t-ratios of the contemporary, lag and lead beta estimates. It is seen that the contemporary market index is significant at the 1% level for all size portfolios and all years. With few exceptions, the lag (lead) market index is significant at 5% or higher. Appendix 4.2 displays the adjusted R sq. and D-W test for serial correlation. All regressions have a good fit with $R^2$ ranging from 0.52 to 0.97. It seems also that serial correlation is not a problem. This, however, is not true for the regressions with a lagged dependant variable. For these regressions Appendix 4.2 exhibits Durbin's h-statistic where a star mark is shown.

Residual diagnostic tests are shown in Appendix 4.3. This includes the Lagrange multiplier test of serial correlation of the residuals, a Normality test based on skewness and kurtosis of residuals, a Heteroscedasticity test and a Chow test of stability of the regression coefficients.

### 4.3.1. Serial Correlation test

Serial Correlation usually occurs when some explanatory variables are omitted. After applying the procedure of correction for the serial correlation described above, there are only a couple of occasions when the Market Model ends up with a rejection of the no serial correlation hypothesis at the 5% level of significance; These are portfolio 2 for 1993 and portfolio 9 for 1992. This is a very small number compared to the total number of regressions (110), and therefore it can be concluded that the Market model regressions have no problems with serial correlation.

### 4.3.2. Normality

As noted above, (Table 4.3), the size portfolios' returns are not normally distributed. Normality is not a pre-requisite for the theoretical CAPM, it is more of a statistical requirement. If returns are independently and identically distributed (IID) through time and jointly multivariate normal then the estimated coefficients and the standard statistics for them are valid. Appendix 4.3 shows no single case where the normality of residuals fails.

### 4.3.3. Heteroscedasticity test

Heteroscedasticity seems to be a prevalent feature of the market models. A test based on the regression of squared residuals on squared fitted values reveals heteroscedasticity in 12 out of 110 regressions.

### 4.3.4. Parameter Stability test

Vasicek (1973) and Blume (1971, 1975) document the mean reversion tendencies of beta and suggest possible adjustment procedures. Handa, Kothari and Wasley (1989) note the sensitivity of beta to the return interval if buy and hold returns are used. Coutts, Mills and Roberts (1996, 1997) apply different methods for testing Market model stability of 56 FT-SE 100 companies. Examining the significance of various structural changes on parameter stability by adopting Chow (1960) breakpoint and Dufour (1982) dummy variable tests, they find parameter shifts for at least one of the events, the most popular being at the Crash of October 1987.

Appendix 4.3 shows the cases where the Chow test rejects stability at the 5% level of significance. It is clear that there is not a systematic pattern of parameter instability, as rejection is randomly spread across the period. This may be because structural changes in one asset are compensated by opposite changes in another asset within the same size portfolio, thus alleviating the instability problem by virtue of portfolio diversification.

## 4.4. The Cross Sectional Relationship between Returns, Beta and Size.

The variable that challenges beta's status in explaining the cross-sectional differences in returns is firm size. Market capitalisation is used here as a proxy for the size of each firm at the end of every calendar year. The market value of a size portfolio is calculated as the equally weighted value of all member firms' market value. Table 4.5 displays the size portfolios' market value in millions of pounds' market capitalisation. The number of firms in a given portfolio is almost equal across portfolios.

**Table 4.5.**

**Size Portfolios Average Market Value as per the end of the previous year**

m. £

| Period / Portf. | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 3.17 | 4.86 | 7.54 | 10.97 | 13.67 | 13.85 | 9.41 | 12.03 | 14.75 | 30.74 | 38.78 |
| 2 | 9.93 | 14.89 | 18.85 | 29.30 | 33.41 | 34.34 | 23.97 | 28.71 | 33.08 | 51.06 | 56.55 |
| 3 | 16.59 | 24.25 | 30.46 | 45.26 | 50.25 | 50.71 | 38.77 | 47.03 | 53.15 | 74.15 | 71.74 |
| 4 | 24.94 | 34.98 | 42.12 | 64.04 | 68.41 | 69.31 | 53.04 | 71.21 | 77.02 | 108.70 | 104.04 |
| 5 | 37.19 | 52.57 | 62.33 | 94.20 | 96.59 | 96.42 | 74.35 | 97.93 | 113.84 | 154.21 | 145.19 |
| 6 | 61.36 | 79.00 | 88.00 | 144.33 | 146.39 | 148.06 | 114.22 | 143.07 | 172.52 | 220.84 | 206.46 |
| 7 | 112.57 | 145.03 | 142.14 | 245.88 | 240.49 | 259.29 | 201.12 | 219.70 | 280.23 | 382.17 | 336.61 |
| 8 | 217.49 | 282.22 | 312.23 | 472.13 | 451.10 | 460.78 | 378.08 | 412.02 | 542.28 | 750.87 | 705.09 |
| 9 | 449.17 | 643.76 | 858.13 | 938.13 | 956.39 | 1077.70 | 857.20 | 944.46 | 1220.27 | 1621.50 | 1527.18 |
| 10 | 2345.91 | 2761.48 | 3533.90 | 3944.39 | 3872.07 | 5331.47 | 4765.98 | 5540.32 | 6371.38 | 7521.58 | 6611.25 |

Testing of the cross-sectional relationship between market risk (beta) and returns is carried out by estimating the cross-sectional model:

$$R_{p,t} - Rf_t = \gamma_{1t} + \gamma_{2t}\beta_{p,t} + \gamma_{3t} LnSZ_{p,t} \tag{4.4}$$

$R_{p,t}$- return on size portfolio $p$ ($p$=1...10), for month $t$= 1/85.... 12/94),

$Rf_t$ - risk free rate of return for month $t$,

$\beta_{p,t}$ - beta risk factor,

$LnSZ_{p,t}$ - size portfolio $p$ market value (logarithm) for year $t$ ($t$=85 ....95).

The above cross-sectional regression is run for every month from January 1985 to December 1995. As beta and LnSz are invariable throughout the year, whereas portfolios' returns vary each month, the sign and magnitude of the explanatory variables modulate month by month. Nonetheless, an average of all 132 cross-sectional regression coefficients should provide a picture of the size effect's overall sign and magnitude. This information is given in Table 4.6, and shows a negative average size effect of -0.0043, higher in absolute terms than the estimated beta coefficient of 0.0038. More importantly, size has an average T-Ratio of -1.74, much higher than beta. These features make beta a marginally significant variable in explaining the cross-sectional return differences at the LSE from 1985 to 1995.

**Table 4.6.**

**Averaged Coefficients and T-ratios of Cross-sectional Regression results 1985-1995**

| | $\gamma_1$ | Beta ($\gamma_2$) | Sz($\gamma_3$) |
|---|---|---|---|
| Coefficient | 0.0113 | 0.0038 | -0.0043 |
| T-Ratio | 1.07 | 0.99 | -1.74 |

The next questions are: To what extent are these results reliable? Is it only a casual relationship or is it a norm? Are there any changes in the relationship across different sub-periods?

To detect any seasonal patterns in the size effect, the estimates of the monthly cross-sectional regression (4.4) are compiled on a monthly basis. For each month, estimated coefficients are averaged and presented in Table 4.7. The shaded cells in Table 4.7 denote cases with T-ratios higher than 1.5. As in the whole period results, beta is statistically insignificant in all monthly results. Furthermore, beta does not have a consistent sign; for 5 of the 12 months its sign is negative, and the T-ratio for the rest of the months fluctuates around 1. The story reverses when size is considered; for nine of the months the sign of the size effect is negative and statistically significant at the 17 percent level and above (lowest T-ratio -1.5). When the size effect has a positive sign, it is also insignificant (January, September) the only exception being August.

The findings displayed in Table 4.7 confirm that there are seasonal patterns in the size effect. In March, April and October the size effect is exceptionally pronounced in magnitude as well as in statistical significance.

It is an interesting feature that the size effect in the LSE is quite noticeable in March and April and not at all in January. Studies on the size effect in the US stock market[8] show (unanimously) a high size effect in the month of January. In fact, most US papers on the size effect report that 50% of small firms' profits are due to the profits in the single month of January (Reinganum (1983)).

One of the hypotheses that offers an explanation of the size anomaly is the tax-selling argument, suggested first by Roll (1983). It might be a good idea for the tax arrangements and institutional differences between the US and UK to be examined in order to establish the viability of the tax-selling argument.

**Table 4.7.**

**Averaged Coefficients and T-ratios of monthly cross-sectional regression**

$$R_{p,t} - Rf_t = \gamma_{1t} + \gamma_{2t}\beta_{p,t} + \gamma_{3t} LnSZ_{p,t}$$

| Month / Coefficient | Jan | Feb | March | Apr | May | June | July | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\gamma_1$ | -0.0087 | 0.0378 | 0.0589 | 0.0279 | 0.0141 | 0.0657 | -0.0446 | -0.0208 | -0.0208 | 0.0239 | -0.0208 | 0.0235 |
| T-ratio | -0.68 | 0.99 | 1.01 | 1.62 | 1.10 | 1.13 | -1.17 | -1.05 | -0.80 | 1.06 | -1.33 | 0.95 |
| $\gamma_2$ (beta) | 0.0099 | 0.0155 | 0.0096 | -0.0075 | 0.0064 | -0.0178 | 0.0402 | 0.0253 | 0.0125 | -0.0103 | -0.0018 | -0.0366 |
| T-ratio | 0.67 | 1.07 | 1.15 | -1.07 | 1.07 | -0.95 | 1.17 | 1.04 | 0.95 | -0.62 | -0.97 | -1.16 |
| $\gamma_3$ (LnSZ) | 0.0080 | -0.0059 | -0.0180 | -0.0063 | -0.0014 | -0.0147 | -0.0018 | 0.0006 | 0.0009 | -0.0111 | -0.0001 | -0.0015 |
| T-ratio | 1.06 | -1.60 | -1.96 | -2.75 | -1.54 | -1.65 | -1.54 | 2.02 | 1.30 | -2.09 | -1.65 | -1.74 |

## 4.5. Size Portfolios Excess Return

The estimation of the cross-sectional relationship between the size portfolios' return and beta and portfolios size is one way of establishing the size effect. Another consists of calculating the so-called 'excess over market risk' return. In fact, both procedures are two sides of the same coin, providing different insights. In the former case $\gamma_2$ from equation (4.4) represents

[8] Keim (1983), Roll (1983), Pettengill and Jordan (1990).

It is an interesting feature that the size effect in the LSE is quite noticeable in March and April and not at all in January. Studies on the size effect in the US stock market[8] show (unanimously) a high size effect in the month of January. In fact, most US papers on the size effect report that 50% of small firms' profits are due to the profits in the single month of January (Reinganum (1983)).

One of the hypotheses that offers an explanation of the size anomaly is the tax-selling argument, suggested first by Roll (1983). It might be a good idea for the tax arrangements and institutional differences between the US and UK to be examined in order to establish the viability of the tax-selling argument.

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| Month / Coefficient | Jan | Feb | March | Apr | May | June | July | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\gamma_1$ | -0.0087 | 0.0378 | 0.0589 | 0.0279 | 0.0141 | 0.0657 | -0.0446 | -0.0208 | -0.0208 | 0.0239 | -0.0208 | 0.0235 |
| T-ratio | -0.68 | 0.99 | 1.01 | 1.62 | 1.10 | 1.13 | -1.17 | -1.05 | -0.80 | 1.06 | -1.33 | 0.95 |
| $\gamma_2$ (beta) | 0.0099 | 0.0155 | 0.0096 | -0.0075 | 0.0064 | -0.0178 | 0.0402 | 0.0253 | 0.0125 | -0.0103 | -0.0018 | -0.0366 |
| T-ratio | 0.67 | 1.07 | 1.15 | -1.07 | 1.07 | -0.95 | 1.17 | 1.04 | 0.95 | -0.62 | -0.97 | -1.16 |
| $\gamma_3$ (LnSZ) | 0.0080 | -0.0059 | -0.0180 | -0.0063 | -0.0014 | -0.0147 | -0.0018 | 0.0006 | 0.0009 | -0.0111 | -0.0001 | -0.0015 |
| T-ratio | 1.06 | -1.60 | -1.96 | -2.75 | -1.54 | -1.65 | -1.54 | 2.02 | 1.30 | -2.09 | -1.65 | -1.74 |

## 4.5. Size Portfolios Excess Return

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[8] Keim (1983), Roll (1983), Pettengill and Jordan (1990).

the slope of the Security Market Line (SML) as a linear relationship between portfolios' return and betas. One has no impression, however, of how scattered the observations are, or if there is a pattern implying either spurious regression or a non-linear form of the relation. The SML in its linear form suggests an equal reward for one unit of risk, each portfolio's deviation from the SML is represented by the difference between the portfolio's actual return and the required return.

Table 4.8 represents the excess return adjusted for the market risk, beta. As returns are calculated from share prices, they do not reflect the total share return and if the risk free interest rate is further subtracted, portfolios' returns will be negative. Furthermore, subtracting the risk free interest rate will affect likewise all portfolios and therefore this way of calculating portfolios' excess returns does not modify the portfolios' relative strength.

**Table 4.8.**

**Monthly Size Portfolios Excess Returns from 1985 to 1995**

| Period / Portf. # | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 85-95 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.0128 | 0.0210 | 0.0151 | 0.0000 | -0.0026 | 0.0073 | 0.0143 | 0.0108 | 0.0357 | 0.0224 | 0.0048 | 0.0129 |
| 2 | 0.0114 | 0.0009 | 0.0174 | 0.0035 | -0.0093 | 0.0027 | 0.0151 | -0.0019 | 0.0168 | 0.0034 | 0.0041 | 0.0058 |
| 3 | 0.0009 | 0.0065 | 0.0132 | -0.0035 | -0.0046 | -0.0047 | 0.0072 | -0.0131 | 0.0010 | -0.0018 | 0.0024 | 0.0003 |
| 4 | -0.0035 | -0.0058 | -0.0032 | -0.0004 | -0.0068 | 0.0012 | 0.0078 | -0.0035 | -0.0074 | 0.0000 | -0.0035 | -0.0023 |
| 5 | 0.0042 | -0.0054 | -0.0036 | -0.0003 | -0.0081 | 0.0001 | 0.0026 | -0.0090 | -0.0015 | -0.0058 | -0.0008 | -0.0025 |
| 6 | -0.0039 | -0.0020 | 0.0017 | 0.0011 | -0.0036 | -0.0067 | -0.0031 | -0.0071 | -0.0117 | -0.0037 | -0.0068 | -0.0042 |
| 7 | -0.0049 | -0.0036 | 0.0015 | -0.0032 | 0.0065 | -0.0019 | -0.0080 | 0.0036 | -0.0095 | -0.0077 | -0.0039 | -0.0028 |
| 8 | -0.0081 | 0.0012 | -0.0171 | 0.0041 | 0.0042 | -0.0012 | -0.0166 | 0.0027 | -0.0042 | 0.0000 | -0.0009 | -0.0033 |
| 9 | 0.0001 | -0.0078 | -0.0128 | 0.0030 | 0.0048 | -0.0017 | -0.0110 | 0.0060 | -0.0101 | -0.0024 | 0.0013 | -0.0028 |
| 10 | -0.0090 | -0.0049 | -0.0122 | -0.0041 | 0.0195 | 0.0049 | -0.0083 | 0.0114 | -0.0091 | -0.0044 | 0.0034 | -0.0012 |

It is clear from Table 4.8 that the returns of the smaller size firms dominate the returns of the larger size firms. If the two extreme cases, portfolio 1 and portfolio 10, are compared, one can see portfolio 1's excess return domination over portfolio's 10. Thus, portfolio 1 always performs better than portfolio 10, except for 1989 and 1992. Hence, if an investor kept a well-balanced portfolio consisting of smallest size firms, rather than a well-balanced one of largest size firms, their return adjusted for market risk would have been 185% higher on a non-compound basis. 1988 and 1992 are poor years for small size firms as portfolios 1 to 6 (except portfolio 1 for 1992) display negative excess returns. On the other hand, 1989 and 1992 are not such bad years for portfolios 6 to 10, as all of them earn positive excess returns, which are above their average excess returns for the whole period. That may imply a pattern of reversion in the size portfolios excess returns, due to investors' overreaction. The overreaction hypothesis appears first in the papers of De Bondt and Thaler (1985). Other papers after De Bondt and Thaler (1985), such as Jegadeesh (1991) contribute to the documentation of the overreaction hypothesis in the US and UK stock markets, confirming a 3 to 5 years pattern of overreaction.

Looking at Table 4.8, however, it is difficult to discern a pattern. A better representation of eventual patterns would be Figure 4.2, which uses a suitable aggregation of the portfolio returns. A natural way of aggregating is to combine the size portfolios into smaller, medium and large firms' portfolios. Thus the average return of portfolios 1 to 3 represents the smaller size firms, the average return of portfolios 4 through to 7 the medium size firms, and the average return of portfolios 8 through to 10 the larger size firms. Figure 4.2 portrays the average monthly excess returns of the smaller, medium and large size firms for each year from 1985 to 1995. Although the average excess return of the small firm portfolio for the whole period is positive and dominates the remaining portfolios, this is not the case for certain years. Figure 4.2 shows that, compared to the large firm portfolios, the small firm portfolios' excess return performs badly for 1989 and 1992. This is only part of the whole picture, though Figure 4.2 also reveals an even more fascinating effect, namely that the smaller size firms' excess returns are a mirror image, along the horizontal axes, of the largest size firms' return.

The medium size firms' excess return is just below zero and is relatively stable throughout the period. In contrast, smaller and larger firms' returns are volatile. They either diverge from or converge to each other. In other words, if the smaller size firms' return increases by, say, 'X%', the larger size firms' return decreases by 'X%' and *vice versa*. There are cases where the positive (negative) deviation of the smaller size firms' excess return from zero is not exactly matched by a negative (positive) deviation of the same magnitude in the larger size firms' excess return. In these cases the difference is offset by the excess return deviation of the medium size firms. If we take 1987, for instance, larger and smaller firms have almost equal deviation from the zero-excess return in absolute terms, but with a different sign. The medium size firms' return is then approximately zero.

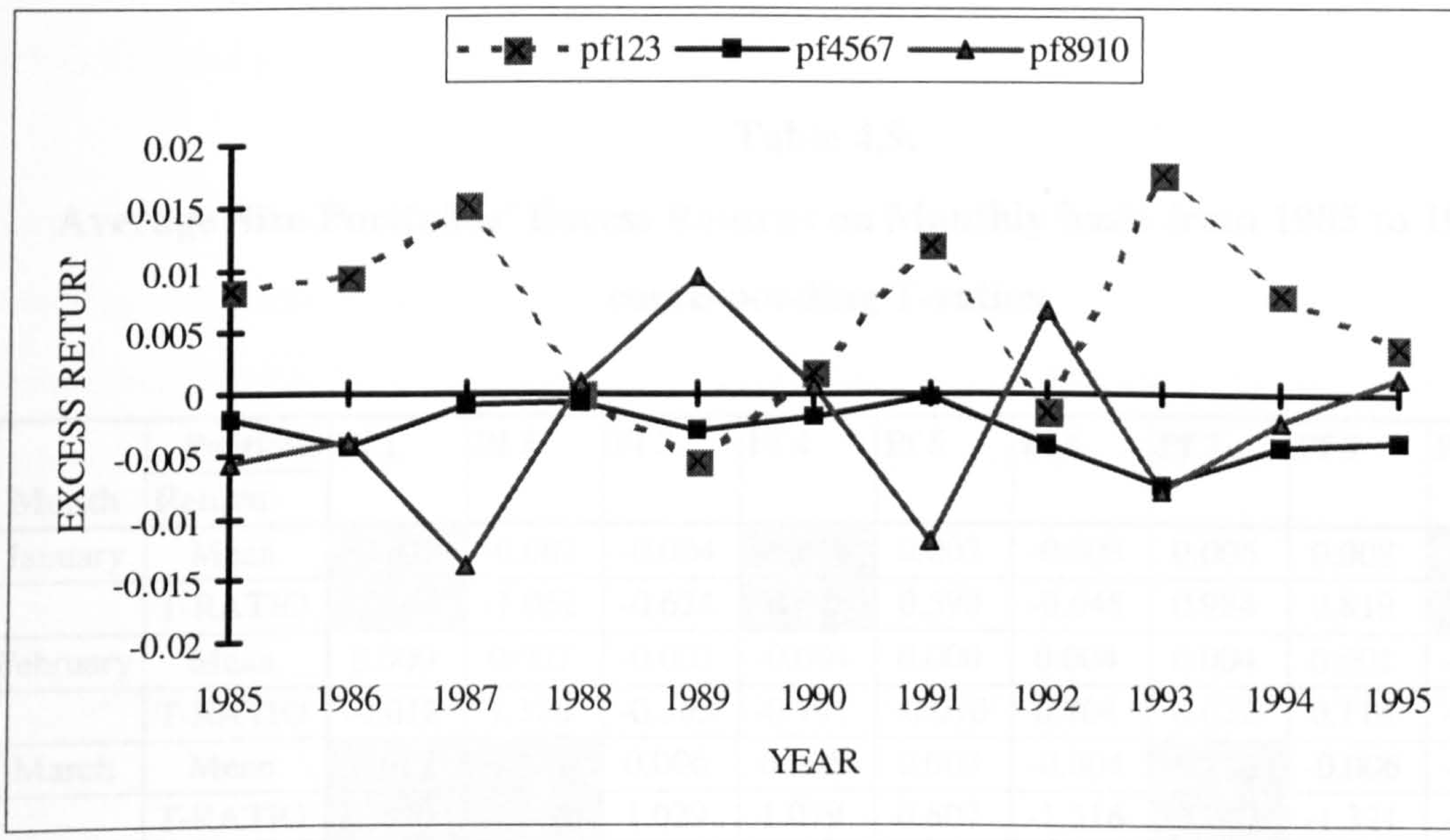
The pattern portrayed in Figure 4.2 implies a shift in demand, or demand waves across the size portfolios. These waves may be due to long term fads or temporary bubbles. Overreaction and stock price reversals are other popular terms to address the process of the stock price aberration from its fundamental value. For our purposes these terms are used interchangeably.

An interesting characteristic is the relative stability of medium size firms' excess returns. That may imply simultaneous spells of alternating demand pressures and demand abatement on smaller size and larger size firms.

To check whether the pattern in Figure 4.2 exists at gross (risk unadjusted) returns, a similar graph is drawn (not supplied here) and it shows the same subordination of returns, although not so noticeably.

**Figure 4.2.**

**Size Portfolios Monthly Excess Returns grouped pf123, pf4567 and pf8910 on yearly basis from 1985 to 1995**




Brown, Kleidon and Marsh (1983) show (Figure 2, p.48) the time series of the estimated excess returns[9] for portfolios 1 (comprising the smallest firms), 5 and 10 over the 150-month period January 1967 to June 1979. The plots suggest that from January 1969 to December 1973 there existed a relatively stable positive relation between excess return and size, and from January 1974 to June 1979 there was a relatively stable negative relation between excess return and size. In addition, they find a time series pattern of portfolios 1, 5 and 10 implying somewhat of a mirror image of one another.

The next step is to find if there are certain regularities in the distribution of the size portfolios' monthly excess returns. Monthly mean excess returns and T-ratios for 10 size

[9]The excess returns are from the estimated intercept $\alpha_{it}$ of the Market Model regression $R_{it} - R_f = \alpha_{it} + \beta_i (R_m - R_f) + \varepsilon_{it}$. In this study, however, the Market Model intercept is not appropriate for a proxy of the excess returns, due to the restrictions imposed on it.

portfolios for each month of the year are calculated and presented in Table 4.9. Table 4.9 conveys certain seasonal patterns in the size portfolios' excess returns. Smallest market value portfolios 1 and 2, when statistically significant (T-ratio 1.5 and above), always have positive excess returns except in January. Conversely, the largest market value portfolios 9 and 10 have positive and statistically significant excess returns *only* in January.

**Table 4.9.**

**Average Size Portfolios' Excess Returns on Monthly basis from 1985 to 1995 and corresponding T-ratios**

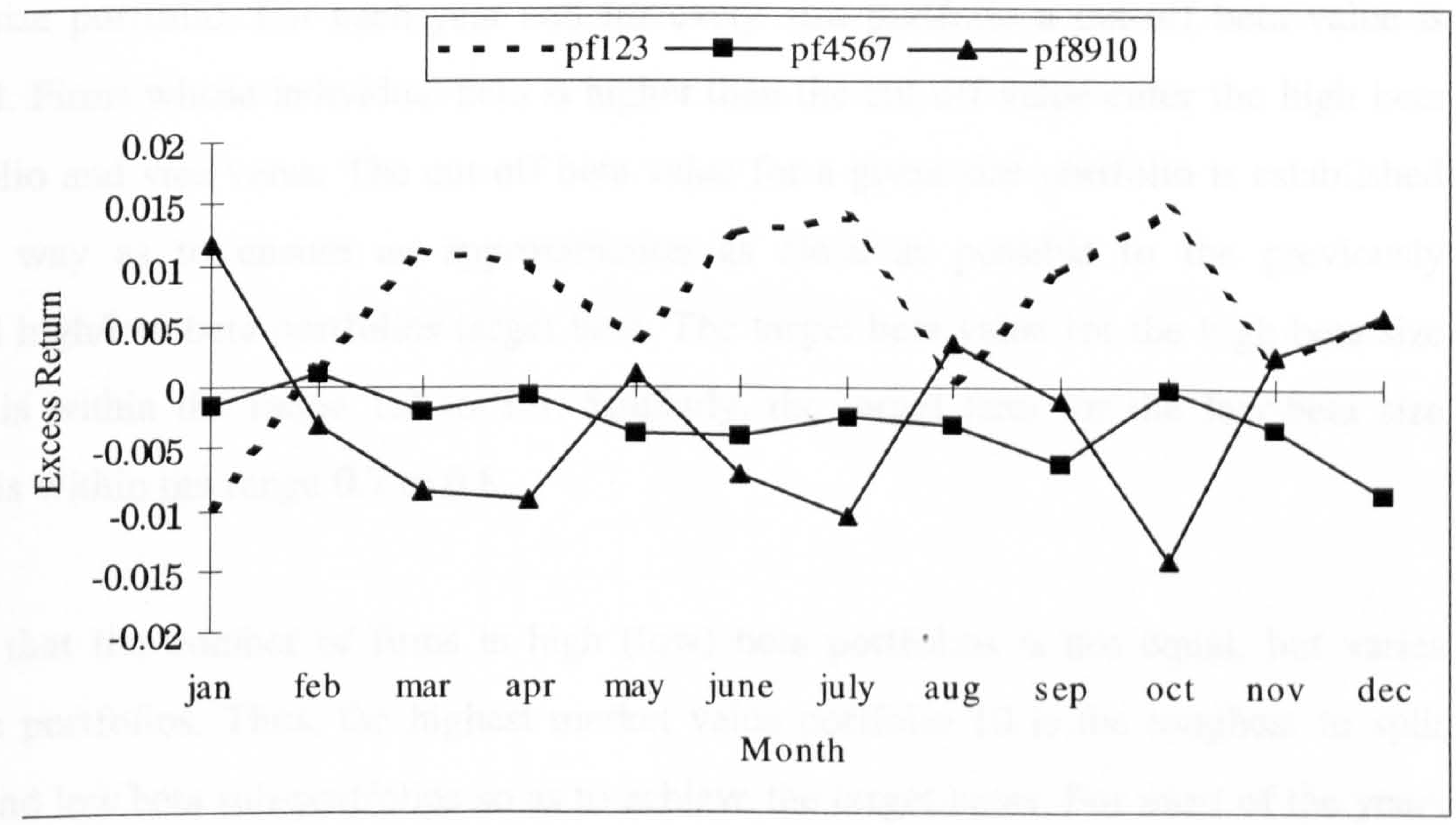
| Month | Portfolio Return | Pf 1 | Pf 2 | Pf 3 | Pf 4 | Pf 5 | Pf 6 | Pf 7 | Pf 8 | Pf 9 | Pf 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| January | Mean | **-0.018** | -0.007 | -0.004 | **-0.010** | 0.002 | -0.003 | 0.005 | 0.008 | **0.016** | **0.011** |
| | T-RATIO | **-2.048** | -1.052 | -0.624 | **-3.048** | 0.590 | -0.648 | 0.984 | 0.819 | **2.827** | **1.880** |
| February | Mean | 0.000 | 0.007 | -0.002 | -0.004 | 0.000 | 0.004 | 0.004 | 0.001 | -0.002 | -0.008 |
| | T-RATIO | -0.018 | 1.180 | -0.203 | -0.791 | -0.010 | 0.704 | 0.622 | 0.114 | -0.336 | -0.725 |
| March | Mean | **0.017** | **0.011** | 0.006 | 0.005 | 0.003 | -0.004 | **-0.012** | -0.006 | -0.007 | **-0.012** |
| | T-RATIO | **1.870** | **2.726** | 1.029 | 1.079 | 0.807 | -1.316 | **-2.321** | -1.321 | -1.325 | **-2.537** |
| April | Mean | **0.013** | 0.010 | 0.008 | 0.005 | -0.003 | **-0.006** | 0.000 | -0.004 | **-0.013** | -0.010 |
| | T-RATIO | **1.535** | 0.860 | 1.140 | 0.724 | -0.433 | **-1.838** | 0.046 | -0.540 | **-1.991** | -1.074 |
| May | Mean | 0.010 | 0.006 | -0.004 | -0.005 | **-0.005** | 0.001 | -0.006 | -0.001 | -0.003 | 0.007 |
| | T-RATIO | 1.492 | 1.347 | -0.567 | -1.060 | **-1.505** | 0.244 | -1.661 | -0.142 | -0.393 | 0.947 |
| June | Mean | **0.019** | **0.019** | -0.001 | -0.003 | -0.002 | -0.004 | -0.007 | -0.007 | **-0.012** | -0.002 |
| | T-RATIO | **1.566** | **1.925** | -0.214 | -0.588 | -0.643 | -1.325 | -1.194 | -1.045 | **-1.826** | -0.264 |
| July | Mean | **0.027** | 0.001 | **0.013** | 0.002 | -0.005 | -0.003 | **-0.005** | -0.013 | **-0.011** | -0.008 |
| | T-RATIO | **4.287** | 0.363 | **1.965** | 0.422 | -1.243 | -1.044 | **-1.807** | -1.718 | **-1.882** | -1.287 |
| August | Mean | 0.015 | -0.005 | **-0.008** | -0.006 | 0.002 | **-0.008** | -0.001 | 0.000 | 0.002 | 0.008 |
| | T-RATIO | 0.991 | -0.757 | **-2.583** | -1.054 | 0.546 | **-1.809** | -0.285 | 0.056 | 0.225 | 1.062 |
| Sept | Mean | 0.014 | 0.009 | 0.006 | 0.000 | **-0.007** | **-0.010** | -0.008 | -0.003 | -0.003 | 0.003 |
| | T-RATIO | 1.496 | 1.281 | 1.336 | -0.115 | **-2.666** | **-2.585** | -1.251 | -0.663 | -0.656 | 0.435 |
| October | Mean | **0.028** | **0.018** | -0.003 | 0.000 | 0.000 | -0.001 | 0.000 | -0.020 | -0.012 | -0.010 |
| | T-RATIO | **2.107** | **1.673** | -0.279 | 0.049 | 0.039 | -0.148 | -0.060 | -2.131 | -1.386 | -0.923 |
| Novemb. | Mean | 0.013 | -0.006 | -0.001 | -0.003 | -0.004 | -0.004 | -0.003 | 0.003 | 0.007 | -0.002 |
| | T-RATIO | 1.236 | -1.071 | -0.174 | -0.625 | -0.623 | -0.744 | -0.545 | 0.371 | 1.142 | -0.294 |
| Dec | Mean | **0.017** | 0.007 | -0.007 | -0.010 | **-0.012** | **-0.012** | -0.002 | 0.003 | 0.005 | 0.009 |
| | T-RATIO | **1.626** | 1.041 | -0.875 | -1.478 | **-3.650** | **-2.143** | -0.480 | 0.450 | 0.520 | 1.211 |

As Table 4.9 has an overwhelming amount of information on display, it is difficult to comprehend it completely. Hence, monthly excess returns of the size portfolios are aggregated as in Figure 4.2. The results are shown in Figure 4.3. In contrast to the findings of US research, smaller size firms in the UK Stock Market earn *negative* excess returns in January. That is particularly pronounced for size portfolio 1, with an average excess return of -0.018 and a T-ratio of 2.05 for January.

Looking at Figure 4.3 in general, a pattern similar to Figure 4.2 appears; once again, smallest and largest firms' excess returns either diverge or converge in different months, in a way resembling a mirror image along the horizontal axis. The medium size firms' return has less volatility, either moving just below or touching the horizontal axis.

**Figure 4.3.**

**Average Size Portfolios' Excess Returns on Monthly basis from 1985 to 1995.**



## 4.6. High and Low Beta Size Portfolios

As the independent variables of the cross-section regression (4.4), beta and LnSz, exhibit a high correlation for some years, this may introduce multicollinearity problems. Therefore, the cross-section regression results have to be treated with some caution.

**Table 4.10.**

**Correlation between Size portfolios LnSz and beta**

| Period | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\rho\beta SZ$ | -0.128 | -0.536 | -0.279 | -0.552 | -0.574 | -0.620 | -0.731 | -0.769 | -0.799 | -0.703 | -0.704 |

An approach adopted by Jegadeesh (1992) is applied to deal with the multicollinearity problem. The procedure consists of estimating each firm's beta for the whole period and then, according to the value of the estimated individual beta, assigning the firm into a high or low beta size portfolio. For each year and for every size portfolio a cut-off beta value is established. Firms whose individual beta is higher than the cut-off value enter the high beta size portfolio and vice versa. The cut-off beta value for a given size portfolio is established in such a way as to ensure an approximation as close as possible to the previously established high/low beta portfolios target beta. The target beta value for the high-beta size portfolios is within the range 1.2 to 1.3. Similarly, the target beta for the low-beta size portfolios is within the range 0.7 to 0.8.

It follows that the number of firms in high (low) beta portfolios is not equal, but varies across size portfolios. Thus, the highest market value portfolio 10 is the toughest to split into high and low beta sub-portfolios so as to achieve the target betas. For most of the years during the period 1985 to 1995, high beta portfolio 10 consists of only 10-15% of the firms forming portfolio 10, and is still below the target beta, whilst low beta portfolio 10 is below its target as well. Further transferring of the next highest beta firm from low to high beta portfolio 10 would worsen, rather then improve, this problem.

As Table 4.11 shows, splitting the existing size portfolios into High and Low beta size portfolios mitigates the multicollinearity problem only for the period 1985-1988.

**Table 4.11.**

**Correlation between High/Low Beta-Size portfolios' LnSz and beta**

| Period | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| High Beta | | | | | | | | | | | |
| ρβSZ | 0.06 | -0.10 | -0.40 | -0.83 | -0.75 | -0.81 | -0.93 | -0.96 | -0.94 | -0.93 | -0.88 |
| Low Beta | | | | | | | | | | | |
| ρβSZ | 0.15 | -0.25 | -0.37 | -0.76 | -0.69 | -0.80 | -0.56 | -0.85 | -0.92 | -0.95 | -0.88 |

In spite of this, it is worth proceeding with the estimations which have already been applied to the size portfolios. Table 4.12 and Table 4.13 show the estimated beta coefficient for the High beta and Low beta size portfolios. It is apparent from Table 4.12 that beta is held within the target for the period 1985-1987. After this period beta is rather unmanageable and returns to the familiar pattern of Table 4.4.

**Table 4.12.**
**Estimated beta for High beta Size Portfolios from 1985 to 1995**

| | 85-bH | 86-bh | 87-bh | 88-bh | 89-bh | 90-bh | 91-bh | 92-bh | 93-bh | 94-bh | 95-bh |
|---|---|---|---|---|---|---|---|---|---|---|---|
| pf1 | 1.154 | 1.288 | 1.252 | 1.672 | 1.417 | 1.780 | 1.462 | 1.580 | 1.387 | 1.512 | 1.574 |
| pf2 | 0.767 | 0.832 | 1.163 | 1.101 | 1.135 | 1.084 | 1.333 | 1.524 | 1.426 | 1.595 | 1.328 |
| pf3 | 1.218 | 1.332 | 1.286 | 1.680 | 1.743 | 1.681 | 1.196 | 1.301 | 1.214 | 1.218 | 1.191 |
| pf4 | 1.194 | 1.187 | 1.066 | 1.137 | 1.232 | 1.180 | 1.239 | 1.196 | 1.192 | 1.034 | 0.913 |
| pf5 | 1.084 | 1.585 | 1.190 | 1.189 | 1.127 | 1.152 | 1.197 | 1.207 | 1.119 | 1.080 | 0.970 |
| pf6 | 1.302 | 1.282 | 1.098 | 1.105 | 1.121 | 1.048 | 1.194 | 1.079 | 1.066 | 0.939 | 0.983 |
| pf7 | 1.032 | 1.131 | 1.016 | 1.092 | 1.144 | 1.072 | 1.126 | 1.132 | 1.125 | 1.004 | 0.915 |
| pf8 | 0.831 | 0.871 | 1.077 | 0.944 | 0.872 | 0.901 | 1.148 | 1.029 | 1.018 | 0.872 | 0.887 |
| pf9 | 1.082 | 1.141 | 1.195 | 0.914 | 0.946 | 0.878 | 1.011 | 0.900 | 1.018 | 0.737 | 0.855 |
| pf10 | 1.229 | 1.250 | 1.116 | 0.793 | 0.826 | 0.862 | 1.037 | 0.784 | 0.800 | 0.540 | 0.514 |

Nonetheless, the differences are alleviated as most of the High beta size portfolios converge towards a beta of 1, with deviation ±10%. A pattern similar to the one in Table 4.12 is observed in Table 4.13. The target portfolios' betas are achieved for the period 1985-1987, after which, the control over betas again gets out of hand.

**Table 4.13.**
**Estimated beta for Low beta Size Portfolios from 1985 to 1995**

| | 85-bl | 86-bl | 87-bl | 88-bl | 89-bl | 90-bl | 91-bl | 92-bl | 93-bl | 94-bl | 95-bl |
|---|---|---|---|---|---|---|---|---|---|---|---|
| pf1 | 1.097 | 0.903 | 1.493 | 1.038 | 1.030 | 0.938 | 0.903 | 0.950 | 1.056 | 1.387 | 1.630 |
| pf2 | 0.674 | 0.975 | 0.647 | 0.916 | 0.946 | 0.967 | 0.719 | 0.898 | 1.045 | 1.200 | 1.232 |
| pf3 | 0.891 | 0.753 | 0.726 | 0.944 | 0.944 | 0.872 | 0.791 | 0.961 | 0.938 | 1.022 | 0.963 |
| pf4 | 1.074 | 1.022 | 0.958 | 0.980 | 0.980 | 1.005 | 0.869 | 1.015 | 0.962 | 1.080 | 0.987 |
| pf5 | 0.682 | 0.833 | 0.839 | 0.902 | 0.958 | 0.914 | 0.848 | 0.851 | 0.868 | 1.071 | 1.076 |
| pf6 | 0.599 | 0.428 | 0.617 | 0.655 | 0.614 | 0.788 | 0.973 | 0.991 | 1.055 | 1.113 | 1.023 |
| pf7 | 0.865 | 0.750 | 0.857 | 0.817 | 0.785 | 0.764 | 0.808 | 0.787 | 0.817 | 0.948 | 0.932 |
| pf8 | 1.405 | 0.778 | 0.833 | 0.651 | 0.664 | 0.665 | 0.748 | 0.618 | 0.683 | 0.620 | 0.971 |
| pf9 | 0.874 | 0.883 | 0.738 | 0.728 | 0.755 | 0.738 | 0.710 | 0.654 | 0.657 | 0.620 | 0.662 |
| pf10 | 0.946 | 0.778 | 0.833 | 0.741 | 0.761 | 0.713 | 0.689 | 0.545 | 0.555 | 0.409 | 0.395 |

Overall, High beta portfolios have higher betas than Low beta portfolios. Figure 4.4 and Figure 4.5 examine the monthly excess returns of small (portfolios 1, 2 and 3), medium (portfolios 4, 5, 6 and 7) and large (portfolios 8, 9 and 10) firms. The patterns that emerge in both Figures are very similar. March, April, June, July and October appear to be strong months for the small size firms. Equally, these are the months in which large size firms have negative excess returns.

**Figure 4.4.**

**Average High Beta Size Portfolios' Excess Returns on Monthly basis from 1985 to 1995.**

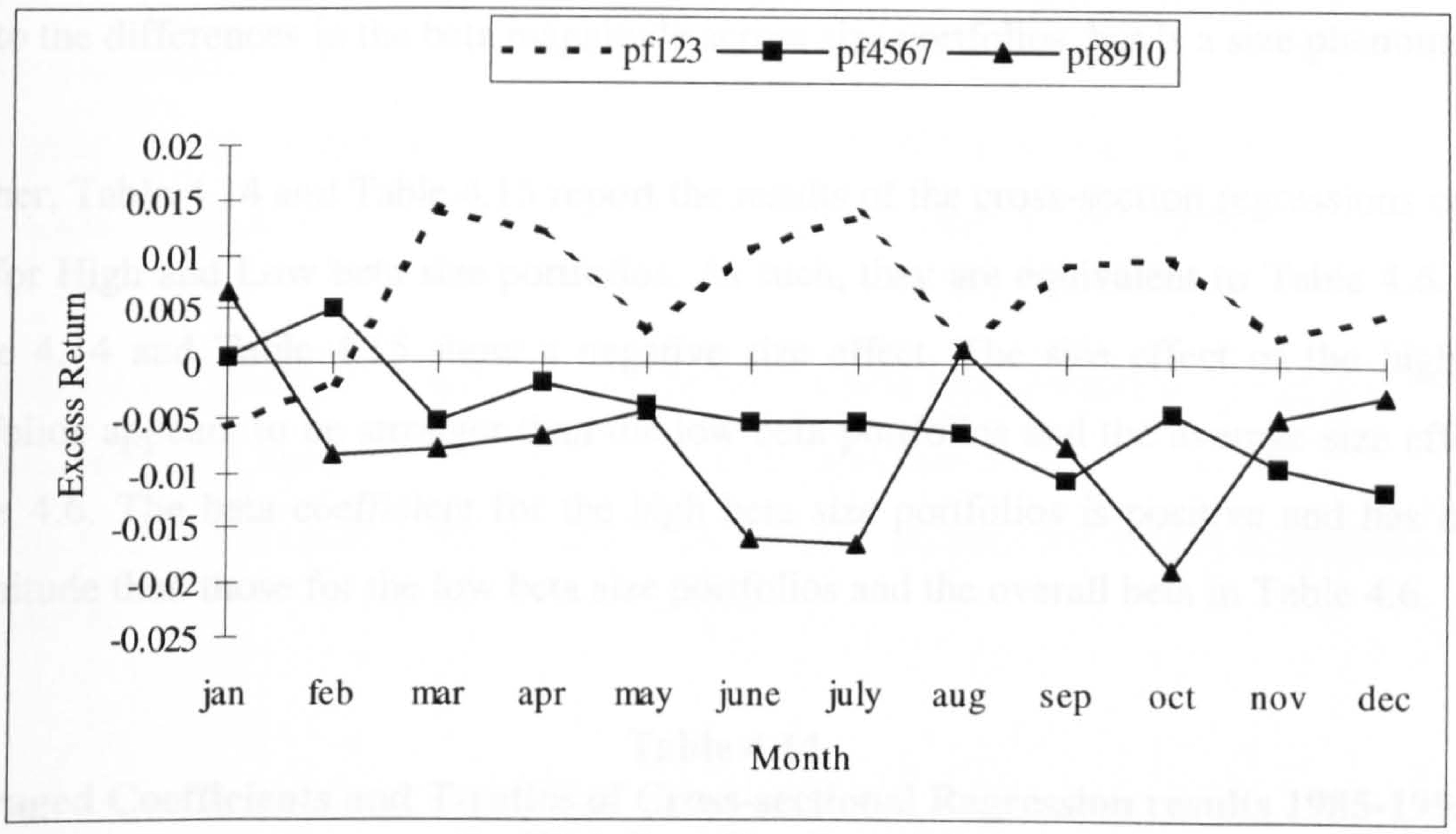
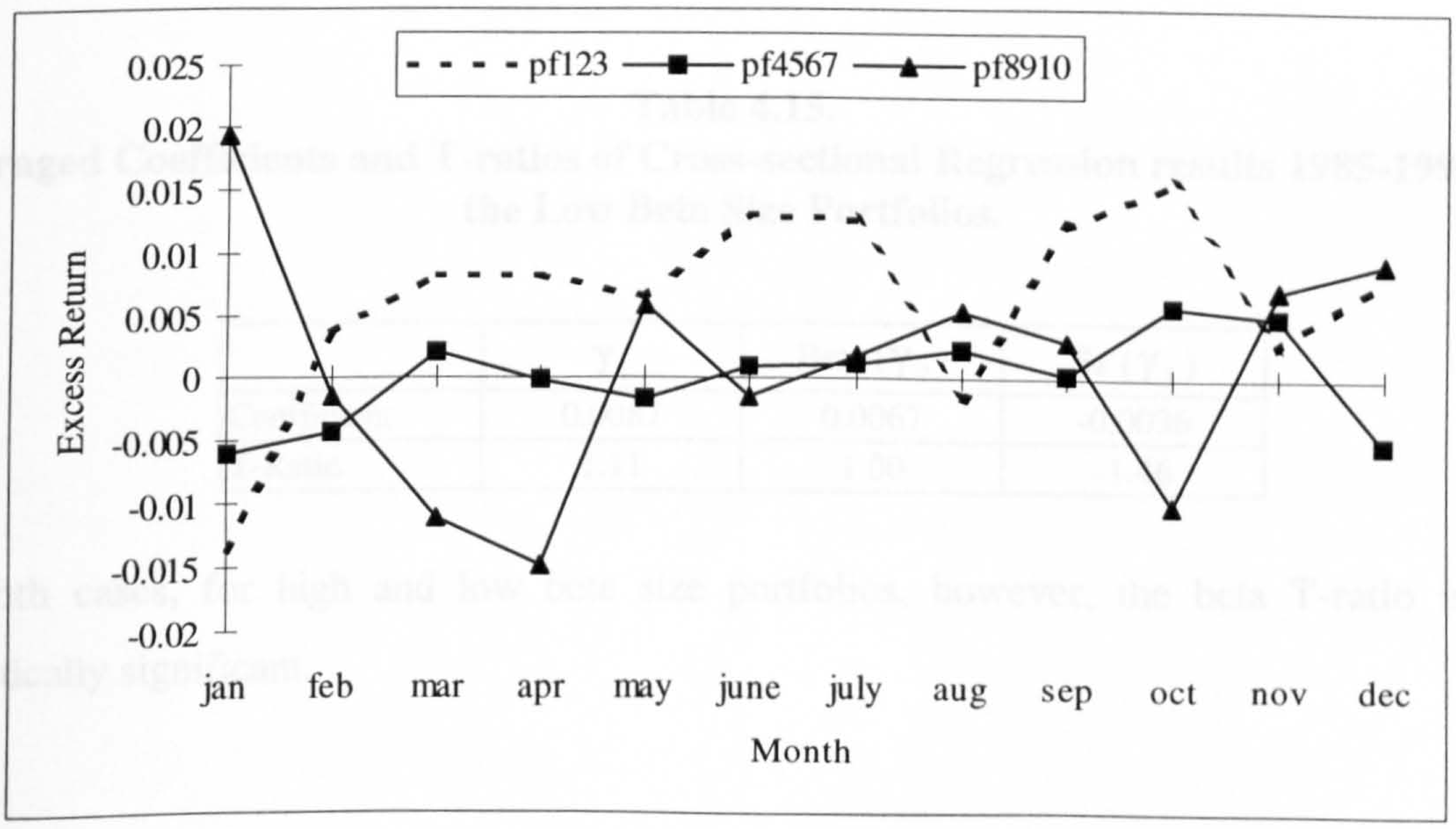



**Figure 4.5.**

**Average Low Beta Size Portfolios' Excess Returns on Monthly basis from 1985 to 1995.**



This tendency is slightly muddied for the Low Beta Size portfolios, where the large firms do not experience negative returns in June and July. As a whole, the patterns for the low and high beta size portfolios' monthly excess return do not deviate significantly from the size portfolio monthly excess return pattern established in Figure 4.3. Thus, the pattern is not due to the differences in the beta magnitude across size portfolios, but is a size phenomenon.

Further, Table 4.14 and Table 4.15 report the results of the cross-section regressions carried out for High and Low beta size portfolios. As such, they are equivalent to Table 4.6. Both Table 4.14 and Table 4.15 show a negative size effect. The size effect of the high beta portfolios appears to be stronger than the low beta portfolios and the average size effect in Table 4.6. The beta coefficient for the high beta size portfolios is positive and has higher magnitude than those for the low beta size portfolios and the overall beta in Table 4.6.

**Table 4.14.**
**Averaged Coefficients and T-ratios of Cross-sectional Regression results 1985-1995 for the High Beta Size Portfolios.**

| | $\gamma_1$ | Beta ($\gamma_2$) | Sz ($\gamma_3$) |
|---|---|---|---|
| Coefficient | -0.0013 | 0.0165 | -0.0054 |
| T-ratio | -1.24 | 1.07 | -1.54 |

**Table 4.15.**
**Averaged Coefficients and T-ratios of Cross-sectional Regression results 1985-1995 for the Low Beta Size Portfolios.**

| | $\gamma_1$ | Beta ($\gamma_2$) | Sz ($\gamma_3$) |
|---|---|---|---|
| Coefficient | 0.0087 | 0.0067 | -0.0036 |
| T-Ratio | 1.11 | 1.00 | -1.46 |

In both cases, for high and low beta size portfolios, however, the beta T-ratio is not statistically significant.

## 4.7 Conclusion

The results so far show that the size effect has persisted in the London Stock Exchange over the period 1985-1995. The gross returns of the portfolios formed on the basis of firms' market capitalisation and rebalanced yearly exhibit diminishing returns as size increases. This relationship is discernible for each year of the period 1985-1995 except for 1989 and 1990. It becomes much more apparent when calculated for the overall 1985-1995 period.

The market risk (beta) also has a certain pattern across size portfolios. Small size firms, in general, have high betas. Large firms, in opposite, have low betas.
The size effect exists even after portfolios' returns are adjusted for market risk (beta), and it is negative.

# Appendix 4.1.
## Beta estimates and t-ratios for Portfolios sorted by Size

| Period portf. # | 85B | T-ratio | 86B | T-ratio | 87B | T-ratio | 88-B | T-ratio | 89B | T-ratio | 90B | T-ratio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **pf1** | 1.14 | | 1.30 | | 1.18 | | 1.41 | | 1.37 | | 1.26 | |
| mkt | 1.14 | 8.99 | | 10.67 | 1.18 | 9.45 | 1.06 | 11.28 | 1.05 | 12.32 | 1.00 | 18.23 |
| mkt(-1) | | | | 2.35 | | | 0.36 | 3.63 | 0.32 | 3.76 | 0.26 | 4.77 |
| mkt(+1) | | | | | | | | | | | | |
| **pf2** | 0.82 | | 0.99 | | 0.80 | | 0.91 | | 0.92 | | 1.02 | |
| mkt | 0.82 | 12.09 | 0.79 | 11.67 | 0.80 | 11.70 | 0.91 | 18.87 | 0.80 | 17.95 | 0.85 | 19.01 |
| mkt(-1) | | | 0.20 | 3.02 | | | | | 0.11 | 2.50 | 0.17 | 3.82 |
| mkt(+1) | | | | | | | | | | | | |
| **pf3** | 1.02 | | 1.04 | | 1.05 | | 1.22 | | 1.20 | | 1.26 | |
| mkt | 1.02 | 13.42 | 0.91 | 13.54 | 0.91 | 16.67 | 0.93 | 21.39 | 0.95 | 22.10 | 0.92 | 23.73 |
| mkt(-1) | | | 0.12 | 1.88 | 0.15 | 2.71 | 0.29 | 6.27 | 0.25 | 5.78 | 0.26 | 6.83 |
| mkt(+1) | | | | | | | | | | | 0.08 | 2.23 |
| **pf4** | 1.12 | | 1.06 | | 1.00 | | 1.05 | | 1.06 | | 1.07 | |
| mkt | 0.98 | 13.03 | | 13.45 | | 15.00 | 0.92 | 19.23 | 0.93 | 21.74 | 0.94 | 29.78 |
| mkt(-1) | 0.14 | 1.94 | | 1.83 | | 2.13 | 0.13 | 2.64 | 0.13 | 3.04 | 0.13 | 3.97 |
| mkt(+1) | | | | | | | | | | | | |
| **pf5** | 1.15 | | 1.19 | | 1.07 | | 1.02 | | 0.99 | | 0.99 | |
| mkt | 0.93 | 11.09 | 1.03 | 11.89 | 1.07 | 18.33 | 1.02 | 24.89 | | 31.42 | 0.99 | 30.32 |
| mkt(-1) | | | 0.16 | 1.79 | | | | | | 2.61 | | |
| mkt(+1) | 0.22 | 2.56 | | | | | | | | | | |
| **pf6** | 0.95 | | 0.95 | | 0.86 | | 0.90 | | 0.94 | | 0.94 | |
| mkt | | 19.51 | | 19.31 | 1.06 | 24.28 | 0.99 | 28.89 | 1.02 | 30.76 | 1.04 | 32.83 |
| mkt(-1) | | -2.80 | | -2.90 | -0.20 | -4.37 | -0.09 | -2.49 | -0.08 | -2.39 | -0.10 | -3.17 |
| mkt(+1) | | | | 1.91 | | | | | | | | |
| **pf7** | 0.99 | | 0.99 | | 0.98 | | 1.05 | | 1.02 | | 1.00 | |
| mkt | 0.99 | 14.51 | 0.99 | 15.81 | 0.98 | 18.93 | 1.05 | 23.61 | 1.10 | 25.44 | 1.11 | 28.90 |
| mkt(-1) | | | | | | | | | -0.08 | -1.83 | -0.11 | -2.85 |
| mkt(+1) | | | | | | | | | | | | |
| **pf8** | 0.95 | | 0.87 | | 1.03 | | 0.86 | | 0.87 | | 0.85 | |
| mkt | | 7.95 | 0.87 | 8.16 | 1.03 | 13.38 | 1.11 | 24.93 | 1.11 | 28.04 | 1.09 | 29.13 |
| mkt(-1) | | -2.42 | | | | | -0.25 | -5.29 | -0.24 | -5.98 | -0.24 | -6.48 |
| mkt(+1) | | | | | | | | | | | | |
| **pf9** | 0.93 | | 1.12 | | 1.02 | | 0.82 | | 0.82 | | 0.84 | |
| mkt | | 14.62 | 1.12 | 18.70 | 1.18 | 18.12 | 1.07 | 18.48 | 1.08 | 21.02 | 1.04 | 26.52 |
| mkt(-1) | | | | | -0.16 | -2.41 | -0.25 | -4.13 | -0.26 | -5.03 | -0.20 | -5.06 |
| mkt(+1) | | | | | | | | | | | | |
| **pf10** | 0.99 | | 0.82 | | 0.89 | | 0.75 | | 0.76 | | 0.75 | |
| mkt | | 9.63 | 0.82 | 11.66 | 0.89 | 11.46 | 0.97 | 17.96 | 0.96 | 18.54 | 0.98 | 18.80 |
| mkt(-1) | | -2.34 | | | | | -0.22 | -3.83 | -0.20 | -3.93 | -0.23 | -4.49 |
| mkt(+1) | | | | | | | | | | | | |

# **Appendix 4.1.** continues

| Period | 91B | T- | 92B | T- | 93B | T- | 94B | T- | 95B | T- |
|---|---|---|---|---|---|---|---|---|---|---|
| portf. # | | ratio | | ratio | | ratio | | ratio | | ratio |
| **pf1** | 1.18 | | 1.27 | | 1.13 | | 1.55 | | 1.76 | |
| mkt | 0.91 | 15.72 | | 20.54 | | 19.81 | | 12.47 | | 11.92 |
| mkt(-1) | 0.26 | 4.99 | | | | | | | | |
| mkt(+1) | | | | | | | | | | |
| **pf2** | 0.91 | | 1.11 | | 1.14 | | 1.36 | | 1.30 | |
| mkt | 0.67 | 13.18 | 0.82 | 11.90 | 0.86 | 11.90 | 1.04 | 14.67 | 1.02 | 13.85 |
| mkt(-1) | 0.24 | 5.24 | 0.29 | 4.25 | 0.28 | 3.80 | 0.33 | 4.64 | 0.28 | 3.84 |
| mkt(+1) | | | | | | | | | | |
| **pf3** | 1.02 | | 1.13 | | 1.07 | | 1.12 | | 1.11 | |
| mkt | 0.90 | 19.94 | 0.98 | 22.25 | 0.94 | 18.70 | 0.97 | 18.03 | 0.90 | 16.34 |
| mkt(-1) | 0.12 | 2.82 | 0.15 | 3.30 | 0.14 | 2.75 | 0.15 | 2.84 | 0.20 | 3.71 |
| mkt(+1) | | | | | | | | | | |
| **pf4** | 1.04 | | 1.13 | | 1.09 | | 1.07 | | 1.01 | |
| mkt | 0.92 | 21.30 | 0.94 | 20.76 | 0.92 | 20.90 | 0.93 | 20.48 | 0.92 | 24.16 |
| mkt(-1) | 0.12 | 3.08 | 0.20 | 4.37 | 0.16 | 3.71 | 0.13 | 2.93 | 0.09 | 2.32 |
| mkt(+1) | | | | | | | | | | |
| **pf5** | 0.95 | | 1.01 | | 1.01 | | 1.03 | | 1.06 | |
| mkt | 1.04 | 24.97 | 1.01 | 27.17 | 1.01 | 28.50 | 1.03 | 25.77 | 1.06 | 22.34 |
| mkt(-1) | | | | | | | | | | |
| mkt(+1) | -0.09 | -1.97 | | | | | | | | |
| **pf6** | 1.15 | | 1.09 | | 1.09 | | 1.05 | | 1.04 | |
| mkt | 1.15 | 29.06 | 1.15 | 31.52 | 1.16 | 29.47 | 1.17 | 26.63 | 1.12 | 23.03 |
| mkt(-1) | | | -0.06 | -1.70 | -0.07 | -1.71 | -0.12 | -2.84 | -0.08 | -1.63 |
| mkt(+1) | | | | | | | | | | |
| **pf7** | 1.01 | | 0.97 | | 1.02 | | 0.96 | | 0.98 | |
| mkt | 1.13 | 29.72 | 1.13 | 26.73 | 1.17 | 26.77 | 1.15 | 23.67 | 1.14 | 22.97 |
| mkt(-1) | -0.12 | -3.55 | -0.16 | -3.67 | -0.16 | -3.56 | -0.19 | -3.95 | -0.16 | -3.17 |
| mkt(+1) | | | | | | | | | | |
| **pf8** | 1.05 | | 0.77 | | 0.73 | | 0.67 | | 0.98 | |
| mkt | | 30.36 | | 20.22 | | 21.54 | | 17.42 | 1.05 | 17.53 |
| mkt(-1) | | | | -3.41 | | -4.53 | | -4.32 | -0.20 | -3.46 |
| mkt(+1) | | | | | | | | | 0.13 | 2.24 |
| **pf9** | 0.92 | | 0.88 | | 0.82 | | 0.66 | | 0.67 | |
| mkt | 1.12 | 20.46 | 0.99 | 14.31 | 1.06 | 15.80 | 0.97 | 16.55 | 0.98 | 18.21 |
| mkt(-1) | -0.20 | -3.94 | -0.22 | -3.22 | -0.25 | -3.66 | -0.31 | -5.20 | -0.31 | -5.64 |
| mkt(+1) | | | 0.11 | 1.64 | | | | | | |
| **pf10** | 0.76 | | 0.61 | | 0.58 | | 0.44 | | 0.45 | |
| mkt | 0.98 | 14.07 | 0.87 | 10.31 | 0.84 | 11.50 | 0.73 | 9.35 | 0.82 | 11.31 |
| mkt(-1) | -0.22 | -3.44 | -0.26 | -3.06 | -0.25 | -3.45 | -0.29 | -3.71 | -0.37 | -5.21 |
| mkt(+1) | | | | | | | | | | |

## Appendix 4.2.
## Adjusted Coefficient of Determination (Rsq), Durban-Watson (D-W) and Durbin's h-statistic Autocorrelation Statistics for the 10 size-sorted portfolio time series regressions 1985-1995.

| Portf. # Year | | pf1 | pf2 | pf3 | pf4 | pf5 | pf6 | pf7 | pf8 | pf9 | pf10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1985 | Rsq | 0.66 | 0.76 | 0.81 | 0.80 | 0.67 | 0.90 | 0.84 | 0.61 | 0.85 | 0.64 |
| | D-W | 1.75 | 2.28 | 1.85 | 2.15 | 1.55 | 1.72 | 1.75 | 1.92 | -1.29* | 1.14* |
| 1986 | Rsq | 0.67 | 0.73 | 0.81 | 0.78 | 0.80 | 0.90 | 0.85 | 0.63 | 0.88 | 0.73 |
| | D-W | 1.92 | 1.65 | 1.75 | 2.06 | 2.00 | 1.66 | 1.83 | 1.88 | 2.14 | 1.57 |
| 1987 | Rsq | 0.52 | 0.67 | 0.86 | 0.83 | 0.87 | 0.93 | 0.89 | 0.82 | 0.89 | 0.75 |
| | D-W | 1.87 | 1.67 | 1.74 | 2.02 | 1.65 | 1.82 | 2.17 | 1.42 | 2.17 | 2.01 |
| 1988 | Rsq | 0.81 | 0.89 | 0.94 | 0.93 | 0.94 | 0.96 | 0.94 | 0.95 | 0.90 | 0.90 |
| | D-W | 1.80 | 1.47 | 2.12 | 2.25 | 2.16 | 1.89 | 2.03 | 1.54 | 1.93 | 2.33 |
| 1989 | Rsq | 0.82 | 0.91 | 0.94 | 0.94 | 0.97 | 0.96 | 0.95 | 0.96 | 0.92 | 0.91 |
| | D-W | 1.53 | 2.23 | 2.42 | 2.43 | -0.204* | 1.80 | 2.18 | 1.55 | 2.11 | 2.34 |
| 1990 | Rsq | 0.93 | 0.92 | 0.96 | 0.97 | 0.96 | 0.97 | 0.96 | 0.96 | 0.95 | 0.91 |
| | D-W | 1.66 | 2.56 | 2.27 | 2.12 | 2.53 | 1.86 | 1.70 | 1.73 | 2.28 | 1.74 |
| 1991 | Rsq | 0.89 | 0.86 | 0.92 | 0.93 | 0.95 | 0.96 | 0.96 | 0.96 | 0.92 | 0.85 |
| | D-W | 1.70 | 2.37 | 2.34 | 1.75 | 2.09 | 1.47 | 1.87 | -0.991* | 2.26 | 1.85 |
| 1992 | Rsq | 0.94 | 0.85 | 0.94 | 0.94 | 0.95 | 0.97 | 0.95 | 0.93 | 0.88 | 0.74 |
| | D-W | 1.48* | 1.85 | 1.89 | 1.72 | 1.97 | 1.67 | 2.25 | -0.177* | 1.92 | 1.86 |
| 1993 | Rsq | 0.94 | 0.84 | 0.92 | 0.94 | 0.96 | 0.96 | 0.95 | 0.95 | 0.88 | 0.79 |
| | D-W | 0.359* | 1.90 | 1.92 | 1.88 | 2.02 | 1.78 | 2.21 | -1.55* | 1.83 | 2.04 |
| 1994 | Rsq | 0.83 | 0.88 | 0.92 | 0.93 | 0.95 | 0.95 | 0.94 | 0.91 | 0.88 | 0.70 |
| | D-W | 0.019* | 1.98 | 1.96 | 1.66 | 1.61 | 1.65 | 2.09 | -0.249* | 1.80 | 1.92 |
| 1995 | Rsq | 0.78 | 0.86 | 0.91 | 0.95 | 0.93 | 0.94 | 0.94 | 0.91 | 0.90 | 0.79 |
| | D-W | -0.196* | 1.89 | 2.20 | 1.94 | 1.82 | 1.88 | 1.57 | 1.67 | 1.81 | 1.74 |

Note: * indicates *Durbin's h-statistic*

## Appendix 4.3.
## Diagnostic Statistics for 10 Size portfolios' beta time series.

Each of the portfolio diagnostic statistics is drawn from the time series with 36 monthly observation prior to the year shown under the column 'Year'. Where a box is left blank, no inferior statistic is diagnosed for the items shown in the legend.

| Portf. # Year | pf1 | pf2 | pf3 | pf4 | pf5 | pf6 | pf7 | pf8 | pf9 | pf10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1985 | | | | HS | C | | | C | | C |
| 1986 | C | | | HS | C | C | | | | |
| 1987 | HS | | | HS | | | | | C | |
| 1988 | | | | | | C | | | | |
| 1989 | | HS/C | | | | C | | | | C |
| 1990 | | HS/C | | | HS | C | | | | C |
| 1991 | C | C | | | | | | | | HS/C |
| 1992 | | HS | | | | | | | SC | HS |
| 1993 | | SC/HS | | | C | | | C | | |
| 1994 | | | | | | | | | | |
| 1995 | HS | | | | | | | | | |

Legend:
SC - Serial Correlations
N - Normality
HS - Heteroscedasticity
C - Chow test for parameter stability

# Chapter 5

# Size Effect Explanations

## 5.1. Introduction

There are different explanations of the Size Effect in the literature and many of them have been reviewed in Chapter 3. The task here is to examine the sample used in this investigation in relation to the returns of the size portfolios between 1985-1995. The return series used in the previous chapter are returns of the different size portfolios, which do not bear much relationship to the individual companies' return series. In this sense these series are artificial. Our guesses are that size portfolios have to exhibit a certain degree of stability of composition throughout different years. Here we are interested in whether applying the strategy described at length in Chapter 4 requires a substantial portfolio rebalancing on a year-to-year basis or whether the portfolios' composition is relatively stable. If a substantial rebalancing is required each year, this may lead to heavy transactional costs and thus reduce profits to a meaningless level. As the literature on size portfolios' composition dynamics is scarce, the findings of Chan and Chen (1991) are of great importance. Chan and Chen categorise the firms in the smallest and largest quintiles by how they enter these quintiles over the 30 years' sample period from 1956 to 1985. Based on the most recent entry, the firms are categorised according to when and how they entered the size quintile (by falling, rising, or being listed into). The most revealing statistics from the bottom quintile is that about 66% of the firms have fallen from the higher quintiles and only 19.8% have been in it over the past 10 years. In contrast, for the top size quintile only about 41% of the firms have gone up from lower quintiles and 51% of the firms have been in it over the past 10 years. These figures obviously led[1] Chan and Chen (1991) to the conclusion that:

> '...most firms in the bottom quintile do not tend to stay there for a long time.'
> (p.1469).

As for the newly listed firms, 14% are listed into the smallest and 8% into the largest quintile over the last 10 years.

Hence, the first objective of this chapter is to investigate the year-to-year change of the portfolios' composition in relation to the overreaction hypothesis. The idea is to see if there are assets entering a size portfolio, staying in it for a year and leaving it the following year. If that is the case, the next question would be: Is there a difference in the pattern of overreaction for the small and large size portfolios?

The second aim is to investigate the impact of New Issues on the Size Effect. The Initial Public Offer (IPO) anomaly concerns the low return performance of IPOs in the first 3 or 5 years after going public. Ritter (1991) performs an investigation of the IPOs anomaly from 1975 to 1984 on the NYSE and finds the average holding period return of IPOs common stock is 34.4% in the 3 years after going public, where the holding period return is measured from the closing market price on the first day of public trading to the market price on the 3 year anniversary. The control sample, matched by industry and market value, produces an average total return of 61.86% over the same 3 year holding period. This is what Ritter calls the long-run underperformance. In addition to this anomaly, numerous studies have documented the so called short-run underpricing phenomenon, where measured from the offering price to the market price at the end of the first day of trading, IPOs produce an average initial return that has been estimated at 16.4%. It has always been a mystery why

[1]The initial purpose of Chan and Chen was to prove that the small firm portfolio is populated basically by *marginal firms*, or according to them firms that have lost market value because of poor performance, high financial leverage and cash flow problems. This line is not pursued here, as only the material facts are of interest.

IPOs are priced in a manner that results in such large positive initial returns. According to Ritter, the offering price is not too low; it is the first aftermarket price that is too high.

Loughran and Ritter (1995) find that companies issuing stock during 1970 to 1990 had an average annual return of only 5% during the five years after an IPO and only 7% for the firms conducting a seasoned equity offering (SEO).

Thus, the first Hypothesis (IPO 1) is that IPO firms do not perform well in the first few years after going public. After this period the market readjusts its view and prices rebound, possibly above the fundamentals. The second Hypothesis (IPO 2) is that most of the IPO firms enter and stay for a period of 3 to 5 years in the smallest size deciles.

The Small Size Anomaly may relate to the Initial Public Offerings Anomaly. As the returns of the size portfolios include firms' returns after three calendar years from the year when they were listed for the first time, our size portfolio return series do not account for the possible IPOs underperformance. After the IPOs firms are included in the size portfolios, e.g. after the third year, their returns may rebound if the smaller size portfolios are populated with more IPOs that may contribute to the higher returns. This research has no intention of focusing on the IPOs anomaly at the LSE for various reasons. Firstly, the procedure established in the previous investigations of coupling one IPO firm to one non-IPO firm by size and industry is an arbitrary procedure. Secondly, the cross-section test performed by Loughran and Ritter (1995) separates the size and IPOs anomalies, rather than associating them, which is the aim here.

Smaller firms may have bigger stock market entry barriers compared to larger firms because:
- the company is relatively unknown;
- the company is small, and will be vulnerable to the greater specific risk associated with small firm performance;
- the size of the issue involved may mean that the amount of shares on offer is so small as to inhibit economic investment by institutional investors;

- scale economies involved in the purchase and sale of securities imply minimum levels of transaction for funds managers, which may amount to a large percentage of a small issue;

Under such circumstances, one way of ensuring full subscription is by offering the purchaser a price incentive in the form of an *introductory discount*, setting the issue price of the new share below what is the equilibrium expected in normal trading. Any such discount enables new shareholders to purchase a share in the profits at a preferential price compared with the intrinsic value to existing shareholders.

Further, the possibilities of association between size, firms' gearing and Book-to-Market (BTM) value are examined. Last, but not least, this chapter inspects the differences in the Bid-Ask spread, Dividend Yield and the Volume-Price pattern of the smallest and largest deciles, portfolio 1 and portfolio 10.

## 5.2. Estimation of the overreaction patterns, IPOs and transaction cost.

### 5.2.1. Size Portfolios' Composition Dynamics as an Indicator of Overeaction Patterns.

As we have already documented that the most significant difference across the size portfolios' returns is between the smallest market capitalisation, portfolio 1, and the largest market capitalisation, portfolio 10, the analysis hereafter is carried out on these portfolios only.

Starting from 1985, for each year, portfolio 1 and portfolio 10 firms' composition is broken down into the following items:

*In-coming firms*:

These assets are tracked from their history a year ago, and consist of:

1. New Issue Firms (IPOs). These are the firms which have been floated between three and four calendar years before becoming eligible for inclusion in any of the size portfolios, a restriction imposed by the portfolios formation procedure (see Table 5.1.).

2. Firms coming from other size portfolios.

3. Firms that were in the portfolio already.

*Out-going firms*:

Each firm movement from portfolio 1 and portfolio 10 is tracked one year after the portfolio is formed. Out-going firms then consist of:

1. Firms going to other size portfolios.

2. Firms staying in.

The items listed above provide a full picture and balance of the formation of portfolio 1 and portfolio 10, although there are some allowances made for firms that are not included in the sample for some years under the item 'deviation'.

## Table 5.1.
## Portfolio's 1 composition on year-by-year basis.

For each year of the period 1985-1995, firms that compose portfolio 1 are tracked by where they were a year ago and where they went the year after. The possible sources are other size portfolios, firms staying in the same portfolio (Pf.1) and firms which enter for the first time. Deviation denotes firms which do not participate in the sample for the relevant period, and thus their whereabouts remain unknown. As for the year 1985, which is the first year of the portfolio formation, all firms are counted as new entrants.

| | PORTFOLIO 1 | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1985 | | 1986 | | 1987 | | 1988 | | 1989 | | 1990 | | 1991 | | 1992 | | 1993 | | 1994 | | 1995 | |
| | 84 | 85 | 85 | 87 | 86 | 88 | 87 | 89 | 88 | 90 | 89 | 91 | 90 | 92 | 91 | 93 | 92 | 94 | 93 | 95 | 94 | |
| | was | | was | | was | | was | | was | | was | | was | | was | | was | | was | | was | |
| | in | to | in | to | in | to | in | to | in | to | in | to | in | to | in | to | in | to | in | to | in | to |
| New comer | 30 | | 2 | | 8 | | 3 | | 5 | | 6 | | 9 | | 6 | | 3 | | 4 | | 1 | |
| pf1 | | 25 | 25 | 20 | 20 | 23 | 23 | 25 | 25 | 27 | 27 | 29 | 29 | 27 | 27 | 32 | 32 | 34 | 34 | 26 | 26 | |
| pf2 | N.A. | 4 | 5 | 7 | 1 | 2 | 6 | 7 | 3 | 6 | 6 | 7 | 3 | 13 | 7 | 10 | 10 | 12 | 7 | 19 | 14 | |
| pf3 | N.A. | 0 | 0 | 3 | 0 | 1 | 1 | 1 | 1 | 2 | 0 | 1 | 1 | 0 | 1 | 0 | 3 | 2 | 2 | 4 | 6 | |
| pf4 | N.A. | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 1 | |
| pf5 | N.A. | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf6 | N.A. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf7 | N.A. | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf8 | N.A. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf9 | N.A. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf10 | N.A. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| Total | | 30 | 32 | 30 | 29 | 28 | 34 | 33 | 35 | 36 | 39 | 37 | 42 | 40 | 42 | 42 | 48 | 48 | 49 | 49 | 48 | |
| deviation | | | 0 | 2 | 0 | 1 | 1 | 2 | 1 | 0 | 0 | 2 | 0 | 2 | 2 | 2 | 0 | 0 | 1 | 1 | 1 | |

Table 5.1 indicates the mobility of the firms that form portfolio 1 for each year of the period 1985-1995. Thus, for the first year of portfolio formation, 1985, all firms are new comers from 1984, as their previous portfolio status is unknown. At the end of 1985, however, 25 out of 30 firms are available for inclusion in portfolio 1 for 1986, whereas 4 move to portfolio 2 and 1 to portfolio 5. If the portfolio 1 formation is looked at in 1986, then the composition consists of 25 firms that stayed in portfolio 1 from 1985, plus 5 that were in portfolio 2 in 1985, and 2 new comers, i.e., firms that are listed at least 3 calendar years before 1986, as set in the criteria for firms' inclusion. The row 'deviation' shows firms that are not included in a portfolio for either the previous or following year. These firms are not included for some years because they show extreme Market-To-Book and Borrowing ratios' values. As the row 'deviation' shows, their number is relatively small, and for some years it is zero.

As Table 5.1. reveals, portfolio 1's main entrants come and go chiefly from and to portfolio 2. Portfolio 3 also maintains a regular presence, supplying and accommodating a marginal number of firms to and from portfolio 1. There is also a small number of firms that move between portfolio 1 and portfolio 4 and higher. In general, the firms that enter portfolio 1 come from either the previous year portfolio 1, or from higher portfolios. The firms that come from the higher portfolios are those that have experienced a reduction in their market value during the year before their inclusion in portfolio 1. On the other hand, the firms that leave portfolio 1 move to higher portfolios, and therefore experience an increase in their market value during the year of their stay in portfolio 1. Therefore, the portfolio 1 formation strategy seems to capture, *inter alia*, firms that have experienced a price fall, and than regained their value while in portfolio 1.

A similar analysis[2] is carried out on the composition of portfolio 10 and presented in Table 5.2. As Table 5.2. shows, the movement of the firms to and from portfolio 10 is almost a mirror image of the portfolio 1 movement of firms, although on a smaller scale; roughly 10

[2]Tediousness of the procedure and willingness to concentrate on the main points are the arguments favouring the composition analysis being carryed on portfolios 1 and 10 only.

percent of portfolio 10's firms have been in portfolio 9 in the previous year and subsequently increased their value. The same percentage leave portfolio 10 to portfolio 9. Thus, a reverse of the conclusion made for portfolio 1 seems to apply to portfolio 10. The portfolio 10 formation strategy appears to capture, *inter alia*, firms that have experienced a price rise and then a decrease in their value while in portfolio 10.

**Table 5.2.**
**Portfolio's 10 composition on year-by-year basis.**

| PORTFOLIO 10 | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1985 | | 1986 | | 1987 | | 1988 | | 1989 | | 1990 | | 1991 | | 1992 | | 1993 | | 1994 | | 1995 | |
| | 84 | 85 | 85 | 87 | 86 | 88 | 87 | 89 | 88 | 90 | 89 | 91 | 90 | 92 | 91 | 93 | 92 | 94 | 93 | 95 | 94 | |
| | was | | was | | was | | was | | Was | | was | | was | | was | | was | | was | | was | |
| | in | to | in | to | in | to | in | to | In | to | in | to | in | to | in | to | in | to | in | to | in | to |
| New | | | | | | | | | | | | | | | | | | | | | | |
| comer | 30 | | 1 | | | | 2 | | 0 | | 1 | | 3 | | 2 | | 1 | | 1 | | 3 | |
| pf1 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf2 | N.A. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf3 | N.A. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf4 | N.A. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf5 | N.A. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | |
| pf6 | N.A. | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf7 | N.A. | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf8 | N.A. | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| pf9 | N.A. | 4 | 2 | 3 | 4 | 4 | 5 | 1 | 4 | 1 | 4 | 3 | 4 | 4 | 4 | 1 | 3 | 4 | 4 | 2 | 3 | |
| pf10 | N.A. | 26 | 26 | 25 | 25 | 26 | 26 | 33 | 33 | 35 | 35 | 36 | 36 | 39 | 39 | 44 | 42 | 42 | 42 | 44 | 44 | |
| | | 30 | 30 | 30 | 30 | 30 | 34 | 34 | 37 | 36 | 40 | 39 | 43 | 43 | 45 | 45 | 46 | 46 | 48 | 46 | 50 | |
| deviation | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | |

Note: For each year of the period 1985-1995, firms that compose portfolio 10 are tracked where they were a year ago and where they went the year after. The possible sources are other size portfolios, firms staying in the same portfolio (Pf.10) and Newcomers which enter for the first time. Deviation denotes firms which do not participate in the sample for the relevant period, and thus their whereabouts remain unknown. As for the year 1985, which is the first year of the portfolio formation, all firms are counted as new entrants.

### 5.2.2. Size, IPOs, Transitory asset returns and longer horizon Range Factor

Tables 5.1 and 5.2 also provide a comparison of the number of newcomers in portfolios 1 and 10. The newcomer rows exhibit a large difference in the number of the firms entering portfolio 1 and 10, after the third calendar year of their listing. Portfolio 1 has accommodated 47 New Issue firms, whereas portfolio 10 has accommodated only 14. That implies that a typical firm enters the market in the lowest band of market capitalisation. The years in which portfolio 10 has a relatively high number of New Issue firms are 1991 (3 firms) and 1995 (3 firms), which may relate to the floating of big publicly owned firms, such as utilities, in 1987 and 1991. In 1987, for example, these firms are *ROLLS ROYCE, EUROTUNNEL UNITS*, and *BAA*. Thus the hypothesis, that most of the IPOs firms enter the small size decile, seems to be confirmed.

The fact of the matter, however, is what the contribution of the transitory and the New Issue firms is. Tables 5.1 and 5.2 provide some insight into what we may expect from the transitory firms. But first, a definition of a 'transitory' firm must be given. A transitory firm, in the context of Tables 5.1 and 5.2, is a firm that enters portfolios 1 or 10 from the pool of other portfolios, stays in the portfolios for a year and then leaves.

In the case of portfolio 1, a transitory firm is one which has devalued first, and then has revalued while in portfolio 1. This definition reverses for portfolio 10. Thus, one might expect that some of the four firms that entered portfolio 1 from portfolio 2 in 1985 will have gone back to portfolio 2 in 1986. If that is the case, the main reason should be the subsequent decrease and increase in the firms' value, although portfolios' changing boundaries on a yearly basis cannot be ruled out.

Table 5.3 attempts to quantify the Transitory and New Issue effects on gross returns. Table 5.3 also gives a general impression of the stability of the portfolio 1 and 10 composition by estimating the so-called *'RANGE FACTOR'*. The information needed for the estimation of the range factor is drawn from Tables 5.1 and 5.2. The *RANGE FACTOR* shows the average weighted distance of the firms entering and leaving a portfolio relative to the portfolios' position. The Range Factor is calculated by applying the following formulas:

$$RF_{pf1} = \sum_{p=1}^{10} (1 - D_p) \bullet N_p / TNPF1$$ , for the firms entering portfolio 1

$$RF_{pf1} = \sum_{p=1}^{10} (D_p - 1) \bullet N_p / TNPF1$$ , for the firms leaving portfolio 1

$$RF_{pf10} = \sum_{p=1}^{10} (10 - D_p) \bullet N_p / TNPF10$$ , for the firms entering portfolio 10

$$RF_{pf10} = \sum_{p=1}^{10} (D_p - 10) \bullet N_p / TNPF10$$, for the firms leaving portfolio 10

$RF_{pf1}$, $RF_{pf10}$ - Range Factor for portfolio 1 and 10.

$D_p$ - Distant portfolio, originating/accommodating a firm that enters/leaves portfolio 1 or 10.

$N_p$ - Number of firms leaving to a distant portfolio.

$TNPF1$, $TNPF10$ - Total number of firms, members of portfolio 1 and 10 for a given year.

For instance, Table 5.3 shows a Range Factor of 0.433 for portfolio 1 for 1986, which applies to the firms that leave portfolio 1. This Range Factor is estimated by using the above formula and data from Table 5.1;

0.433=[(2-1).7+(3-1)]/30

The Range Factor gives a rough idea of the changes in the portfolio's composition; by comparing the range factor for portfolio 1 and portfolio 10 it is obvious that portfolio 1 has a more volatile composition.

Table 5.3 also provides information on the returns of New Issue firms that enter portfolio 1 and 10. As is seen, this return does not explain the return differences between the high and low capitalisation portfolios. Returns on new issues are rather lower than the gross return of portfolio 1. It may be the case that the New Issue firms' return increases only after the fifth year from their listing. Thus the hypothesis of higher returns of the New Issue firms in their fourth year does not seem viable, despite the proved validity that higher number New Issue firms populate portfolio 1.

The estimated return on transitory firms relates to the Range Factor, but the number of transitory firms is always less than the firms used for the estimation of the Range Factor, as not all firms that enter the portfolios stay for just a year and then leave (as the transitory firms do).

For portfolio 1, the return on the transitory firms, appears to be (except for 1986) higher than the portfolio 1 gross return. The return on the transitory firms of portfolio 10 appears to be less than the gross return and for many years is negative.

**Table 5.3.**
**Portfolios' 1 and 10 Range Factor, Yearly Return, Return on New Issue, Return on Transitory Firms and Net of Transitory Return**

| | 1985 | | 1986 | | 1987 | | 1988 | | 1989 | | 1990 | | 1991 | | 1992 | | 1993 | | 1994 | | 1995 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 84 | 85 | 85 | 87 | 86 | 88 | 87 | 89 | 88 | 90 | 89 | 91 | 90 | 92 | 91 | 93 | 92 | 94 | 93 | 95 | 94 | |
| | was | | was | | was | | was | | was | | was | | was | | was | | was | | was | | was | |
| | in | to | in | to | in | to | in | to | in | to | in | to | in | to | in | to | in | to | in | to | in | to |
| PORTFOLIO 1 | | | | | | | | | | | | | | | | | | | | | | |
| RANGE FACTOR | | 0.267 | 0.167 | 0.433 | 0.034 | 0.464 | 0.400 | 0.273 | 0.267 | 0.361 | 0.182 | 0.243 | 0.152 | 0.325 | 0.389 | 0.238 | 0.356 | 0.333 | 0.378 | 0.551 | 0.617 | |
| Pf1 Yearly Return | 0.042 | | 0.052 | | 0.035 | | 0.026 | | 0.006 | | -0.006 | | 0.040 | | 0.018 | | 0.073 | | 0.030 | | 0.023 | |
| Ret. on the New Issue | | | 0.002 | | 0.037 | | 0.020 | | 0.008 | | 0.004 | | 0.023 | | -0.011 | | 0.040 | | 0.028 | | | |
| Ret. on Transitory Firms | | | 0.048 | | | | 0.032 | | 0.015 | | 0.003 | | 0.056 | | 0.060 | | 0.096 | | 0.038 | | | |
| Net Transitory | | | 0.053 | | 0.035 | | 0.026 | | 0.005 | | -0.007 | | 0.039 | | 0.015 | | 0.070 | | 0.029 | | | |
| PORTFOLIO 10 | | | | | | | | | | | | | | | | | | | | | | |
| RANGE FACTOR | | 0.133 | 0.172 | 0.300 | 0.267 | 0.133 | 0.219 | 0.029 | 0.108 | 0.028 | 0.103 | 0.077 | 0.100 | 0.093 | 0.093 | 0.022 | 0.067 | 0.087 | 0.191 | 0.043 | 0.064 | |
| Pf10 Yearly Return | 0.0163 | | 0.015 | | 0.003 | | 0.010 | | 0.024 | | -0.003 | | 0.009 | | 0.015 | | 0.010 | | -0.002 | | 0.008 | |
| Ret. on the New Issue | | | 0.023 | | 0.000 | | 0.017 | | 0.000 | | 0.007 | | 0.008 | | 0.023 | | 0.013 | | 0.008 | | | |
| Ret. on Transitory Firms | | | -0.005 | | 0.000 | | -0.024 | | 0.000 | | 0.000 | | -0.070 | | -0.028 | | 0.006 | | -0.014 | | | |
| Net Transitory | | | 0.179 | | 0.003 | | 0.011 | | 0.024 | | -0.003 | | 0.010 | | 0.016 | | 0.010 | | -0.002 | | | |

Note: Table 5.3 derives from Table 5.1 and Table 5.2. The range factor is a measure of how remote on average the firms composing a portfolio were prior (after) the portfolio was formed and thus it is a weighted average; If all firms stay in the same portfolio and there no new entrants, then the Range factor will be zero. For portfolio 1, the value of the Range factor denotes how many portfolios on average the existing current year firms are demoted compared to a year ago, and how many portfolios are promoted a year after. For portfolio 10 that meaning reverses. Yearly Return is an average 12-month return of a size portfolio. Return on the New Issue is the average return on the firms that enter a portfolio for the first time, e.g., after the third calendar year from the date of their flotation. Return on Transitory firms is the return of those firms which enter portfolio 1 or 10 and leave in the subsequent year. Net Transitory is the return of a size portfolio if the transitory firms are ignored.

The next step is to see what the impact of the transitory firms' return is on the gross return. To do so, the yearly return is readjusted by excluding the effect of the transitory firms' return. As a result, the portfolio 1 return net of transitory firms is reduced for six of the nine years, is unchanged for two years, and increased for one year. For portfolio 10 the net of transitory firm return increases for five of the nine years and remains unchanged for the remaining four years.

The changes are in the expected directions and the impact of the transitory firm return should not be underestimated. In this example, the limited transitory effect is due to the restricted number of transitory firms defined under the established criteria. Thus the approach used here for estimation of the transitory effect may represent only a fraction of the total transitory effect, and if longer horizons are considered the effect may be significantly higher. If the price reversals terminology is adopted, then the transitory firms definition will be those firms whose prices drop/overshoot disproportionally to the overall market and then regain/lose their value within a year. There are firms that reverse over horizons longer than a year, which is why the transitory effect may constitute only a portion of the total reversal effect.

The initial idea for a full analysis of price reversals was to account for all firms that enter and leave a portfolio in a particular year, rather than the transitory firms only. This was deemed unfair because, amongst the firms that leave portfolio 1 for instance, there may exist genuinely fast growing firms.

The higher return of the smaller firms can be looked at by considering longer horizons of price reversals. Thus, for the period from 1986 to 1994, portfolio 1 is entered by 62 firms coming from higher portfolios and by 46 new entrants. Only 29 of the 62 firms are transitory, i.e., enter and leave portfolio 1 within a year. This implies that the 33 remaining firms stay in portfolio 1 for more than a year, before leaving to larger size portfolios. Portfolio 10 exhibits lower transitory behaviour; 37 firms enter from lower capitalisation deciles, only 8 of which are 1-year-transitory firms.

Therefore, for a full analysis of the price reversal effect, longer horizons should be considered. The Range Factor is estimated for each year between 1985-1995 for all years backwards and forwards. The formula is slightly modified to that used in Table 5.3, as the absolute values 1 and 10 are ignored. The results for portfolio 1 and 10 are exhibited in Table 5.4 and Table 5.5 respectively.

**Table 5.4.**

**Portfolio 1's Range Factor based on various formation years and time spans**

The Range Factor shows the average portfolio value prior to and after a given year of the firms which form the first decile (portfolio 1) in that year; The value of '1' along the diagonal corresponds vertically to the year in which the firms were categorised as portfolio 1 by their market value. Across values show the average portfolio value for given years in the past or in the future for the same firms that were in portfolio 1.

| PERIOD OF FORMATION | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | WAS IN | | PORTFOLIO 1 | | | WENT TO | | | |
| 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
| 1 | 1.27 | 2.00 | 2.39 | 2.62 | 2.79 | 2.90 | 3.25 | 3.38 | 3.54 | 3.64 |
| 1.17 | 1 | 1.43 | 2.13 | 2.42 | 2.81 | 2.78 | 2.94 | 3.09 | 3.32 | 3.39 |
| 1.15 | 1.05 | 1 | 1.46 | 1.69 | 2.10 | 2.36 | 2.67 | 2.86 | 2.93 | 2.96 |
| 1.38 | 1.28 | 1.39 | 1 | 1.27 | 1.76 | 1.97 | 2.25 | 2.61 | 2.74 | 2.66 |
| 1.62 | 1.48 | 1.54 | 1.23 | 1 | 1.36 | 1.77 | 2.03 | 2.23 | 2.17 | 2.28 |
| 1.50 | 1.50 | 1.52 | 1.36 | 1.18 | 1 | 1.24 | 1.49 | 1.95 | 2.00 | 2.05 |
| 1.50 | 1.69 | 1.74 | 1.40 | 1.32 | 1.18 | 1 | 1.33 | 1.80 | 1.93 | 2.20 |
| 2.13 | 1.94 | 2.06 | 1.59 | 1.56 | 1.69 | 1.39 | 1 | 1.24 | 1.45 | 1.72 |
| 2.85 | 2.91 | 2.91 | 2.27 | 2.14 | 2.19 | 1.86 | 1.36 | 1 | 1.33 | 1.70 |
| 2.53 | 2.81 | 2.95 | 2.22 | 2.11 | 2.00 | 1.88 | 1.60 | 1.35 | 1 | 1.55 |
| 2.89 | 2.80 | 2.24 | 2.15 | 2.20 | 1.91 | 2.30 | 1.95 | 1.98 | 1.62 | 1 |

If the composition of portfolio 1 is taken as for 1985, and thus the value for 1985 is 1, the same firms have an average portfolio value of 1.27 in 1986. This value relates to the Range Factor of 0.267 in Table 5.3 for the firms that move out of portfolio 1 at the end of 1985, e.g., 1.27-1=0.27.

Fortunately, Table 5.4 and Table 5.5 provide an opportunity for the Range Factor to be traced for periods longer than a year. For portfolio 1, its 1985 composition rates as portfolio

2 in 1987, 2.39 in 1988, and 3.64 in 1995. At first glance it seems that the asset prices of portfolio 1 grow faster, and therefore implies a lack of cohesion between average market growth and portfolio 1's growth. If the 1995 composition of portfolio 1 is taken and then the growth is looked at retrospectively, another regularity is revealed. In its 1995 composition portfolio 1 grows steadily (except for 1990) the further it moves backwards. It looks as if the 1985 composition of portfolio 1 contains firms with imminent future growth, whereas the same portfolio's 1995 composition contains firms which experience a reduction in their value and a gradual descent from an average portfolio 2.89 down to portfolio 1.

This tendency persists no matter which year is taken as a benchmark year. Thus, if 1990 is taken as a middle-point-year, the asset composition of portfolio 1 is gradually descending before 1990 and gradually ascending after 1990 in its ranking among the other size portfolios. Although the rate of losing/gaining a portfolio rank reduces as the distance from the benchmark portfolio increases, the trend is still obeyed, which suggests an asset-combined pattern of reversion as long as 10 years.

Table 5.5 provides the same Range Factor estimation applied to portfolio 10. The main differences for portfolio 10, compared to portfolio 1, are two:

Firstly, the pattern is opposite to portfolio 1. In the years prior to its formation, portfolio 10 gains rank, and loses rank afterwards. Secondly, the reversion is much milder in terms of rank gain/loss.

**Table 5.5.**

**Portfolio 10's Range Factor based on various formation years and time spans**

The Range Factor shows the average portfolio value prior and after a given year of the firms which form the tenth decile (portfolio 10) in that year; The value of '10' along the diagonal corresponds vertically to the year in which the firms were categorised as portfolio 10 by their market value. Across values show the average portfolio value for given years in the past or in the future for the same firms that were in portfolio 10.

| PERIOD OF FORMATION | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | WAS IN | | | PORTFOLIO 10 | | WENT TO | | | |
| 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
| 10 | 9.87 | 9.63 | 9.67 | 9.63 | 9.67 | 9.66 | 9.55 | 9.48 | 9.45 | 9.39 |
| 9.83 | 10 | 9.70 | 9.63 | 9.57 | 9.60 | 9.62 | 9.55 | 9.52 | 9.45 | 9.39 |
| 9.69 | 9.73 | 10 | 9.87 | 9.87 | 9.86 | 9.82 | 9.75 | 9.68 | 9.75 | 9.74 |
| 9.61 | 9.65 | 9.78 | 10 | 9.97 | 9.94 | 9.91 | 9.82 | 9.73 | 9.79 | 9.48 |
| 9.64 | 9.58 | 9.74 | 9.89 | 10 | 9.97 | 9.92 | 9.83 | 9.72 | 9.72 | 9.47 |
| 9.66 | 9.60 | 9.67 | 9.79 | 9.90 | 10 | 9.92 | 9.87 | 9.77 | 9.74 | 9.76 |
| 9.65 | 9.60 | 9.64 | 9.77 | 9.85 | 9.90 | 10 | 9.91 | 9.86 | 9.81 | 9.83 |
| 9.56 | 9.49 | 9.62 | 9.64 | 9.77 | 9.85 | 9.91 | 10 | 9.98 | 9.87 | 9.88 |
| 9.36 | 9.35 | 9.57 | 9.54 | 9.63 | 9.76 | 9.87 | 9.94 | 10 | 9.88 | 9.89 |
| 9.23 | 9.22 | 9.50 | 9.46 | 9.54 | 9.65 | 9.74 | 9.78 | 9.81 | 10 | 9.96 |
| 9.18 | 9.17 | 9.50 | 9.42 | 9.50 | 9.62 | 9.74 | 9.76 | 9.82 | 9.94 | 10 |

### 5.2.3. Return profile of un-rebalanced and rebalanced portfolio 1 and portfolio 10.

For an affirmation of the conclusion based on the Table 5.4 and Table 5.5 data, the portfolio 1 and portfolio 10 compositions for 1985 are taken as benchmarks. Then, the return of the benchmark portfolios is estimated for each year from 1986 to 1995. The reason for choosing 1985 as a benchmark year is that all firms included in the 1985 portfolio 1 and 10 will be present throughout the whole period, which is not the case with the 1995 portfolio composition.

As a result of the estimation, there are 4 return series to be compared. First, there are two return series of the rebalanced portfolios, and second, a further two series of the un-rebalanced portfolios. Table 5.6 provides the returns for all four portfolios.

**Table 5.6.**

**Return on benchmark 1985 portfolio 1 and 10 composition and yearly rebalanced portfolio 1 and 10**

| Period | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 85-95 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio # | | | | | | | | | | | | |
| pf1-un-rbl | 0.042 | 0.059 | 0.036 | 0.028 | -0.005 | -0.001 | 0.038 | 0.001 | 0.042 | 0.011 | 0.013 | 0.024 |
| pf1-rbl. | 0.042 | 0.052 | 0.035 | 0.026 | 0.006 | -0.006 | 0.040 | 0.018 | 0.073 | 0.030 | 0.023 | 0.031 |
| pf10-un-rb | 0.016 | 0.015 | 0.005 | 0.010 | 0.025 | -0.003 | 0.006 | 0.016 | 0.015 | -0.001 | 0.017 | 0.011 |
| pf10-rbl | 0.016 | 0.015 | 0.003 | 0.010 | 0.024 | -0.003 | 0.009 | 0.015 | 0.010 | -0.002 | 0.008 | 0.010 |

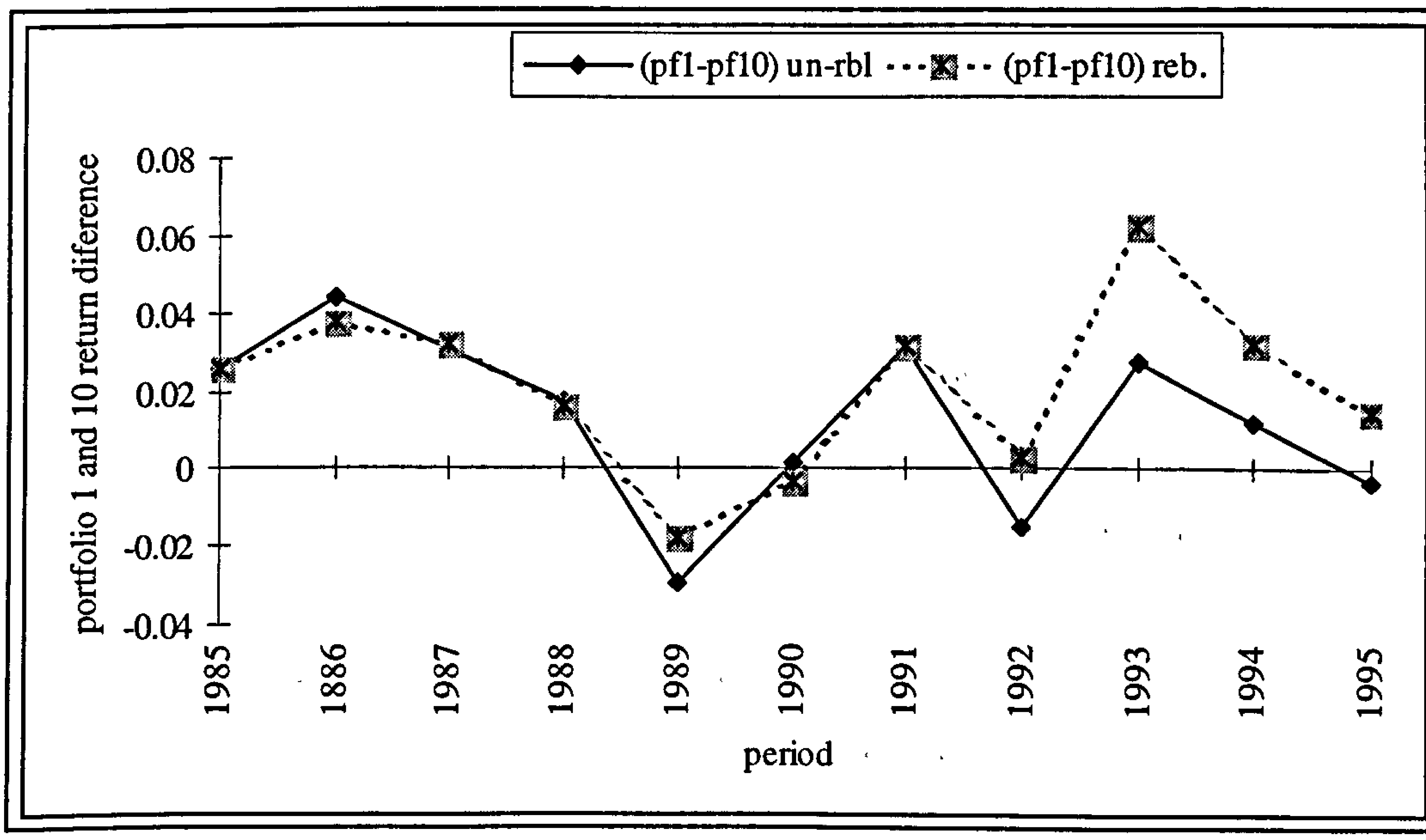
By and large, Table 5.6 confirms the expected return difference between the rebalanced and un-rebalanced portfolios. The difference between the un-rebalanced and rebalanced portfolios is more pronounced for portfolio 1, as un-rebalanced portfolio 1 earns a 23 percent lower return than rebalanced portfolio 1 for the whole period 1985-1995. Un-rebalanced portfolio 10 earns a 10 percent higher return than rebalanced portfolio 10. The divergence between the un-rebalanced and rebalanced portfolios takes place only after 1990. This suggests that un-rebalanced portfolio returns track rebalanced portfolio returns for 5 years, due to the momentum that they have not yet exhausted.

To compare the actual impact of the yearly portfolios' rebalancing, Figure 5.1 shows the spread between the rebalanced and unbalanced portfolios.

**Figure 5.1.**

**Differentials between the returns of the benchmark and rebalanced portfolio 1 and 10**

The returns of benchmark portfolios 1 and 10 are estimated by keeping their 1985 composition unchanged. The returns of rebalanced portfolios are estimated by rebalancing them according to the firms market capitalisation at each calendar year-end.




Thus the dashed line shows the difference between the rebalanced portfolio 1 and portfolio 10, which derives from Table 5.6 The continuous line is the difference between the return of portfolio 1 and 10 under the condition of constant 1985 composition.

As is seen, the spread between rebalanced and un-rebalanced portfolios is more or less the same up until 1991. Since then, however, the spread between the returns of the unbalanced portfolios diminishes. It is sensible to expect un-rebalanced and rebalanced portfolio 1 and 10 to converge for some time, e.g. 5-6 years, because:

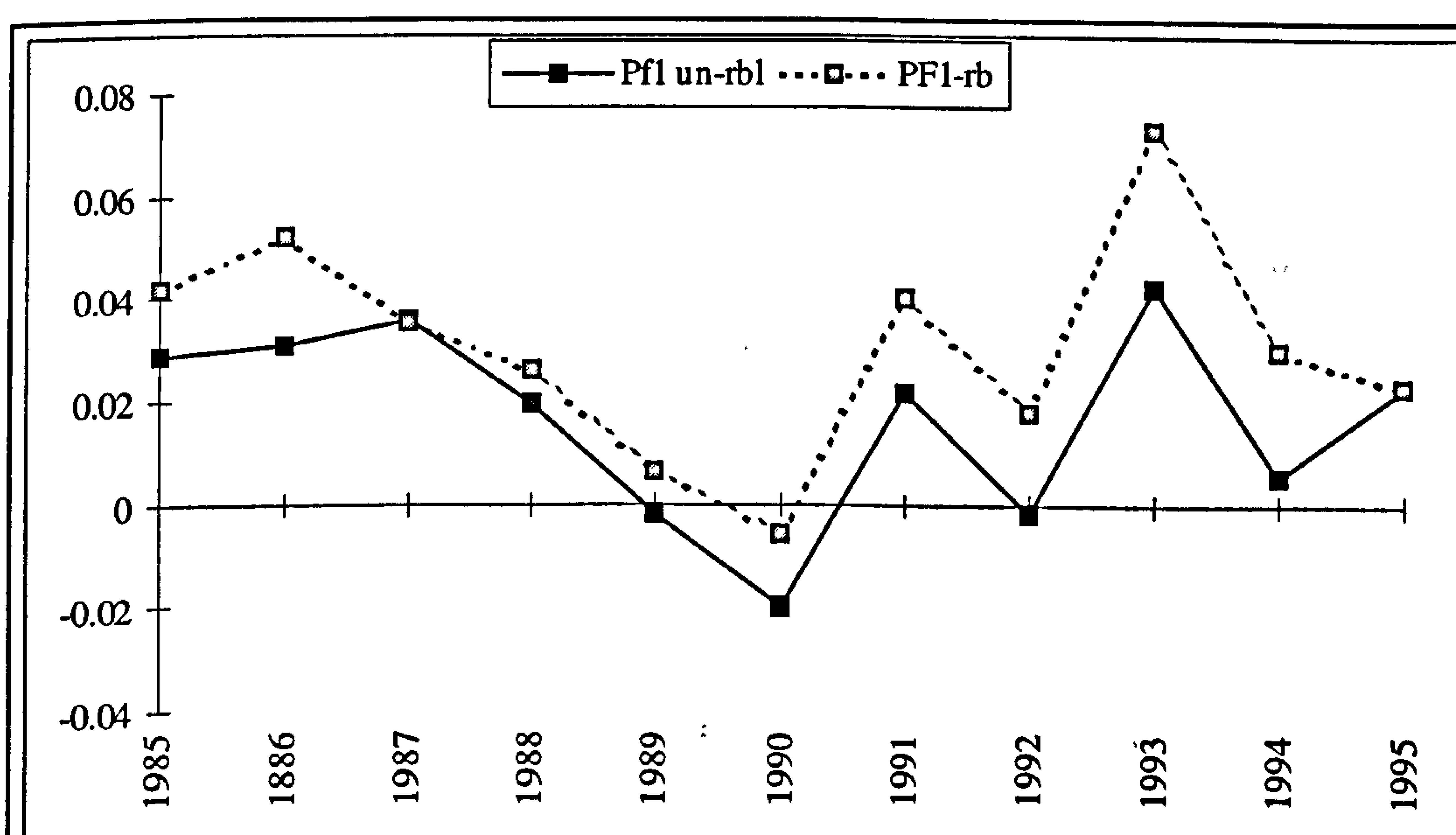
1. The structure of the rebalanced portfolios is changed relatively slowly, as only few firms are replaced with new ones each year. This is particularly true for portfolio 10, where 22 out of 30 member-firms in 1985 are still available for portfolio 10 in 1995. The number for portfolio 1 is only 5.

2. The effect of firms' mobility across the size portfolios is especially noticeable for portfolio 1, which has the larger return difference between the rebalanced and un-rebalanced portfolios. In spite of the active process of replacing portfolio 1 firms, it seems that the high growth of the portfolio's value does not stop immediately after the process of rebalancing is abandoned. For three years (86,87,88) the un-rebalanced portfolio 1 outperforms the rebalanced one (See Figure 5.1). This may imply a strategy of rebalancing over longer periods in order to save on transaction costs of trading.

Thus, the results of the investigation into the portfolio 1 and 10 composition dynamics provide strong evidence supporting the overreaction or price reversals hypothesis in explaining the size anomaly. One must bear in mind that the returns for the rebalanced and un-rebalanced portfolios are gross, and no provisions are made to accommodate risk.

To reaffirm the points drawn in this section, an un-rebalanced 1995 portfolio 1 composition is used and returns for each year back to 1985 are estimated for this composition. Our hypothesis, based on Table 5.4, is that portfolio 1 returns based on its 1995 asset composition will be subordinate to the constantly rebalanced portfolio 1. Indeed, this is true, as Figure 5.2 indicates.

**Figure 5.2.**
**Benchmark 1995 Monthly Portfolio 1 return and Yearly Rebalanced Monthly Portfolio 1 Return**



## 5.3. Cross-section of individual firms' Market Value, Book-to-Market, Borrowing Ratio and Industry factors.

According to Fama and French (1992), firms with higher Book-to-Market ratios are undervalued by the market and therefore they should earn higher returns. To test whether MV and BTMV (MTB) are likely to affect the return relationship, cross-section regressions are estimated for each year between 1985-1995. Yearly returns on the firms included in portfolios 1-10, described at length in Chapter 4, are used for the dependent variable, the independent variables being the market value of firms and Market-to-Book value. In addition, the Borrowing Ratio (BR) and an Industry dummy for each asset are included in the right-hand side of the regression as well.

Although the term 'Book-to-Market' is more popular, the ratio provided by *DATASTREAM* is described by the reverse relation, i.e., Market-to-Book value (MTBV). For the sake of consistency, except for this section, the term 'Book-to-Market value' is adopted. Thus a negative loading on MTBV will correspond to a same magnitude positive loading on BTMV. By definition, Market-to-Book value (also called discount to net asset value) expresses the market value of a company as a percentage of its total equity capital plus reserves less total intangibles. The calculation is as follows:

$$MTBV = \frac{MV}{NTA}$$

where $NTA$ is Net tangible assets and $MV$ is the Market value. Net tangible assets is defined as fixed assets less depreciation, plus longer-term investments and current assets, less current and deferred liabilities and prior charge capital and minority interest. The Borrowing Ratio (BR), known also as the 'Debt to Equity ratio', represents total borrowings (short term plus subordinated debt plus total loan capital) divided by total equity (equity capital and reserves plus total deferred tax less total intangibles).

Using dummy variables, firms are assigned to one of the 5 industry groups, General Industries (d1), Consumer Goods (d2), Services (d3), Mineral Extraction (d4) and Utilities (d5).

The estimated model is:

$$R_i = \alpha + \gamma_1 MV + \gamma_2 MTBV + \gamma_3 BR + \gamma_4 d_1 + \gamma_5 d_2 + \gamma_6 d_3 + \gamma_7 d_4 + \gamma_8 d_5 + \varepsilon$$

A regressor in the above equation is dropped if it is not significant at the 10% level. The results are shown in Table 5.7.

**Table 5.7.**

**Estimated Coefficients and T-ratios of the Regression**

$$R_i = \alpha + \gamma_1 MV + \gamma_2 MTBV + \gamma_3 BR + \gamma_4 d_1 + \gamma_5 d_2 + \gamma_6 d_3 + \gamma_7 d_4 + \gamma_8 d_5 + \varepsilon$$

| Estimated Coefficients | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Year | α | mv | mtb | br | d1 | d2 | d4 | R2 |
| 1985 | 0.033 | | -0.004 | | | | | |
| T–ratio | 11.88 | | -3.08 | | | | | |
| 1986 | 0.043 | -0.010 | | 0.003 | | | | 0.12 |
| T–ratio | 12.04 | -6.02 | | 1.81 | | | | |
| 1987 | 0.044 | -0.014 | -0.001 | 0.008 | | | | 0.18 |
| T–ratio | 9.92 | -6.93 | -2.35 | 3.21 | | | | |
| 1988 | 0.032 | -0.004 | -0.002 | | | | | 0.07 |
| T–ratio | 9.40 | -2.92 | -3.90 | | | | | |
| 1989 | -0.012 | 0.008 | | | | | 0.026 | 0.11 |
| T–ratio | -3.11 | 4.74 | | | | | 4.12 | |
| 1990 | -0.004 | | | -0.008 | -0.006 | | | 0.03 |
| T–ratio | -1.69 | | | -3.14 | -1.99 | | | |
| 1991 | 0.054 | -0.013 | | | -0.007 | | -0.035 | 0.15 |
| T–ratio | 11.55 | -6.64 | | | -2.36 | | -4.29 | |
| 1992 | 0.003 | | 0.002 | | | | -0.023 | 0.03 |
| T–ratio | 1.15 | | 2.30 | | | | -2.86 | |
| 1993 | 0.078 | -0.020 | -0.001 | 0.006 | | -0.013 | | 0.28 |
| T–ratio | 18.89 | -11.39 | -2.69 | 3.65 | | -3.54 | | |
| 1994 | 0.026 | -0.009 | | | | -0.006 | 0.009 | 0.10 |
| T–ratio | 8.18 | -6.76 | | | | -2.33 | 1.89 | |
| 1995 | 0.025 | -0.005 | | | -0.004 | | | 0.03 |
| T–ratio | 6.13 | -3.31 | | | -2.07 | | | |

Table 5.7 provides yet more evidence of the Size effect. A negative size effect, which is also significant, exists in 7 years. In 3 years the size effect is not significant, and in one (1989) it is positive. This pattern is consistent with the ranking pattern in Table 4.2 and the excess return pattern in Table 4.8, both of which are in Chapter 4. On average, however, market value seems to be the strongest determinant of the return. Market-to-book value is significant in 4 years, insignificant in 6 and has an unexpected sign in 1992.

The above evidence does not come as a surprise, bearing in mind the results obtained in Chapter 4. Of more interest, however, is the behaviour of the Borrowing Ratio (BR) throughout the period.

It is fascinating that the Borrowing Ratio has a positive contribution to returns in the years with a strong negative size effect, i.e., 1986, 1987, 1993. The only occasion when BR's estimated coefficient takes a negative value is in 1990. The only year when MV has a positive coefficient is 1989 and it is not significant in 1990. This result implies that the MV and the BR relate somehow, and this relationship is more pronounced and complex than the relationship between MV and BTMV. Appendix 5.1 shows the relationship between portfolio monthly returns and the normalised Borrowing ratios for the same size portfolios for each year and the average for the period 1985-1995. Portfolio Borrowing Ratios have been normalised by dividing them by a normalising factor for every year. The normalising factor for each year is estimated as follows:

$$NF_t = \frac{\sum_{1}^{n} BR_{n,t}}{\sum_{1}^{n} R_{n,t}}$$

Thus, each portfolio gearing is reduced to a level such that the average of all portfolios' gearing and the average of all portfolios' returns are equal. This allows us to compare the relative ratio between the return and the gearing as well as their absolute levels for each size portfolio.

Appendix 5.1 presents high absolute gearing for the lowest MV decile and for the highest portfolios 8, 9 and 10 as an average for the period 1985-1995. As for the relative return/gearing ratio, small size firms have relatively high returns, whereas larger firms have relatively high gearing. In other words, small firms produce a higher return from a unit of borrowed funds than large firms do. Appendix 5.1 thus suggests a hypothesis for the size effect explanation. According to the Wilson Report (1979), small firms are characterised by higher ratios of bank borrowing and of current liabilities in general than the typical large firm. Therefore, with a relatively high cost of borrowing, a poor performance of the small capitalisation stocks is expected. With cheap credit, however, high market returns of the small capitalisation stocks is expected. This hypothesis is particularly relevant for the period after the late 1970s and early 1980s, because of financial market deregulation and the implementation of a floating borrowing rate by the financial institutions. 1990 is known as a year with hiking interest rates. Appendix 5.1 1990's section shows what a damaging affect this had on returns. This is especially true for the returns of small size firms, which plummet below the level of normalised BR for 1990 and the previous year1989. It may be the case that small firms have a higher BR, as well as a higher cost of borrowing. The latter, though, is difficult to document, due to restricted access to information on specific lending rates. Hence, the importance of the BR in explaining return differences of the size portfolios will not be pursued further in this section; however, the relevance of the Book-to-Market factor is considered in depth.

## 5.4. Book-to-Market, Size and Beta in a Conditional Asset Pricing Model

Fama & French's (1992) aim is to evaluate the joint roles of market β, size, E/P, leverage and book-to-market equity in the cross section of the average returns on NYSE, AMEX and NASDAQ stocks.

Like Banz (1981), Reinganum (1981) and others, Fama & French find that the relation between beta and average returns disappeared during the most recent 1963-1990 period, even when beta was used alone to explain average returns. Fama & French obtained post-ranked monthly returns from July 1963 to December 1990 on 100 portfolios formed on size and pre-ranking beta. Betas of every size–beta portfolio are estimated, using the full sample (330 months) of post ranking returns on each portfolio. Beta is estimated as the sum of the slopes in the regression of the return on a portfolio on the current and previous month's market return. According to Fama & French, additional leads and lags of the market return have little effect on the beta estimates. When common stock portfolios are formed on size alone, Fama & French find that average returns are positively related to beta. Average returns fall from 1.64% per month, for the smallest capitalisation portfolios, to 0.90% for the largest. Post-ranking betas also declined from 1.44 for the smallest portfolio to 0.90 for the largest. However, size portfolios' betas are almost perfectly correlated with size, so that the test is unable to distinguish between the beta and size influence on returns. When Fama & French investigate portfolios based on pre-ranking betas, they find a strong relationship between average returns and size, but no relationship between average return and beta.

Like the size portfolios, the beta sorted portfolios do not support the SLB[3] model. There is a little spread in average returns across the beta portfolios, and there is no an obvious relationship between beta and average returns. This leads Fama & French to the conclusion that:

> 'The proper inference seems to be that there is a relationship between size and average return, but controlling for size, there is no relationship between beta and average return.'
>
> (Fama and French, 1992, p. 433)

Fama & French underline that book-to-market equity played a consistently stronger role in average returns, although the size effect had attracted more attention.

In order to test for the existence of the Book-to-Market effect in the London Stock Exchange between 1985-1995, 10 high and low beta portfolios, used in Chapter 4, are further sorted into high, average and low Market-to-Book portfolios to produce the return series of 60 portfolios. The results are exhibited in Table 5.8.

[3] The CAPM tests of Sharpe (1964), Lintner (1965) and Black (1972), or SLB static CAPM.

**Table 5.8.**

**Return on Portfolios sorted by their Market Capitalisation first, and then by Beta and Book-to-Market value for the period 1985-95.**

| | High Beta | | | Low Beta | | |
|---|---|---|---|---|---|---|
| SIZE | Market-to-Book-Value | | | Market-to-Book-Value | | |
| | low BTM | ave. BTM | high BTM | low BTM | ave. BTM | high BTM |
| 1 | 0.034 | 0.028 | 0.037 | 0.022 | 0.024 | 0.030 |
| 2 | 0.017 | 0.023 | 0.027 | 0.018 | 0.022 | 0.018 |
| 3 | 0.017 | 0.018 | 0.018 | 0.017 | 0.012 | 0.013 |
| 4 | 0.012 | 0.015 | 0.012 | 0.015 | 0.012 | 0.013 |
| 5 | 0.010 | 0.015 | 0.015 | 0.010 | 0.014 | 0.012 |
| 6 | 0.007 | 0.011 | 0.009 | 0.010 | 0.013 | 0.014 |
| 7 | 0.009 | 0.009 | 0.016 | 0.013 | 0.009 | 0.016 |
| 8 | 0.005 | 0.009 | 0.012 | 0.017 | 0.011 | 0.018 |
| 9 | 0.004 | 0.011 | 0.010 | 0.014 | 0.014 | 0.011 |
| 10 | 0.004 | 0.006 | 0.004 | 0.010 | 0.010 | 0.010 |

Table 5.8 does not confirm Fama and French (1992) findings. Size Effects persists in all beta portfolios for the first five deciles, whereas the remaining five low beta portfolios earn higher return than the high beta portfolios. It is, however, impossible for any pattern among low, average and high BTMV to be discerned.

After Fama and French (1992), Fama and French (1995, 1996a) continue to deal with the three factor asset-pricing model that includes a market factor and risk factors related to size and BE/ME. Fama and French admit that size and BE/ME remain arbitrary indicator variables that, for some unexplained economic reasons, are related to risk factors in returns. The goal they specified is 'to begin to fill this economic void' (Fama and French (1995), p.131). The theoretical model they offer relates a firm's Equity Income to the same firm Market Equity to Book Equity ratio. Using the ratio of Equity Income to Book Equity as a proxy for a firm's profitability, Fama and French allot the firms in the NYSE, AMEX and NASDAQ into four portfolios, i.e., B/L, B/H, S/L and S/H, where B and S stand for big and small firms. For each year from 1963 to 1991 the whole sample is split by the median Market Value into Small (S) and big (B) firms. Stocks in the bottom 30 percent or top 30 percent of the values of the Book-to-market equity are assigned to Low (L) and High (H) Book-to-Market value. The four portfolios (B/L, B/H, S/L and S/H) are intersection of the four groups, i.e., B, S, L and H. Then, Fama and French (see Figure 1, p.136, FF, 1995) produce the 11-year evolution of earnings on book equity for size-BE/ME portfolios formed in June of year *t*. Their Figure 1 shows that in year 0 relative to the ranking year, B/L performs best, (equity income/book equity = 0.18) followed by S/L, B/H and S/H. This result supports the simple model offered by Fama and French (1995, p.135). It even goes to establish Book-to-Market value superiority over the Size Effect. Although low-BE/ME equities tend to be highly profitable long before and after they are sorted into portfolios, Figure 1 (Fama and French (1995)) shows that their profitability improves prior to portfolio formation, and deteriorates a bit thereafter. The reverse pattern of decay and then improvement in EI/BE is observed for high-BE/ME stocks.

It will be of interest to see whether or not such a pattern exists in the London Stock Exchange during the period 1985-1995. This study, however, uses the stock market returns as a proxy for profitability, rather than the ratio of the Equity Income to the Book Equity, and this creates a potential obstacle for comparing the two sets of findings. Luckily, Panel C in Fama and French (1995) provides average monthly percent returns for the same portfolios, i.e., S/L, S/H, B/L and B/H, for 11 years around portfolio formation. Due to having a shorter sample period, here the evolution of portfolio returns is carried out for 5 years, rather than 11. Figure 5.3 shows the Fama and French (1995) equivalent of the 5 year evolution of the US stock returns for the relevant portfolios.

**Figure 5.3.**

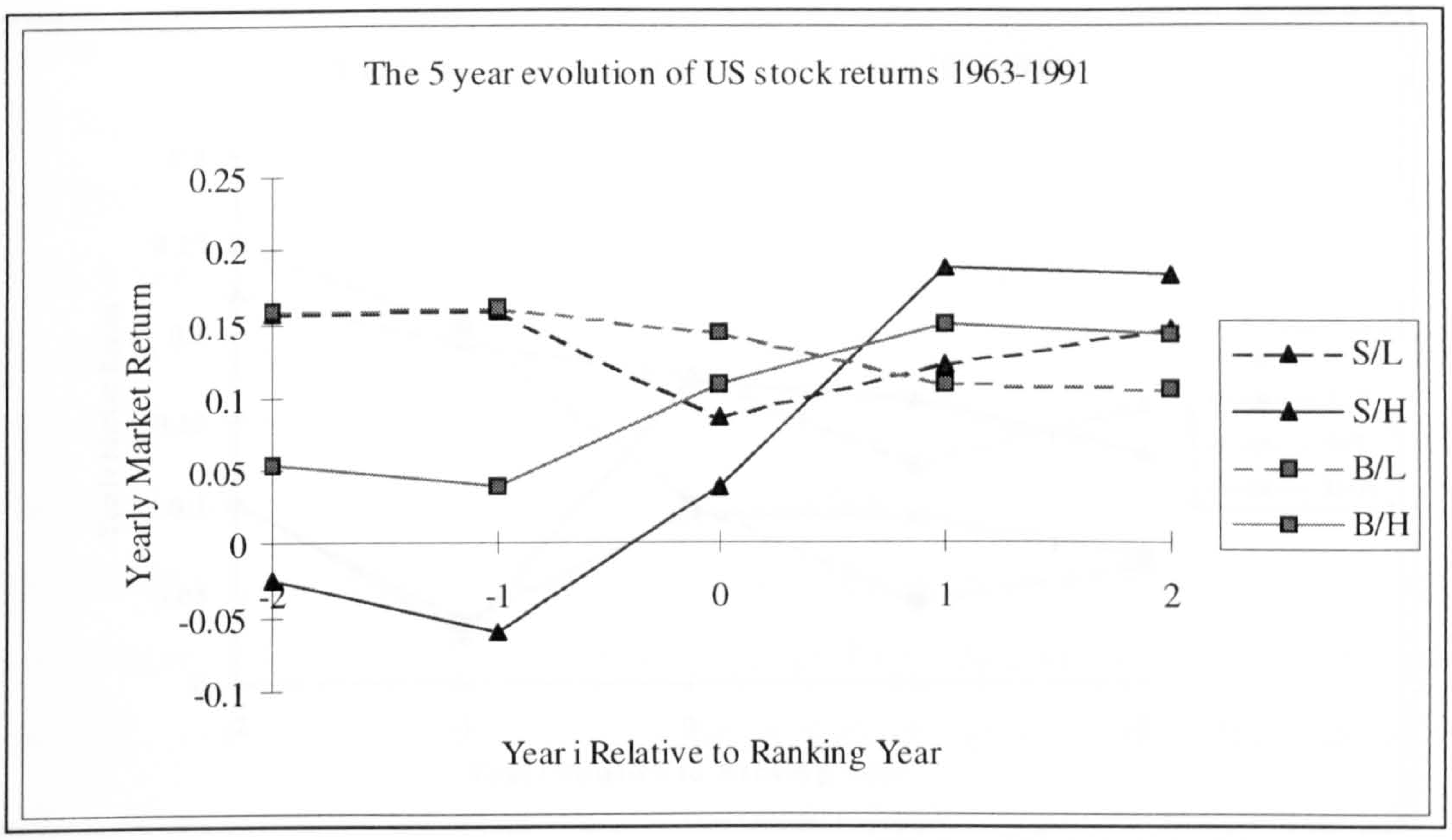
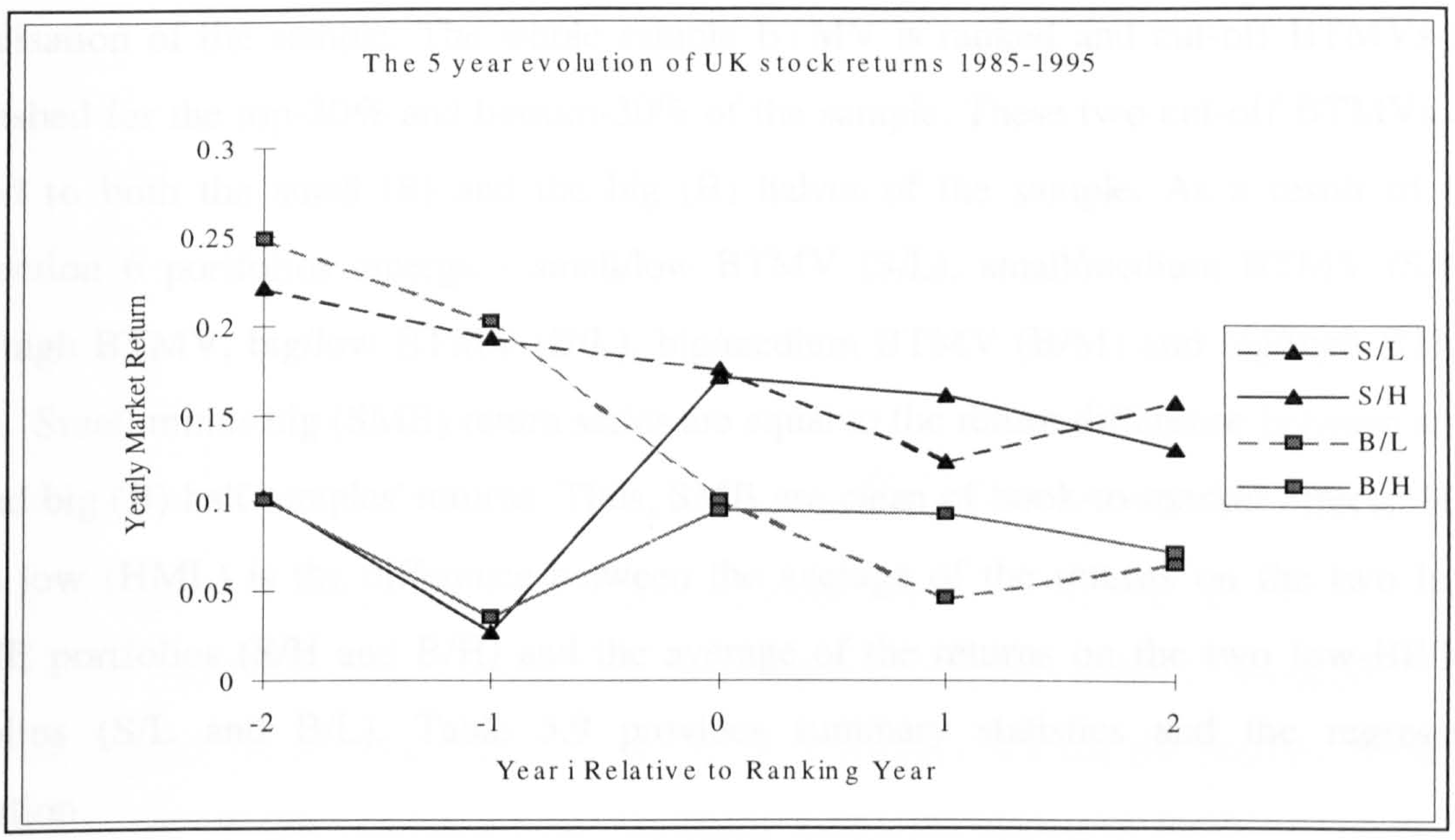



Figure 5.3 differs from the one in which Fama and French use earnings over book equity as a proxy for profitability, rather than the market return. Both B/L and B/H portfolio returns dominate S/L and S/H, which implies an inverse size effect. Both low BTMV portfolios (dashed line), however, do not dominate high BTMV ones (continuous line). In addition, the ellipse shapes are not present.

Figure 5.4 shows the 5 year evolution of the UK stock returns for S/L, S/H, B/L and B/H portfolios, formed by following Fama and French's equivalent procedure. It seems that the UK returns follow a similar pattern to the US returns', except that small size portfolio returns categorically dominate the BTMV returns.

**Figure 5.4.**




Following Fama and French (1995), excess returns on the six size-BE/ME portfolios are regressed on MKT-RF, SMB and HML. As Fama and French claim in a subsequent paper (Fama and French, (1996a)),

> 'many of the CAPM average-return anomalies are related, and they are captured by the three factor model ... The model says that the expected return on a portfolio in excess of the risk free rate $\left[E(R_i)-R_f\right]$ is explained by the sensitivity of its return to three factors: (1) the excess return on a broad market portfolio $(R_M - R_f)$; (ii) the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB, small minus big); and the difference between the return of low-book-to-market stocks *(and high-book-to-market stocks)* (HML, high minus low).'
>
> (Fama and French, 1996, p. 55)

Hence, the model is:

$$R(t)-RF(t)=a+b[RM(t)-RF(t)]+sSMB(t)+hHML(t)+e(t)$$

The portfolio formation procedure is as follows: For each year all available assets are split into two groups - small (S) and big (B) by the end-of-calendar-year median market capitalisation of the sample. The whole sample BTMV is ranked and cut-off BTMVs are established for the top-30% and bottom-30% of the sample. These two cut-off BTMVs are applied to both the small (S) and the big (B) halves of the sample. As a result of this intersection 6 portfolios emerge - small/low BTMV (S/L), small/medium BTMV (S/M), small/high BTMV, big/low BTMV (B/L), big/medium BTMV (B/M) and big/high BTMV (B/H). Small minus big (SMB) return series are equal to the return difference between small (S) and big (B) half samples' returns. Thus, SMB are clean of book-to-market effects. High minus low (HML) is the difference between the average of the returns on the two high-BE/ME portfolios (S/H and B/H) and the average of the returns on the two low-BE/ME portfolios (S/L and B/L). Table 5.9 provides summary statistics and the regression estimation.

**Table 5.9.**

**Excess Returns on the Six-Size-BE/ME Portfolios Regressed on RM-RF, SMB, and HML. Summary Statistics for the Dependent and Explanatory Returns (in Percent): January 1985 to December 1995, 132 Monthly Observations**

**Panel A. Summary Statistics**

| | Mean | Std | t(Mn) |
|---|---|---|---|
| MKT-RF | 0.66 | 0.48 | 1.39 |
| SMB | 0.67 | 0.25 | 2.74 |
| HML | 0.25 | 0.22 | 1.16 |

| | | | |
|---|---|---|---|
| S/H-RF | 0.99 | 0.52 | 1.91 |
| S/M-RF | 0.69 | 0.47 | 1.47 |
| S/L-RF | 1.04 | 0.49 | 2.11 |

| | | | |
|---|---|---|---|
| B/H-RF | 0.27 | 0.55 | 0.49 |
| B/M-RF | 0.16 | 0.51 | 0.32 |
| B/L-RF | 0.16 | 0.47 | 0.34 |

**Panel B. Full Sample**

$$R(t)-RF(t)=a+b[RM(t)-RF(t)]+sSMB(t)+hHML(t)+e(t)$$

| | a | b | s | h | t(a) | t(b) | t(s) | t(h) | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| B/H | 0.00 | 0.97 | -0.67 | 0.64 | -0.62 | 38.06 | -13.13 | 10.70 | 0.94 |
| B/M | 0.00 | 1.00 | -0.57 | 0.06 | -1.56 | 63.82 | -18.19 | 1.73 | 0.98 |
| B/L | 0.00 | 0.95 | -0.42 | -0.30 | -1.63 | 73.72 | -16.25 | -10.07 | 0.98 |
| | | | | | | | | | |
| S/H | 0.00 | 0.97 | 0.34 | 0.53 | -0.25 | 76.67 | 13.48 | 17.79 | 0.98 |
| S/M | 0.00 | 0.96 | 0.47 | -0.06 | -2.40 | 50.07 | 12.42 | -1.41 | 0.96 |
| S/L | 0.00 | 1.02 | 0.61 | -0.59 | 0.69 | 39.40 | 11.72 | -9.75 | 0.93 |

Panel A of Table 5.9 shows summary statistics, firstly for the three conditional factors-the market (MKT-RF), the size (SMB) and the Book-to-Market (HML), secondly for 6 portfolios formed on the basis of Size and Book-to-Market. As for the factors, evidently small minus big (SMB) performs best, providing an excess return of 0.67 for the period 1985-1995. In addition, SMB exhibits a modest standard deviation of 0.25 and a convincing T-ratio of 2.74. Thus, the excess over the risk free interest rate returns do not come as a surprise. The three small size portfolios dominate the three large size portfolios. It is, however, impossible for a pattern to be established across the Book-to-Market sorted portfolios.

Panel B of Table 5.9 reports the results of the regressions for the returns of the 6 Size-Book-to-Market portfolios on the market, size and book-to-market factors. Apparently the BTM is either insignificant or lacks consistency in explaining the portfolios' return variation. Both the Market (*b*) and Size (*s*) are highly significant. In addition, the size sign is what should be expected; large firms load negatively, small firms positively.

Thus, the role of the Book-to-Market in explaining the differences of asset returns and proxying for the size factor should be ruled out. Appendix 5.2 and Appendix 5.3 provide further evidence of Size superiority over Book-to-Market. Both appendices report the results of time series regressions, which differ to those in Panel B, Table 5.9, only by their independent variables. Appendix 5.2 uses the returns of 30 High-Beta portfolios, sorted by Size and BTM. Appendix 5.3 uses the returns of 30 Low-Beta portfolios, sorted by Size and BTM.[4]

## 5.5. The interaction between cost of borrowing, cover ratio and returns

Earlier in chapter 4 and also in this chapter it has been hypothesised that the size effect may be related to the difference in the sources of funding for small and large size firms. Small size firms may experience difficulties in raising finance in the stock market and thus resort to bank loans. By employing more borrowed funds, small size firms benefit from the lower cost of the borrowed funds compared to the cost of raising their own funds. This process refers to the Modigliani-Miller (1958) hypothesis, and the increased return on capital is a part of it.

The other implication is higher risk entailed by increased gearing. One of the most important functions of capital is in providing a cushion to absorb the shock of the reductions in the value of net assets, i.e., own funds. A higher gearing ratio means that a firm is less likely to meet its liabilities to lenders and suppliers, should the value of its fixed assets or working capital drop for some reason.

Equally, the amount of this risk should be priced by the CAPM. Higher gearing ratios introduce higher volatility in the security price. If prospects are good, then investors foresee windfall profits and shareholders set a protective high price, or the price is levered up. If prospects are bleak, the share price of highly geared firms falls sharply, as the firms must pay a fixed or increasing variable interest rate while the gross profit is plummeting.

The data explored so far fails to establish any significant relation between size and the borrowing ratio, this being a candidate for the missing variable that proxies the size effect. Table 5.7 shows a significant positive contribution to returns by the borrowing ratio in 1986,

[4]These are the portfolios whose returns are shown in Table 5.8.

1987, 1993 and a negative one in 1990. Appendix 5.1 confirms for 1986, 1987 and 1993 a similar pattern between portfolios' returns and the normalised borrowing ratio. In general, smaller size portfolios, and portfolio 1 in particular, tend to earn relatively higher returns than the normalised borrowing ratio predicts, whereas this is inverted for large size portfolios. Table 5.10 shows the nominal borrowing ratios at the end of year $t-1$ and returns for year $t$ for size portfolio 1 and portfolio 10.

**Table 5.10.**
**Nominal Borrowing Ratios and Annual Returns of Portfolio 1 and Portfolio 10 1985-1995**

| Year / Indicator | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BRpf1 | 0.67 | 1.04 | 0.74 | 0.78 | 0.67 | 0.61 | 1.60 | 0.68 | 0.85 | 0.78 | 0.61 |
| ret_pf1 | 0.50 | 0.63 | 0.42 | 0.31 | 0.08 | -0.07 | 0.48 | 0.21 | 0.88 | 0.36 | 0.27 |
| | | | | | | | | | | | |
| BRpf10 | 0.41 | 0.46 | 0.45 | 0.52 | 0.50 | 0.51 | 5.67 | 0.79 | 0.76 | 0.78 | 0.80 |
| ret_pf10 | 0.20 | 0.18 | 0.04 | 0.12 | 0.29 | -0.03 | 0.10 | 0.18 | 0.12 | -0.03 | 0.09 |
| | | | | | | | | | | | |
| 3-Mth Tr.Bill | 0.11 | 0.10 | 0.09 | 0.09 | 0.13 | 0.13 | 0.10 | 0.09 | 0.05 | 0.05 | 0.06 |

It is apparent that portfolio 1 has a higher borrowing ratio than portfolio 10 for every year, except 1991, 1992 and 1995. Portfolio 1 also has a higher return than portfolio 10 for each year except 1990. Consequently, 1989 and 1990 are the years in which the interest rate reached its peak for the period 1985-1995, i.e., 13 percent. The other interesting period is when the interest rate reaches its lowest level, i.e., 1993 and 1994. Then the return of portfolio 1 outperforms the return of portfolio 10 significantly.

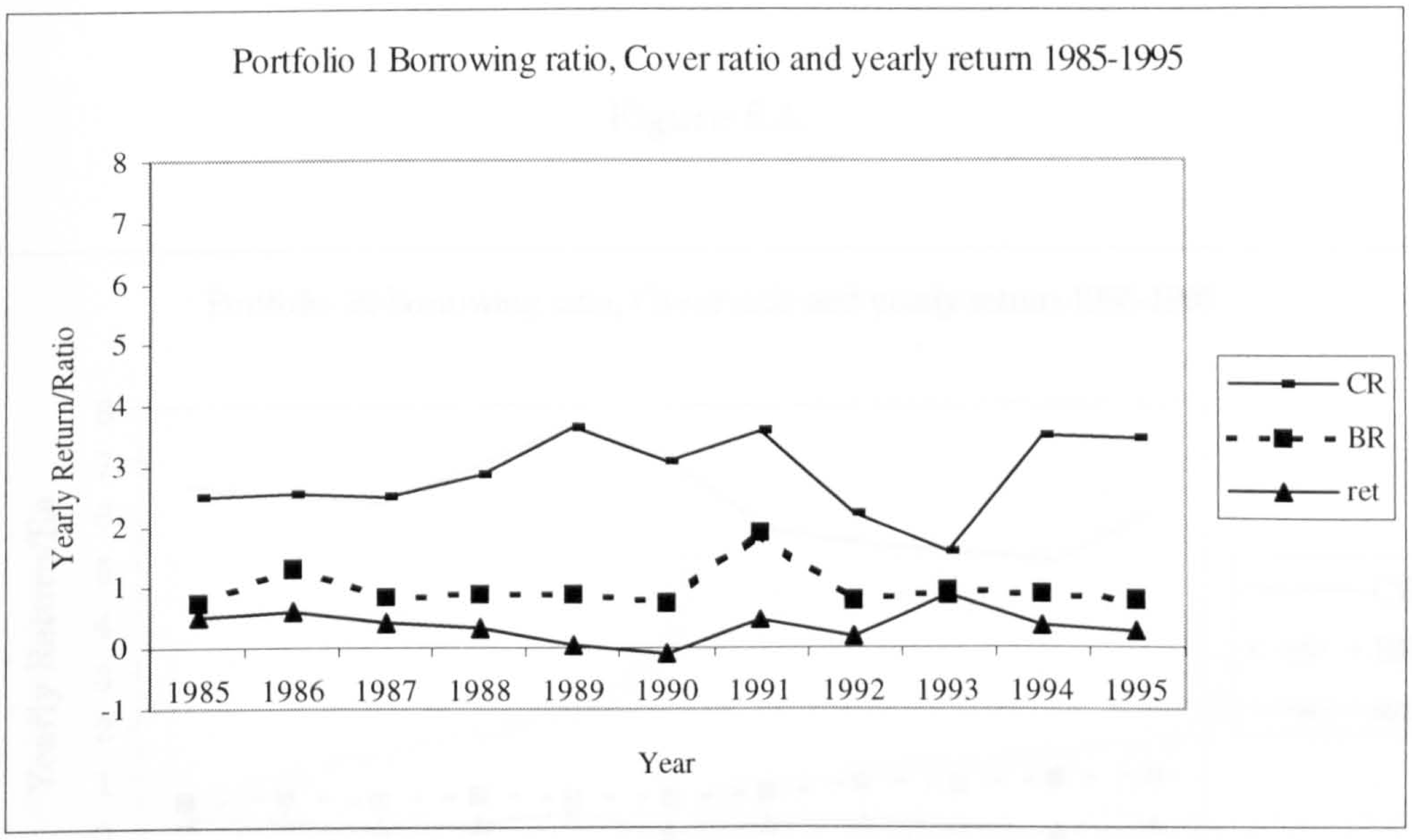
In general, changes in the interest rate seem to affect small size firms more than large size ones. It may be the case that small firms are not just forced to borrow more than large firms; it may also be the case that they face a higher cost of borrowing. To answer this question, one would need the actual interest rates on the outstanding loans of the sample firms. This information, however, is not easily available.

One way to overcome this problem is through using the firms' Cover Ratio to get an idea of how heavy the cost of borrowing is to small and large size firms. The Cover Ratio for portfolio 1 and portfolio 10 firms is end-of-year accountancy information available as *DATASTREAM* item 1503. The cover ratio (CR) represents the ratio between the profit before interest and taxes (PBIT) and the interest on the loans outstanding. It (CR) may take values from + to – infinity. A negative CR implies a loss, as the denominator can only be zero or positive.

In the course of processing the data, there were some exceptionally high cover ratios. Mostly this is due to the fact that firms with these high ratios have negligible borrowing. Inclusion of these CRs would lead to severe distortion in a portfolio's CR, estimated as a simple average of firms' CRs. Therefore an arbitrary CR level of 15 is established and observations with CR of absolute value higher than 15 are trimmed off. For various periods and portfolios this procedure excludes between 10 and 30 percent of the observations.

Figure 5.5 and Figure 5.6 show CRs, borrowing ratios and returns for portfolio 1 and portfolio 10 from 1985-1995. The borrowing ratios may differ from these in Table 5.10, due to the trimming procedure.

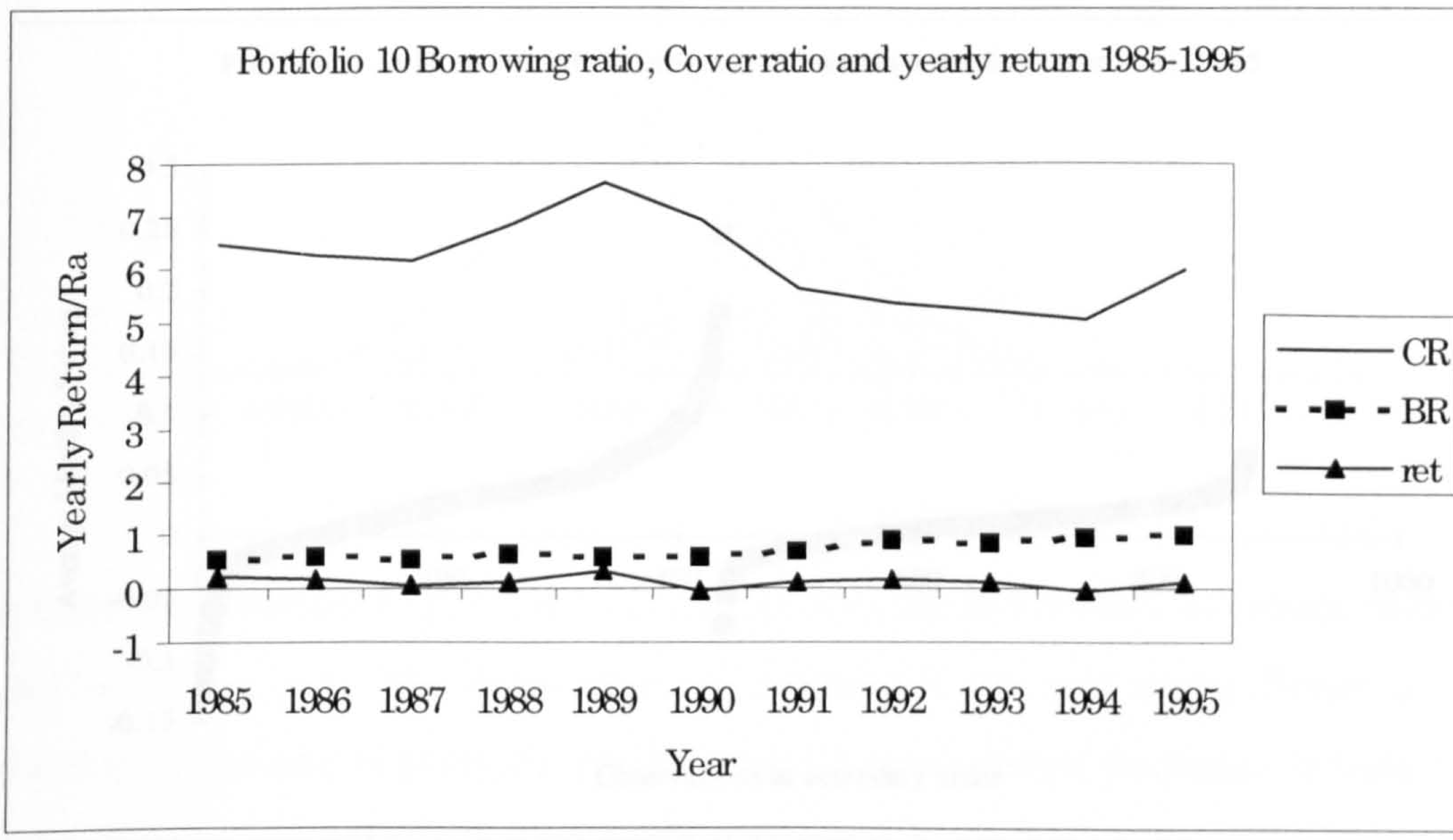
**Figure 5.5.**




As Figure 5.5 shows for Portfolio 1, there is no clear relationship between the Cover ratio and the return. The Cover ratio, however, has a dual meaning. On the one hand, the higher the CR, the higher companies' profits are and *vice versa*. On the other hand, the cover ratio depends on the cost of borrowing, i.e., the higher these costs are, the lower the CR. The cost of borrowing, in general, is affected by the movement of the interest rate, and for the period 1985-1995 there is one distinctive period of high interest rates (1989, 1990) and one of low interest rates (1993, 1994). Although portfolio 1 maintains a higher than average CR, and slightly reduces the borrowing ratio, returns for 1989 and 1990 plummet. The opposite action takes place in 1993, when the CR falls to its lowest level (bear in mind this is end-of 1992 CR), BR is unchanged and the return marks its peak for the period.

In short, the interaction between the CR, the BR and the return of portfolio 1 does not seem to yield conclusive results. More insight is provided by a comparison of the behaviour of the same variables for portfolio 1 and portfolio 10. Figure 5.6 for portfolio 10 differs significantly from Figure 5.5 for portfolio 1. Firstly, the CR is maintained at a much higher level and is less volatile. Secondly, changes in the interest rate do not seem to affect portfolio 10's return. In addition, portfolio 10's CR and return have a more established relationship, which is also less affected by outside factors as is the case with portfolio 1.

**Figure 5.6.**

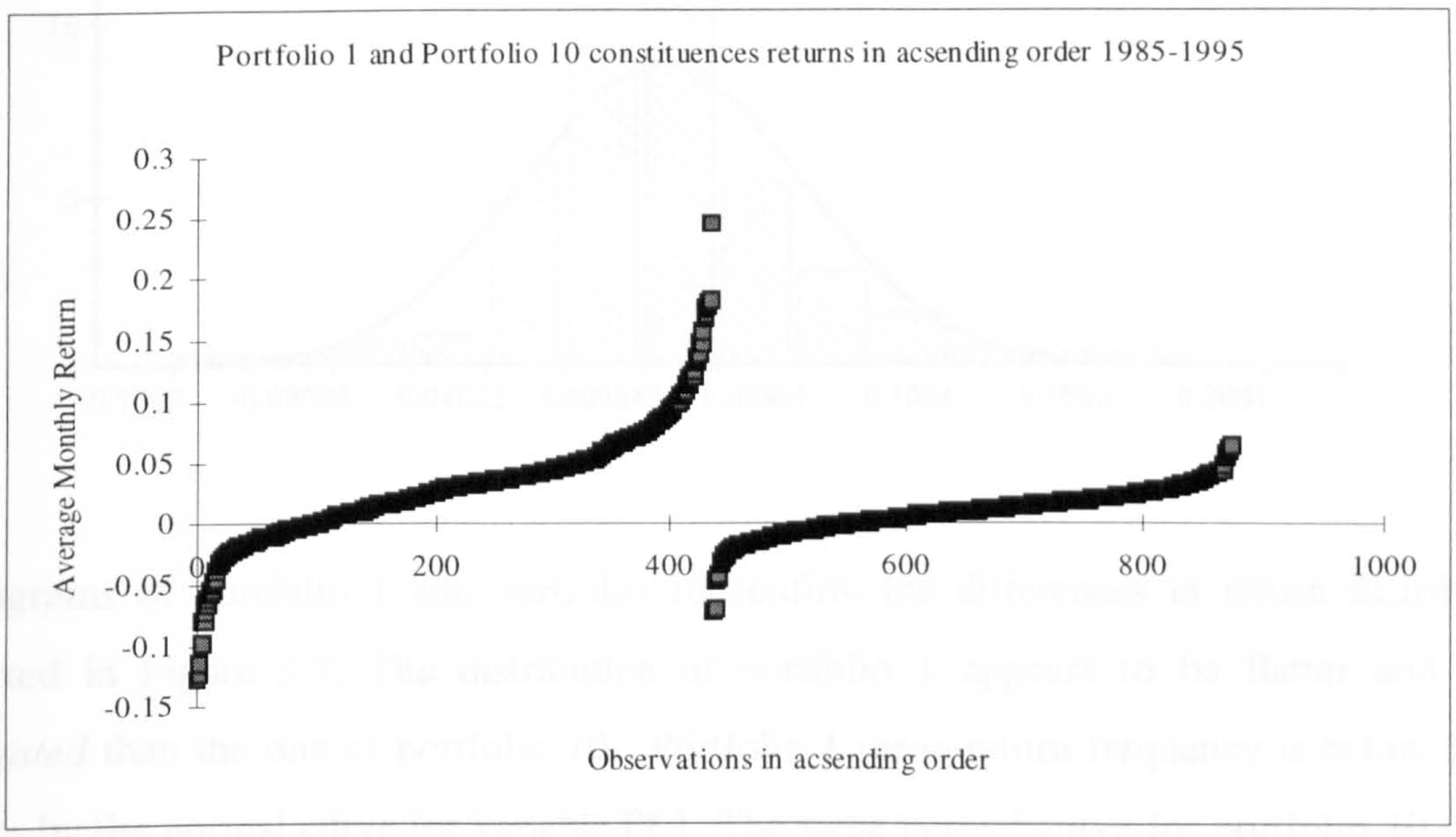



Thus, the conclusion from this section is that stock returns of the small firms are influenced more by factors other than their borrowing ratios and cover ratios than large firms.

## 5.6 Portfolio 1 and Portfolio 10 Return Distribution by Constituencies

Another question, the answer to which may contribute to disentangling the size puzzle, is the return distribution of the firms participating in the size portfolios. To analyse this issue, the two extreme portfolios are again examined. The return of every firm participating in portfolio 1 and portfolio 10 is estimated for each year of the period 1985-1995. Then, returns of the firms in portfolio 1 and portfolio 10 are sorted in ascending order and plotted in Figure 5.7, on the left hand side for portfolio 1 and on the right hand side for portfolio 10. The result of 435 observations for each portfolio is astonishing. The returns of the individual firms in portfolio 10 seem to keep together, leaving a very narrow margin between the best and worst performing firms of 0.136, compared with 0.374 for the portfolio 1.

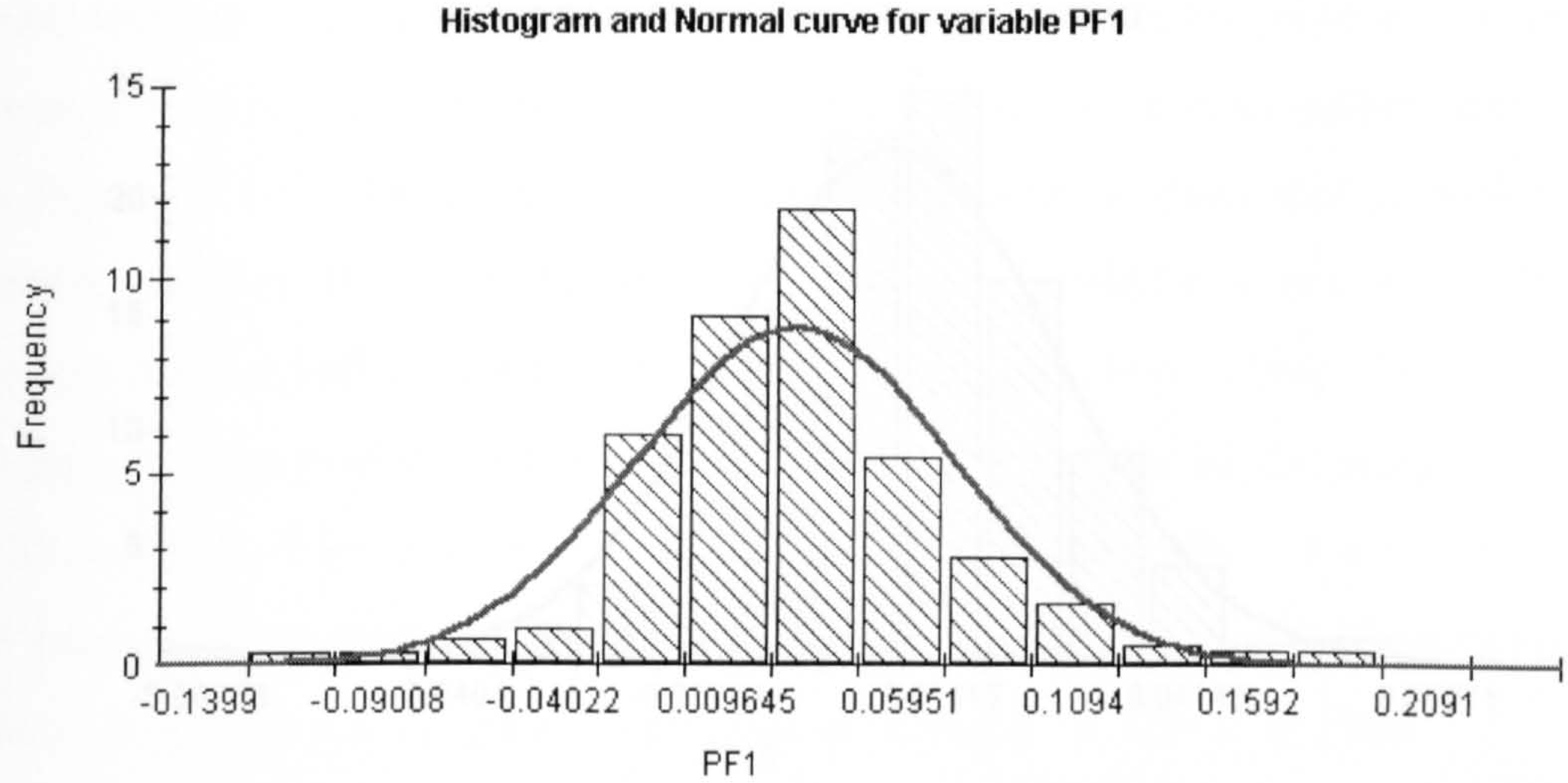
**Figure 5.7.**




Certainly, the difference between the minimum and maximum observations is a rough measure of the return dispersion in portfolio 1 and portfolio 10. In this respect, Figure 5.7 appears to be useful, as it reveals different patterns of return distributions for the two portfolios. Portfolio 1's return distribution resembles a vertically flipped letter 'S', whereas portfolio 10's resembles a flat-forward dash with a little tag at each end.

To examine the return distributions further, Figure 5.8 and Figure 5.9 provide histograms and normal curves for these portfolios.

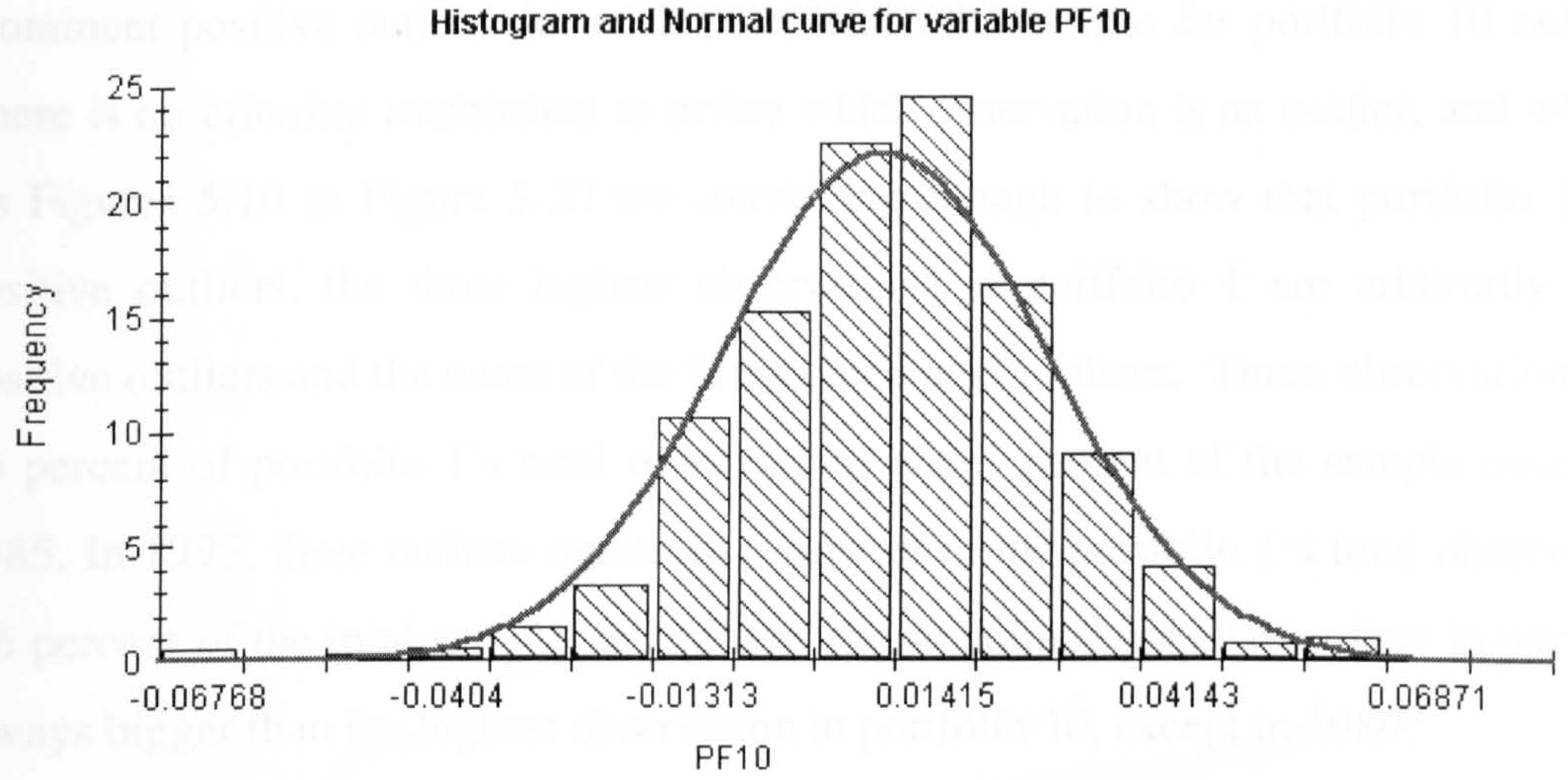
**Figure 5.8.**




Histograms of portfolio 1 and portfolio 10 confirm the differences in return distribution detected in Figure 5.7. The distribution of portfolio 1 appears to be flatter and more *elongated* than the one of portfolio 10. Portfolio 1 mean return frequency is below 10, as shown by the normal curve for variable Pf 1. The same normal curve for portfolio 10 shows a mean frequency of over 20. Not surprisingly, Portfolio 1's Standard Deviation is 0.046, whereas it is 0.018 for Portfolio 10.

The differences between the return distribution of a portfolio consisting of small firms and the return distribution of a portfolio consisting of large firms may have far reaching implications for return forecasting and portfolio investment strategies. These issues, however, are not pursued here.

**Figure 5.9.**




The objective is to continue with the inspection of the return distribution of portfolio 1 and portfolio 10 on a yearly basis. The idea is to see whether or not the exceptionally high returns of portfolio 1 are due to just a few outliers and how this relates to the particularly good returns of portfolio 1 in 1985, 1986, 1987, 1991, 1993 and 1994.

Knez and Ready (1997) argue that Fama and MacBeths' (1973) least squares (LS) objective function is sensitive to outliers in both the *y*-direction (outliers in the errors) and the *x*-direction (leverage points). Therefore, they propose a 'robust regression technique' called least trimmed squares (LTS) that trims a proportion of the influential observations and then fits the remaining observations using LS. After applying the LTS, Knez and Ready find that the size effect either disappears or becomes positive even by discarding less than 1 percent of each month's data.

While the application of LTS confronts the standard statistic and econometric cornerstone 'the more observations, the better', an inspection of the plots of portfolio 1 and portfolio 10 constituents' yearly returns does indeed contribute to the size anomaly explanation.

Figures 5.10 to Figure 5.20 plot the portfolio 1 and portfolio 10 constituents' returns for each year from 1985 to 1995. The common feature of all plots is that portfolio 1 has quite prominent positive outliers for each year, whilst this is true for portfolio 10 only in 1989. There is no criterion established to define which observation is an outlier, and which is not. As Figures 5.10 to Figure 5.20 are convincing enough to show that portfolio 1 possesses positive outliers, the three highest observations in portfolio 1 are arbitrarily defined as positive outliers and the name of the firms typed next to them. Three observations represent 10 percent of portfolio 1's total observations and 1 percent of the sample observations in 1985. In 1995, three outliers represent 6 percent of the portfolio 1's total observations, and 0.6 percent of the total sample. In addition, the so defined positive outliers in portfolio 1 are always bigger than the highest observation in portfolio 10, except in 1989.

**Figure 5.10.**

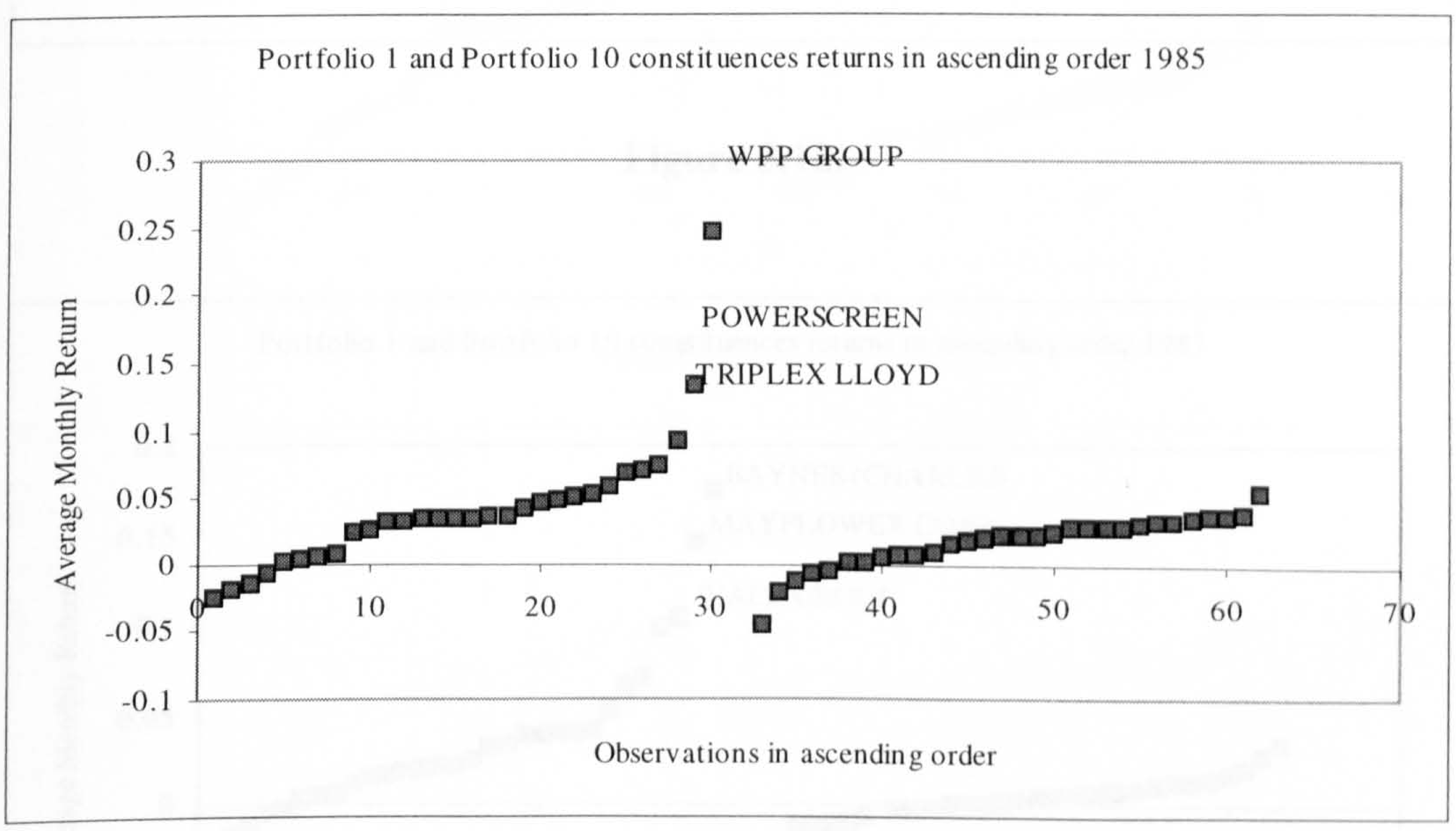


**Figure 5.11.**

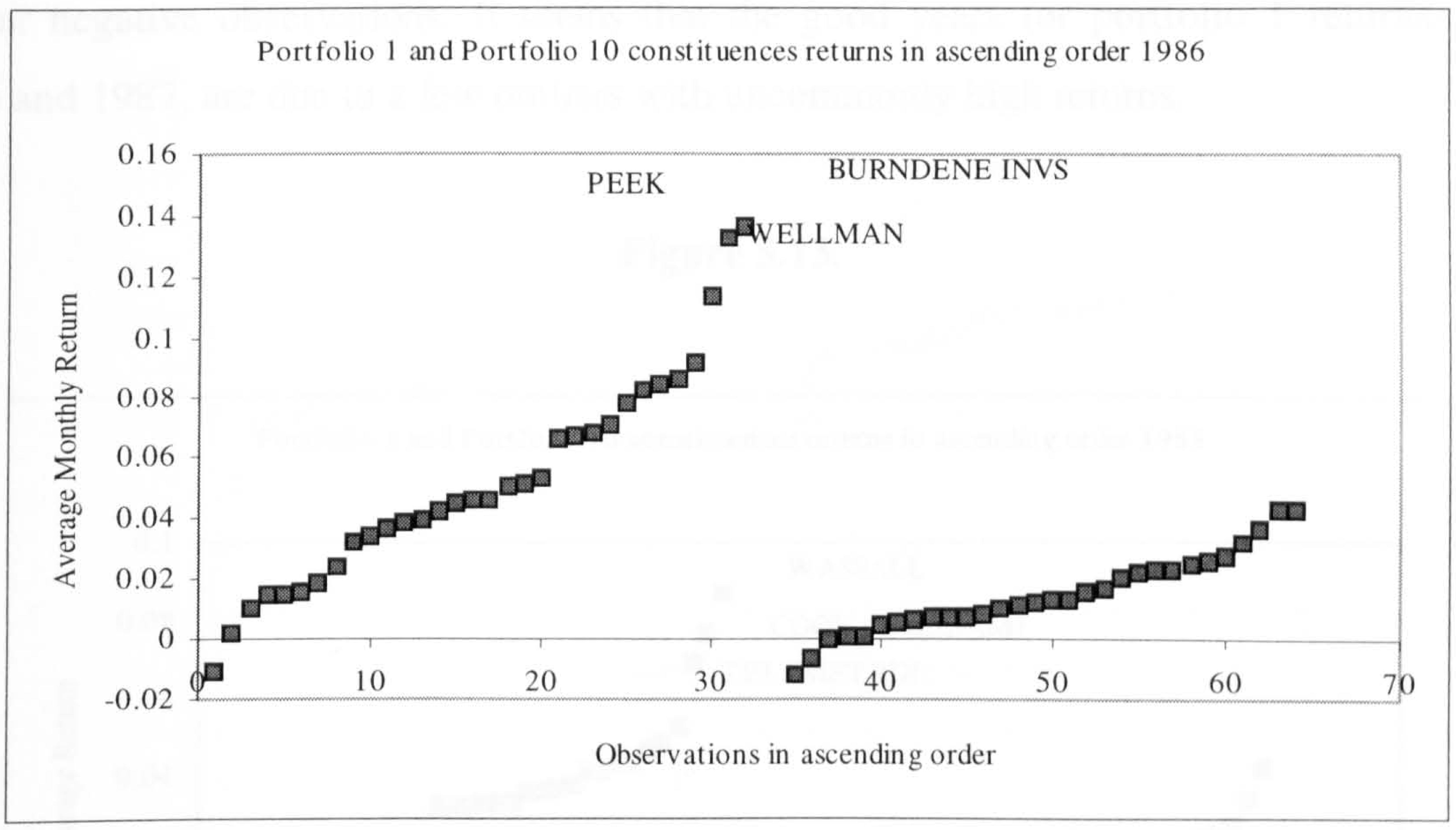
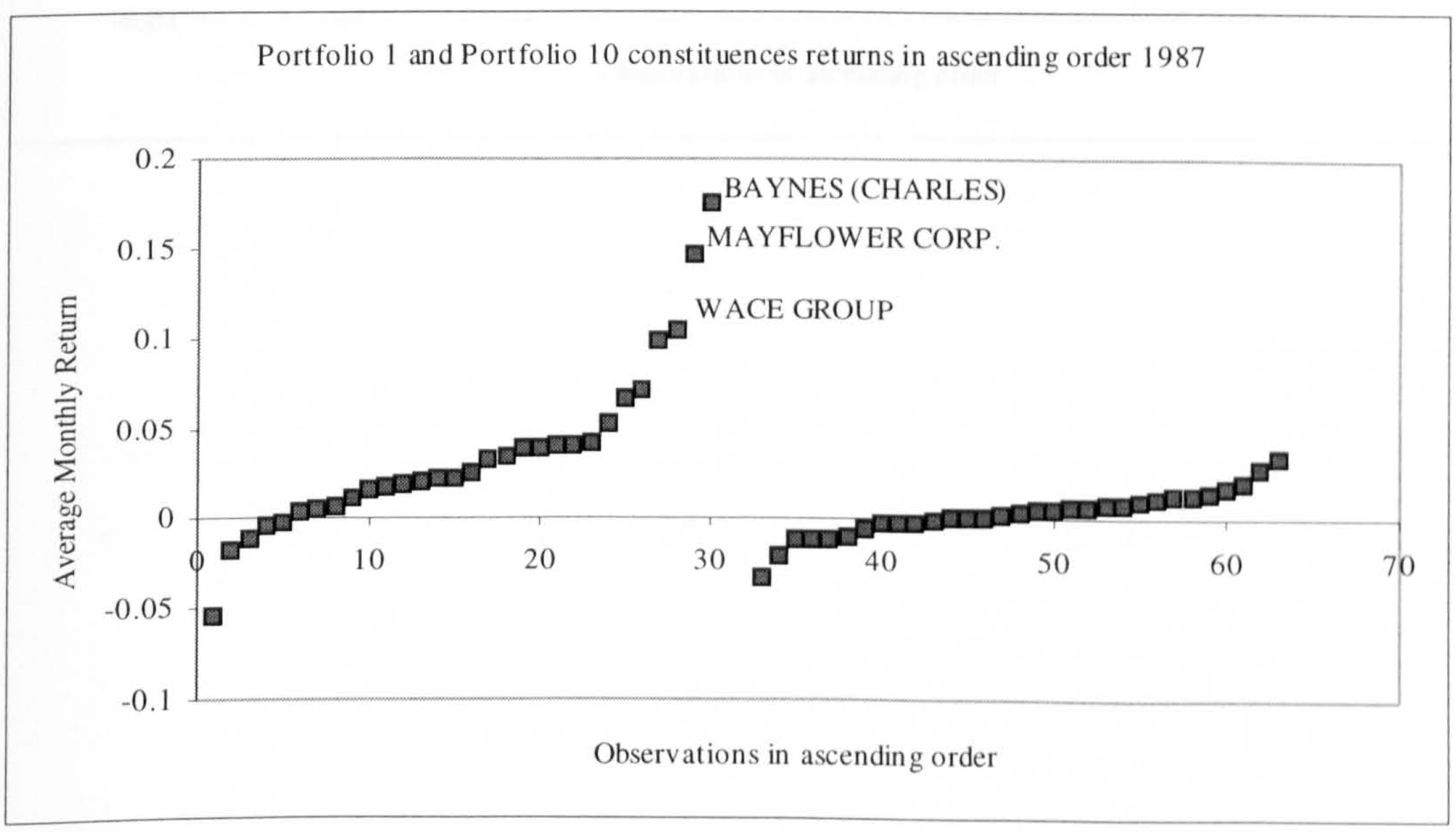



**Figure 5.12.**



For 1985, 1986, and 1987 the three highest observations in portfolio 1 produce extremely high returns, ranging between 10 and 25 percent a month, whilst portfolio 10's highest observations barely reach 5 percent. At the same time, portfolio 1 and portfolio 10 have very similar negative observations. It seems that the good years for portfolio 1 returns-1985, 1986 and 1987, are due to a few outliers with uncommonly high returns.

**Figure 5.13.**

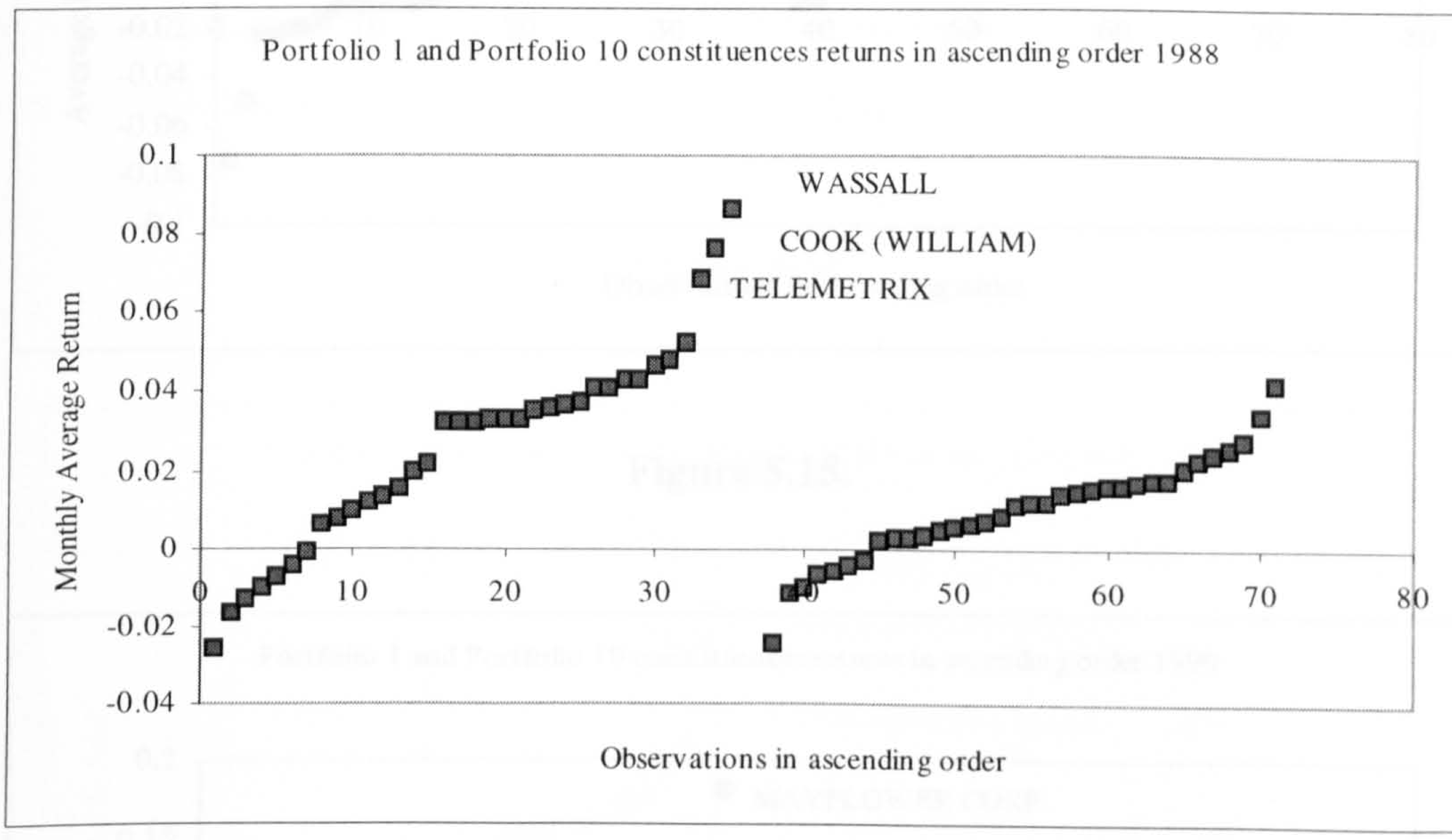


**Figure 5.14.**

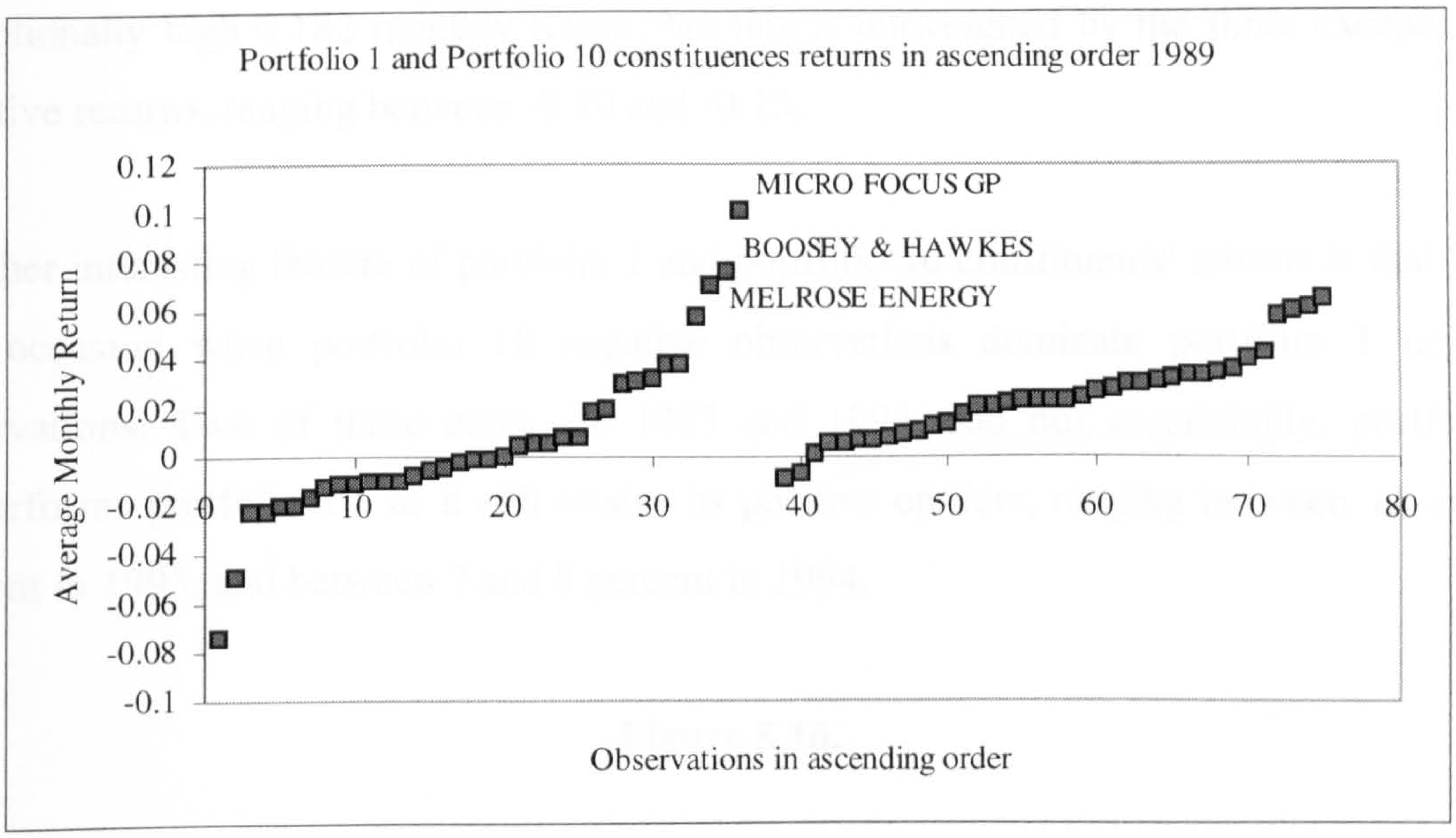
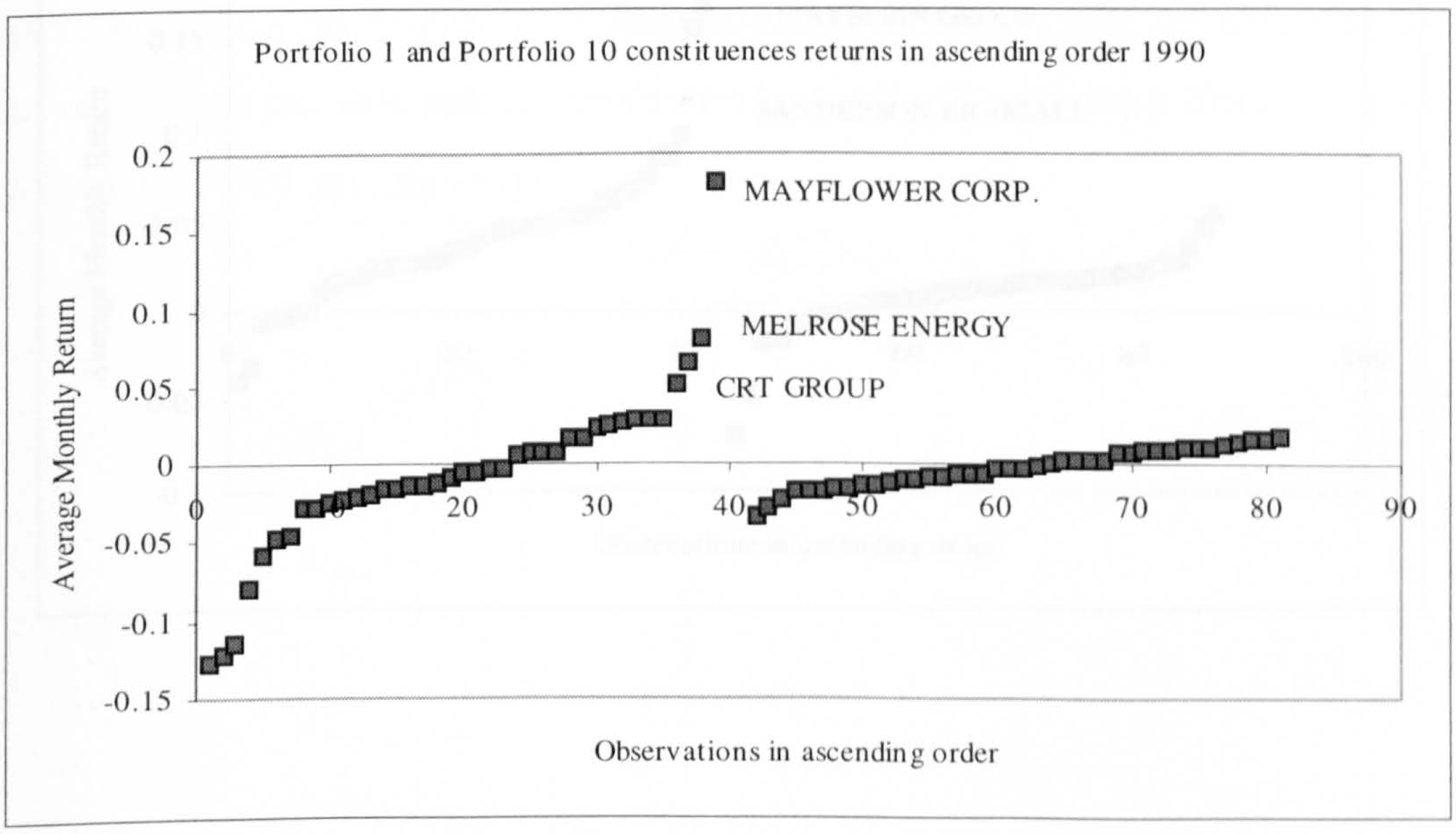



**Figure 5.15.**



The next three years, 1988, 1989 and 1990, witness much lower returns of portfolio 1 outliers, ranging between 6 and 10 percent. In 1990, though, *MAYFLOWER CORP.* has an exceptionally high 0.182 monthly return, but this is outweighed by the three exceptionally negative returns, ranging between -0.10 and -0.15.

Another interesting feature of portfolio 1 and portfolio 10 constituents' returns is that it is a rare occasion when portfolio 10 negative observations dominate portfolio 1 negative observations. Two of these cases are 1993 and 1994, and not surprisingly, portfolio 1 outperforms portfolio 10, as it still retains its positive outliers, ranging between 15 and 20 percent in 1993, and between 7 and 8 percent in 1994.

**Figure 5.16.**

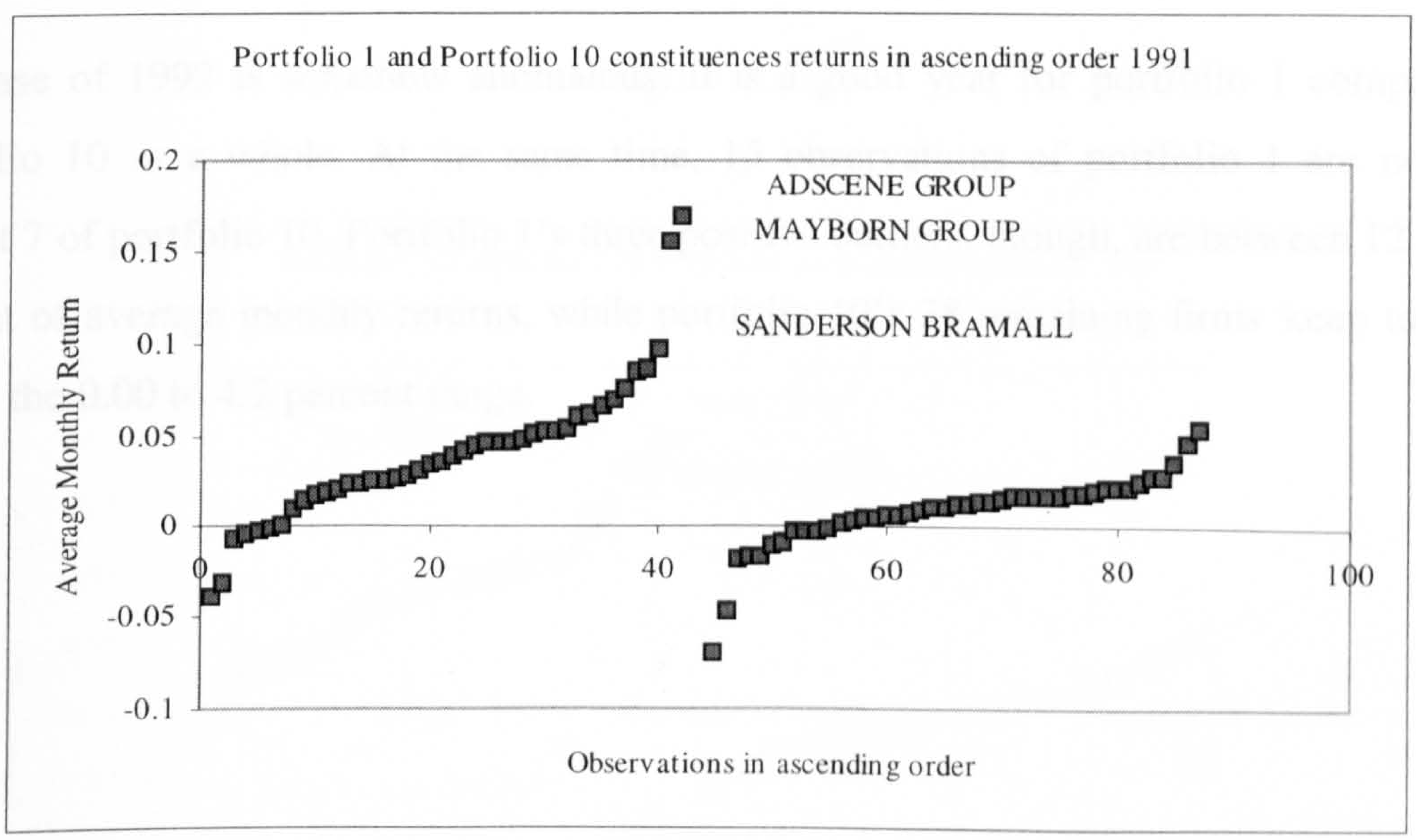
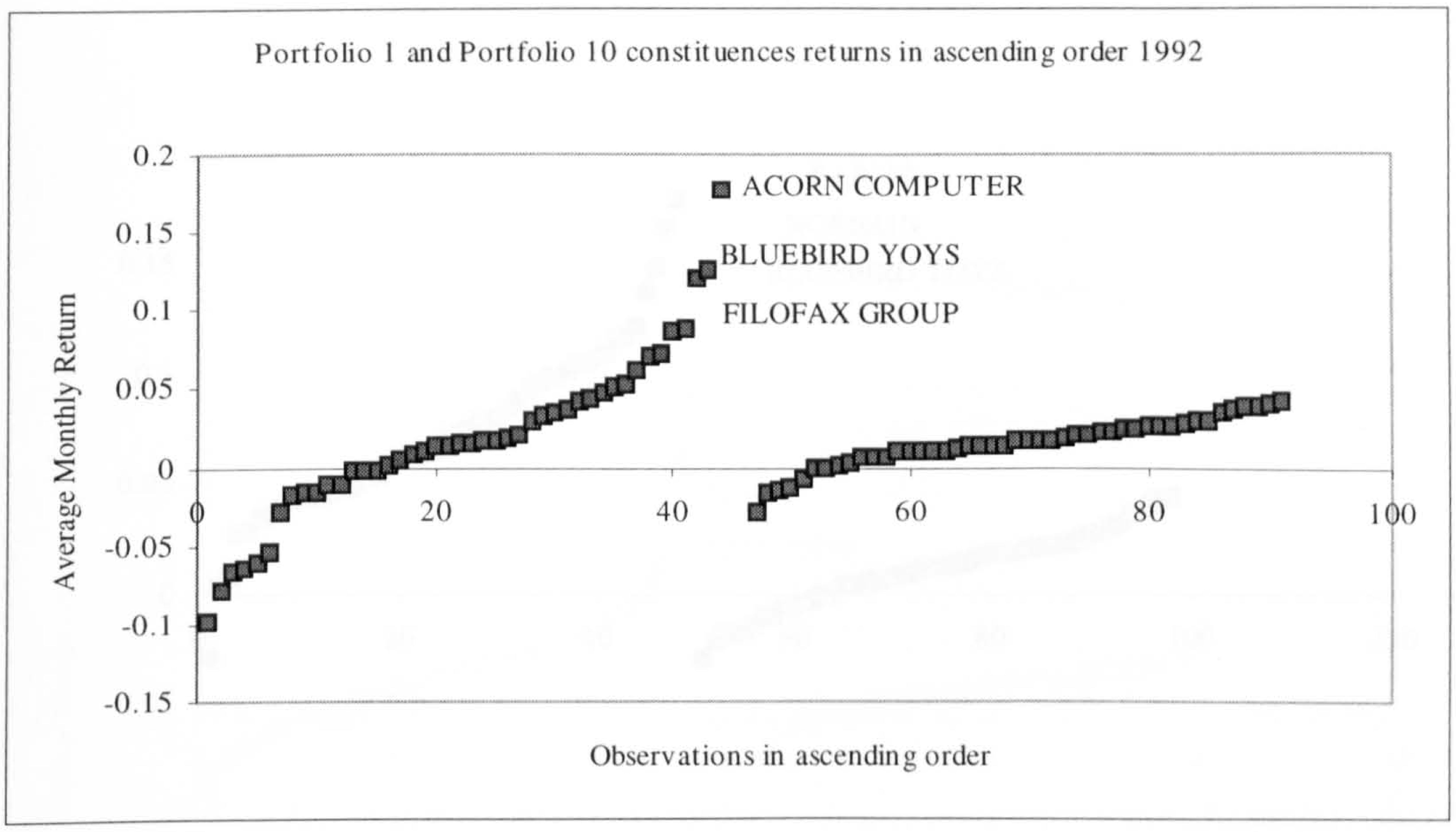


**Figure 5.17.**




The case of 1992 is somehow anomalous. It is a good year for portfolio 1 compared to portfolio 10 as a whole. At the same time, 15 observations of portfolio 1 are negative, against 7 of portfolio 10. Portfolio 1's three positive outliers, though, are between 12 and 18 percent of average monthly returns, while portfolio 10's 38 remaining firms 'keep together' within the 0.00 to 4.2 percent range.

**Figure 5.18.**

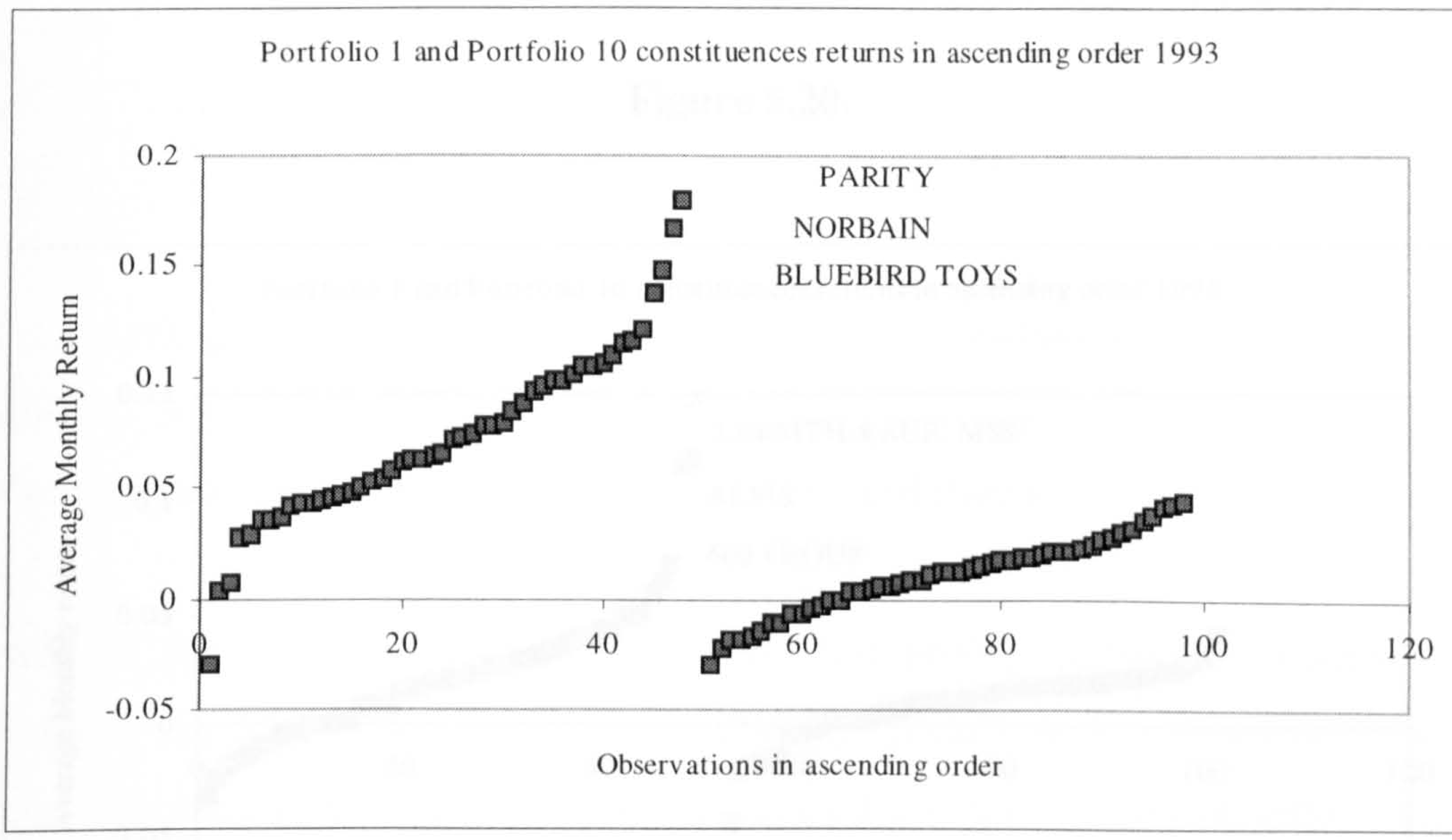
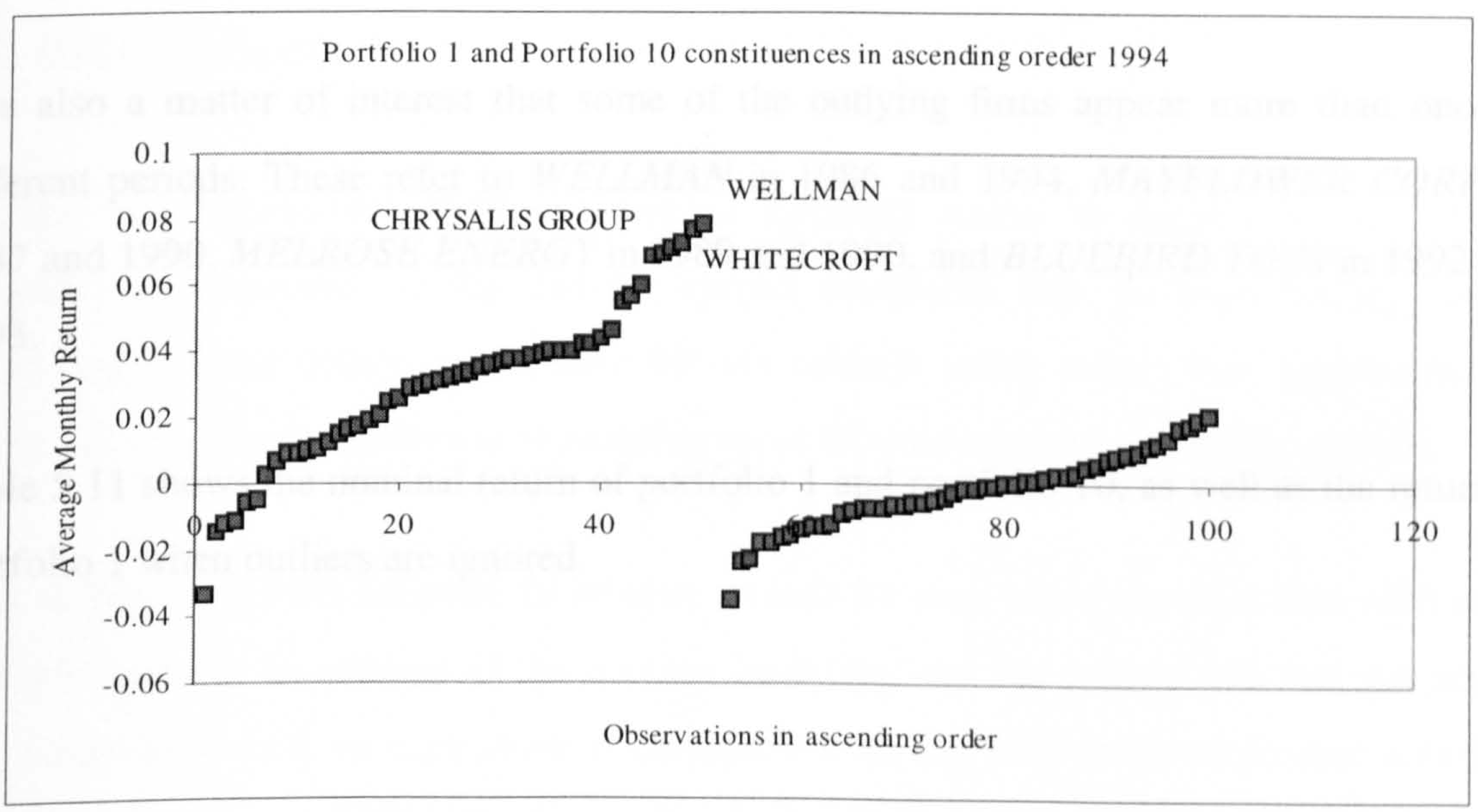
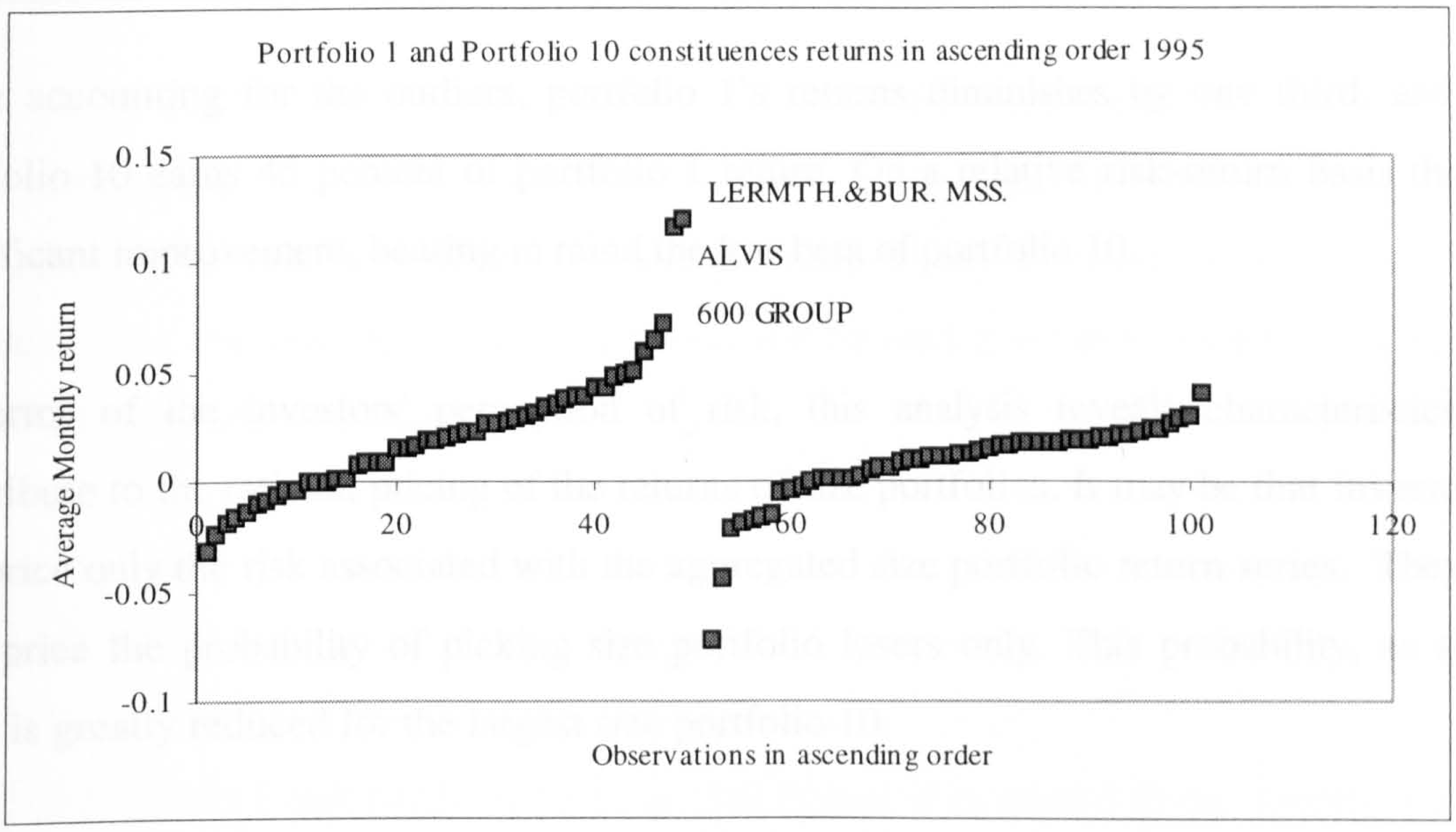



**Figure 5.19.**



Finally, 1995 is an unusual year for portfolio 10, as a couple of observations shoots away from the pack, sustaining significant negative returns.

**Figure 5.20.**




It is also a matter of interest that some of the outlying firms appear more than once in different periods. These refer to *WELLMAN* in 1986 and 1994, *MAYFLOWER CORP.* in 1987 and 1990, *MELROSE ENERGY* in 1989 and 1990, and *BLUEBIRD TOYS* in 1992 and 1993.

Table 5.11 shows the nominal return of portfolio 1 and portfolio 10, as well as the return of portfolio 1 when outliers are ignored.

**Table 5.11.**

| Year / Return | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 85-95 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| pf1 | 0.042 | 0.052 | 0.035 | 0.026 | 0.006 | -0.006 | 0.040 | 0.018 | 0.073 | 0.030 | 0.023 | 0.031 |
| pf1-outl. | 0.029 | 0.045 | 0.023 | 0.021 | 0.000 | -0.016 | 0.033 | 0.009 | 0.067 | 0.027 | 0.017 | 0.023 |
| pf10 | 0.016 | 0.015 | 0.003 | 0.010 | 0.024 | -0.003 | 0.009 | 0.015 | 0.010 | -0.002 | 0.008 | 0.010 |

After accounting for the outliers, portfolio 1's returns diminishes by one third, and now portfolio 10 earns 45 percent of portfolio 1 return. On a relative risk-return basis this is a significant improvement, bearing in mind the low beta of portfolio 10.

In terms of the investors' perception of risk, this analysis reveals characteristics that contribute to the rational pricing of the returns of size portfolios. It may be that investors do not price only the risk associated with the aggregated size portfolio return series. They may also price the probability of picking size portfolio losers only. This probability, as shown here, is greatly reduced for the largest size portfolio 10.

## 5.7. Bid-Ask Spread

Amihud and Mendelson (1989) suggest an illiquidity model to explain excess returns. Illiquidity is measured by the bid-ask spread integrated into an asset-pricing model. According to their theory, assets have bid-ask spreads which reflect their transaction (or illiquidity) costs and investors have heterogeneous liquidation plans or holding periods.

Stoll & Whaley (1983) estimate the relative spreads for each of the stocks within each of 10 size portfolios as an average of the average beginning and end-of-year bid and ask prices. The commission rate on each stock is computed from the minimum commission schedule. Subsequently, they estimate the mean abnormal returns on the lowest total market value portfolio for various investment horizons, before and after transaction costs.

It is found, that after accounting for transaction costs, small firm abnormal returns are dramatically reduced, as the transaction costs for small capitalisation assets are 2-3 times higher than big capitalisation assets[5]. The small capitalisation assets still earn excess returns, but only for investment horizons greater than 4 months. For investment horizons less than 4 months small firm excess returns are negative.

In a manner similar to Stoll and Whaley, the relative Bid-Ask spread is estimated for all firms participating in portfolio 1 and portfolio 10 from November 1986 to December 1995.[6] Bid and ask prices for both portfolio 1 and portfolio 10 are not available for 17 out of the 110 months of observations[7]. For every month and for each asset in portfolio 1 and portfolio 10, the Bid-Ask spread is estimated as

$$B/A = \frac{P_a - P_b}{(P_a + P_b)/2}$$

and then portfolio 1 and portfolio 10's Bid-Ask spread is estimated as the equally-weighted average Bid-Ask spread of individual assets. For the months where Bid-Ask prices are not available, Bid-Ask spread is estimated as an average of neighbouring months. Resulting Bid-Ask spread series are plotted in Figure 5.21

[5] See Stoll & Whaley, (1983), Table 5, p.72.
[6] Bid and Ask prices are not available on *DATASTREAM* prior to November 1986.
[7] These are Jan-87, Jan-88, Apr-88, May-88, Jan-89, May-89, Jan-90, Jan-91, Apr-91, Jan-92, Jan-93, May-93, Jan-94, Apr-94, May-94, Aug-94, Jan-95.

**Figure 5.21.**

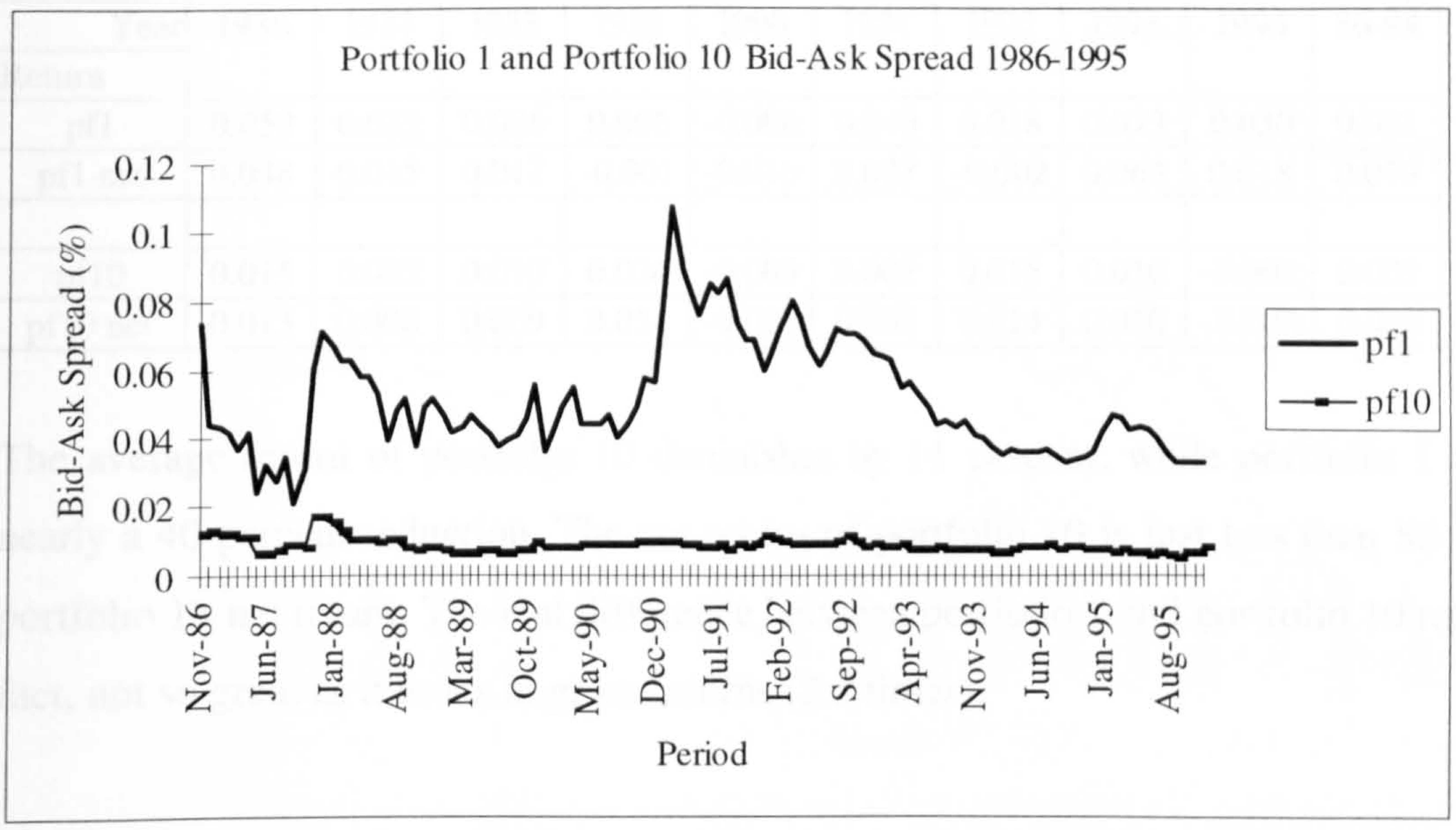



Figure 5.21 provides unequivocal evidence of a great disparity between the percentage Bid-Ask spread, *ergo,* the cost of transacting within the smallest and largest decile firms. The average cost of transacting is 0.051 for portfolio 1 and 0.0086 for portfolio 10. Another interesting feature is the stability of the Bid-Ask spread of portfolio 10 over time. The spread of portfolio 10 peaks at October-December 1987, the time of the big-bang. The spread of portfolio 1 reaches its peak in 1990, during the time of high interest rates.

Table 5.12 shows the gross return of portfolio 1 and portfolio 10, as well as the net return, after accounting for the Bid-Ask spread. The average percentage Bid-Ask spread cost per portfolio is estimated as the number of firms that leave (sold) and enter (bought) portfolio 1 (10) multiplied by portfolios' 1 (10) average Bid-Ask spread in the month of December, for the relevant years between 1986-1994.

**Table 5.12.**

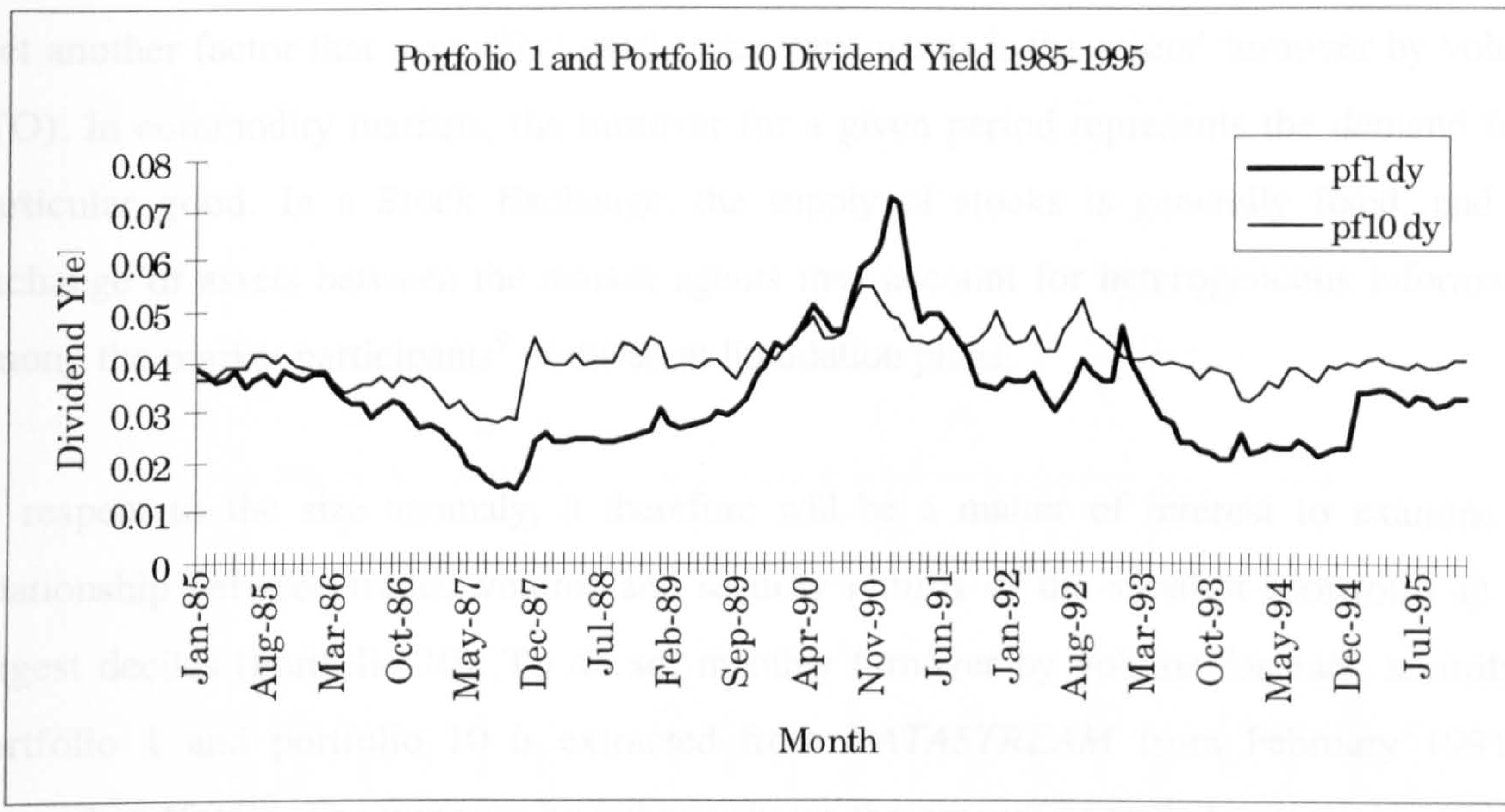
| Year / Return | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 86-94 |
|---|---|---|---|---|---|---|---|---|---|---|
| pf1 | 0.052 | 0.035 | 0.026 | 0.006 | -0.006 | 0.040 | 0.018 | 0.073 | 0.030 | 0.031 |
| pf1 net | 0.048 | 0.015 | 0.017 | -0.001 | -0.016 | 0.027 | -0.002 | 0.063 | 0.018 | 0.019 |
| | | | | | | | | | | |
| pf10 | 0.015 | 0.003 | 0.010 | 0.024 | -0.003 | 0.009 | 0.015 | 0.010 | -0.002 | 0.009 |
| pf10 net | 0.013 | 0.000 | 0.009 | 0.024 | -0.004 | 0.008 | 0.014 | 0.010 | -0.003 | 0.008 |

The average return of portfolio 10 diminishes by 11 percent, while portfolio 1 undergoes nearly a 40 percent reduction. The net return of portfolio 10 is just less than 50 percent of portfolio 1's net return. The real difference between portfolio 1 and portfolio 10 returns is, in fact, not so great as it looks in gross returns (3.5 times).

## 5.8. Dividend Adjusted Returns

In chapter 4, where the investigation on the size effect is carried out, it is assumed that dividends are fully incorporated into security prices. To discard any doubt that dividend payments do not play a significant role in return differences across size portfolios, Figure 5.22 displays the dividend yield (DY) for portfolio 1 and 10 from 1985 to 1995. It is apparent that portfolio 10 maintains a slightly higher DY throughout the period.

**Figure 5.22.**




The only period when the DY of portfolio 1 is higher than the DY of portfolio 10 is in 1991, when the prices of portfolio 1 were depressed most[8]. Also, the DY of portfolio 10 looks more stable, compared to the DY of portfolio 1.

On a whole, the DY of portfolio 1 is 0.033 and 0.040 for portfolio 10 - a difference of 0.007. This difference is obviously too small to justify the significant gap between the returns of portfolio 1 and portfolio 10, even when adjusted for risk. In addition the dividend yield (DY) is an indicator that relates last year's dividend to this year's price and thus is greatly affected by the current prices. As portfolio 1 performs better in the year following the formation year, whereas portfolio 10 does the opposite, even the above difference of DYs may be superficial.

[8]The interesting feature in Figure 5.22 is that the DY series of portfolio 1 resembles very much the 3-Month Treasury Bill Monthly Rate, pictured further in Figure 7.2.

## 5.9. Sales Turnover and Portfolios' Return

Yet another factor that may affect stock price movements is the assets' turnover by volume (TO). In commodity markets, the turnover for a given period represents the demand for a particular good. In a Stock Exchange, the supply of stocks is generally fixed, and the exchange of assets between the market agents may account for heterogeneous information among the market participants[9] or different liquidation plans.

In respect to the size anomaly, it therefore will be a matter of interest to examine the relationship between traded volume and security returns of the smallest (portfolio 1) and largest deciles (portfolio 10). To do so, monthly turnover by volume for each security in portfolio 1 and portfolio 10 is extracted from *DATASTREAM* from February 1991 to December 1995[10]. The turnover by volume shows the amount of traded volume in an asset, excluding the trade between the market-makers.

The turnover by volume of a portfolio is assessed as a sum of the turnover of each member-asset, for each month from February 1991 to December 1995. Portfolio 1 and portfolio 10s' average monthly trading volume is estimated for every year, and each month volume is divided by the average for the year, thus yielding the Coefficient of Trading Volume (CTV). CTV is above 1.00 for the months with trading volume above the average for the year, and below 1.00 *vice versa.*

The returns are normalised such that the sum of the normalised returns equals the sum of the CTVs for the period February 1991 to December 1995. Figures 5.23 and 5.24 plot normalised returns and CTVs for both portfolio 1 and portfolio 10 respectively.

[9] In this case the CAPM's assumption that all market agents possess homogeneous information will be violated.
[10] For the smallest size portfolio 1 turnover by volume is not available before February 1991.

**Figure 5.23.**

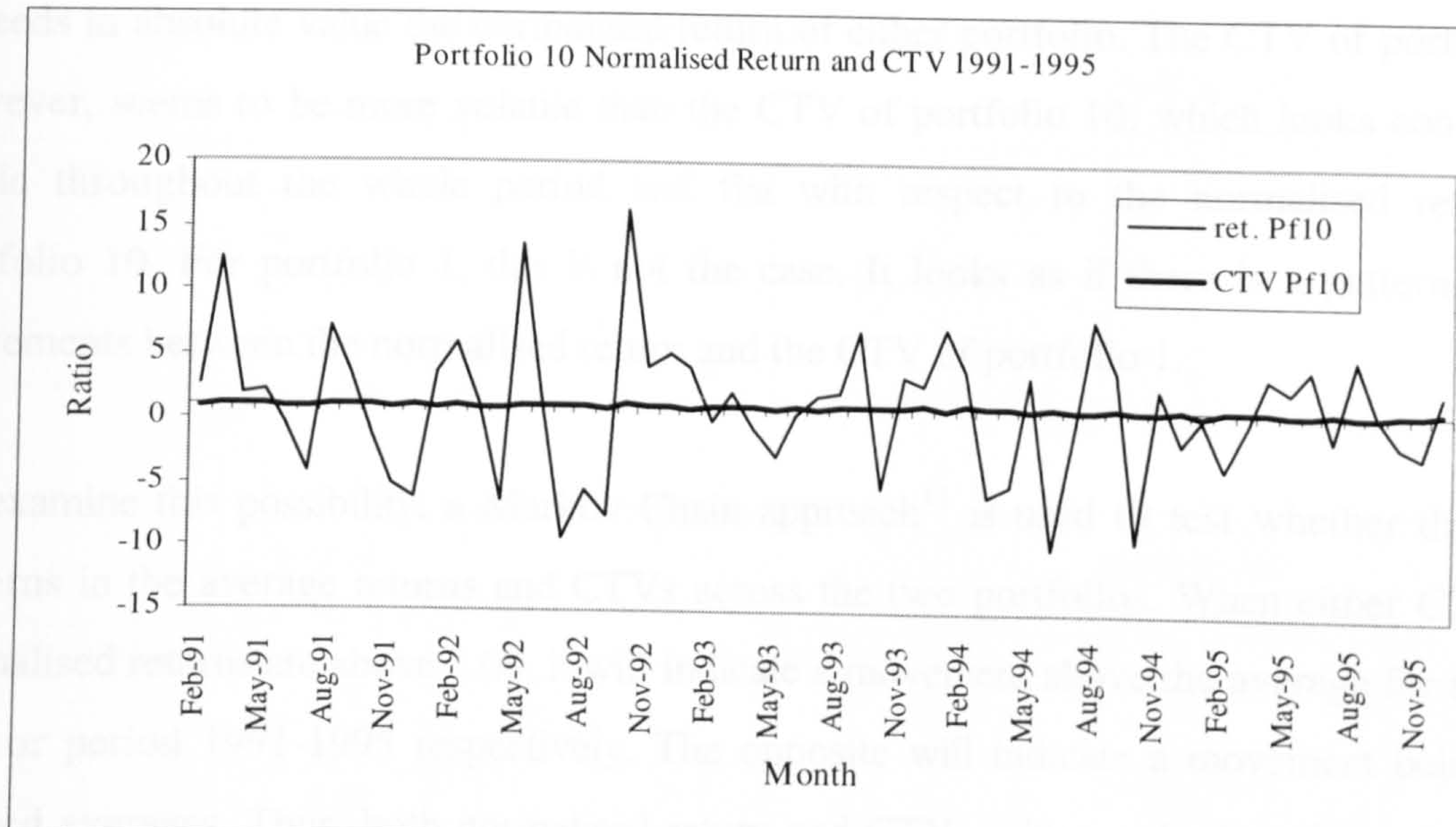
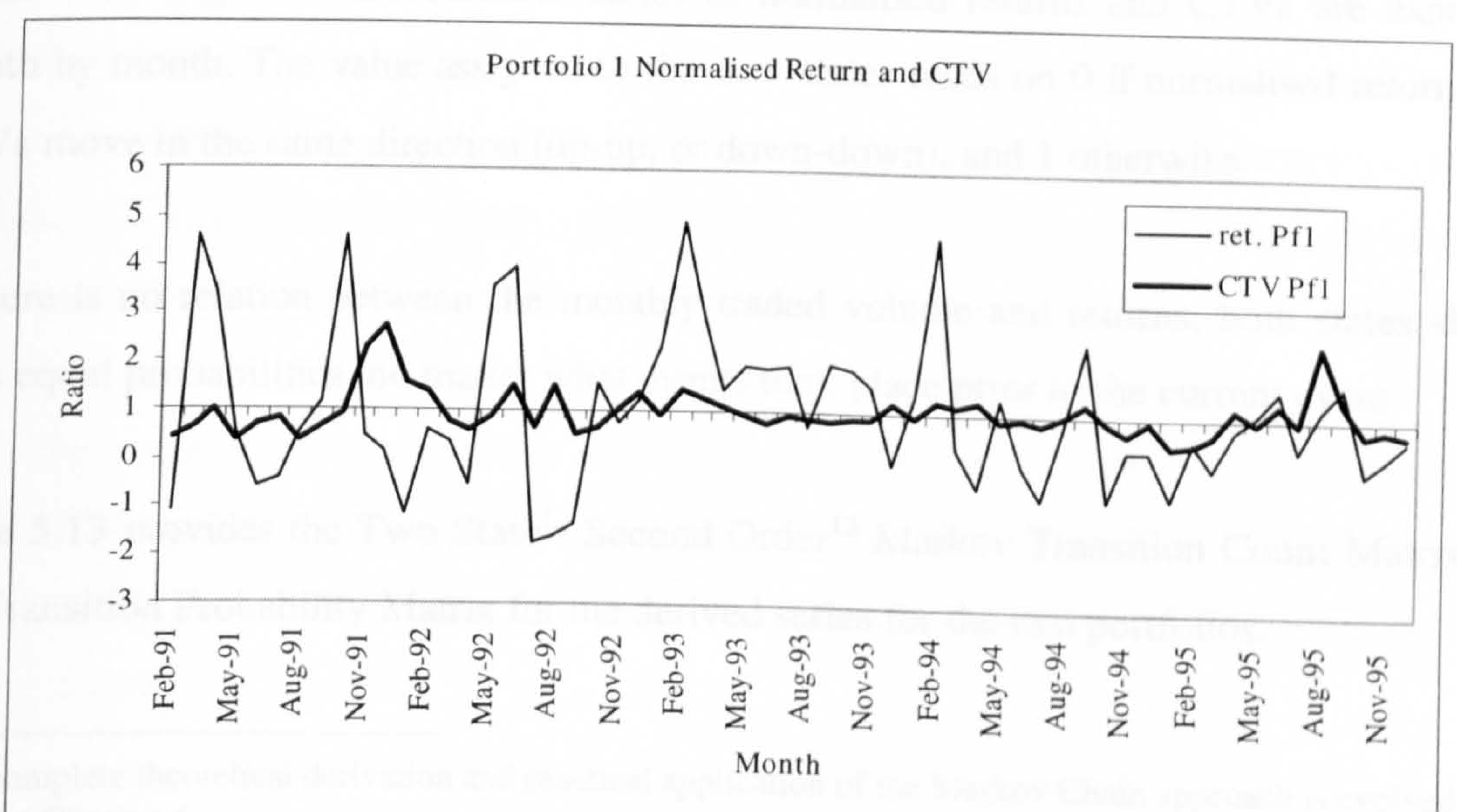



**Figure 5.24.**



Both Figures 5.23 and 5.24 show that return series of portfolio 1 and portfolio 10 are more volatile than trading volume. Both the normalised returns and the CTVs for portfolio 1 and portfolio 10 sum to 1 for the period 1991-1995. There is not a single case where the CTV exceeds in absolute value the normalised return of either portfolio. The CTV of portfolio 1, however, seems to be more volatile than the CTV of portfolio 10, which looks completely stable throughout the whole period and flat with respect to the normalised return of portfolio 10. For portfolio 1, this is not the case. It looks as if there is a pattern of co-movements between the normalised return and the CTV of portfolio 1.

To examine this possibility, a Markov Chain approach[11] is used to test whether there are patterns in the average returns and CTVs across the two portfolios. When either CTVs or normalised returns are above 1.00, it will indicate a movement above the average for a given year or period 1991-1995 respectively. The opposite will indicate a movement below the defined averages. Thus, both normalised return and CTV series are broken down into two states-up and down.

In the next stage, the dichotomous series of normalised returns and CTVs are examined month by month. The value assigned to the new series takes on 0 if normalised returns and CTVs move in the same direction (up-up, or down-down), and 1 otherwise.

If there is no relation between the monthly traded volume and returns, both states should have equal probabilities, no matter what events took place prior to the current event.

Table 5.13 provides the Two State[12] Second Order[13] Markov Transition Count Matrix and the Transition Probability Matrix for the derived series for the two portfolios.

[11] A complete theoretical derivation and practical application of the Markov Chain approach is evolved in the next Chapter 6.

[12] Here the state 0 represents movements in same direction, the state 1 represents movements in different direction.

[13] It exausts all possible combinations between the states for two periods $T_{n-2,}T_{n-1}$ before the current event $T_n$, i.e., 00, 01, 10, 11.

**Table 5.13.**

Transition Counts Matrix

Portfolio 1

| Previous states | | Current event 0 | Current event 1 |
|---|---|---|---|
| 0 | 0 | 14 | 6 |
| 0 | 1 | 5 | 6 |
| 1 | 0 | 7 | 4 |
| 1 | 1 | 6 | 9 |
| | Sum | 32 | 25 |

Portfolio 10

| Previous states | | Current event 0 | Current event 1 |
|---|---|---|---|
| 0 | 0 | 7 | 8 |
| 0 | 1 | 6 | 8 |
| 1 | 0 | 8 | 6 |
| 1 | 1 | 8 | 6 |
| | Sum | 29 | 28 |

Transition Probability Matrix

Portfolio 1

| Previous states | | Current event 0 | Current event 1 |
|---|---|---|---|
| 0 | 0 | 0.70 | 0.30 |
| 0 | 1 | 0.45 | 0.55 |
| 1 | 0 | 0.64 | 0.36 |
| 1 | 1 | 0.40 | 0.60 |

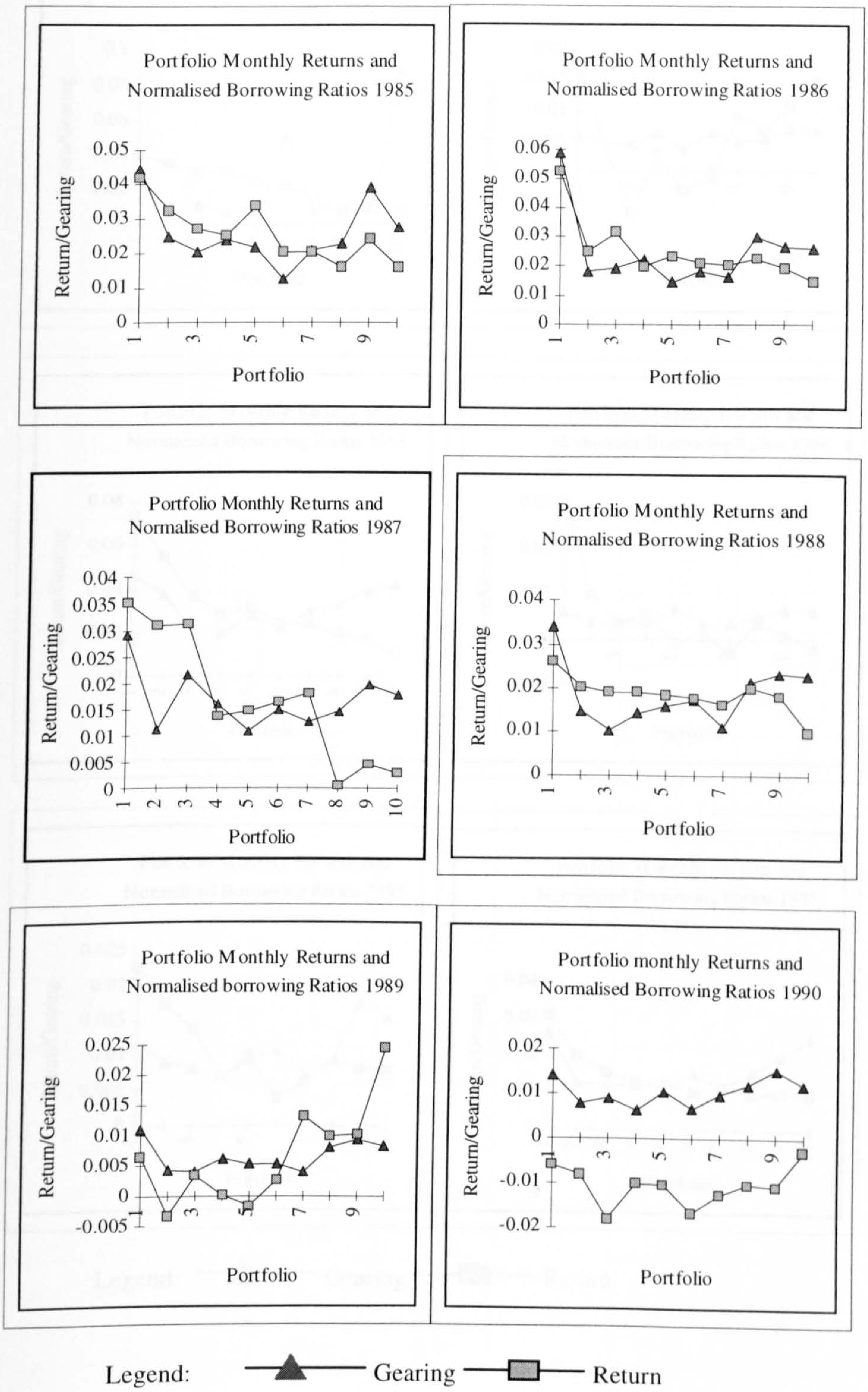
Portfolio 10

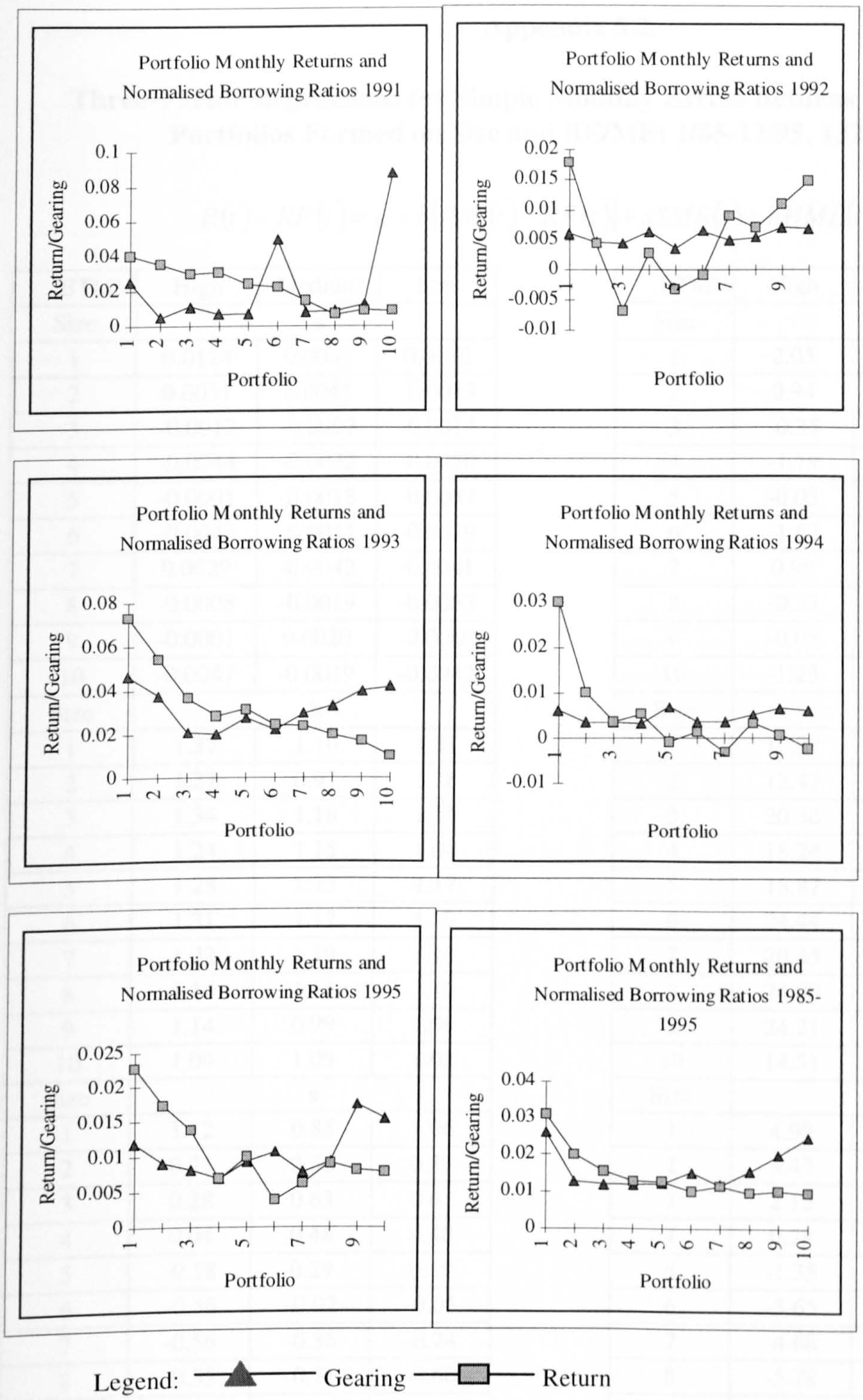
| Previous states | | Current event 0 | Current event 1 |
|---|---|---|---|
| 0 | 0 | 0.47 | 0.53 |
| 0 | 1 | 0.43 | 0.57 |
| 1 | 0 | 0.57 | 0.43 |
| 1 | 1 | 0.57 | 0.43 |

As Table 5.13 shows, the probability of the occurrence of current events 0 and 1 are almost equal at portfolio 10, no matter what the previous state was. This is not the case with portfolio 1, where the probability of a current state 0 following previous state 00 is 0.70. Thus, if the CTV and the normalised return move in the same direction for two consecutive periods, it is more likely for them to do so in the third period. Equally, if they did not move in the same direction for two consecutive periods it is less likely to do so in the third period.

The observed relationship between the volume of trade and returns for portfolio 1 and portfolio 10 implies certain inefficiency in the price dynamics of portfolio 1. Security prices should reflect the intrinsic value of assets, rather than being affected, or themselves affect trading activity.

# Appendix 5.1.


Portfolio Monthly Returns and Normalised Borrowing Ratios 1985
Portfolio Monthly Returns and Normalised Borrowing Ratios 1986
Portfolio Monthly Returns and Normalised Borrowing Ratios 1987
Portfolio Monthly Returns and Normalised Borrowing Ratios 1988
Portfolio Monthly Returns and Normalised borrowing Ratios 1989
Portfolio monthly Returns and Normalised Borrowing Ratios 1990
Return/Gearing
Portfolio
Legend: Gearing Return



Portfolio Monthly Returns and Normalised Borrowing Ratios 1991
Portfolio Monthly Returns and Normalised Borrowing Ratios 1992
Portfolio Monthly Returns and Normalised Borrowing Ratios 1993
Portfolio Monthly Returns and Normalised Borrowing Ratios 1994
Portfolio Monthly Returns and Normalised Borrowing Ratios 1995
Portfolio Monthly Returns and Normalised Borrowing Ratios 1985-1995
Return/Gearing
Portfolio
Legend: Gearing Return

## Appendix 5.2.

### Three-Factor Regressions for Simple Monthly Excess Returns on 30 High Beta Portfolios Formed on Size and BE/ME: 1/85-12/95, 132 Months

$$R(t)-RF(t)=a+b[RM(t)-RF(t)]+sSMB(t)+hHML(t)+e(t)$$

| BTMV | High | Medium | Low |
|---|---|---|---|
| Size | | a | |
| 1 | 0.0124 | 0.0062 | 0.0132 |
| 2 | 0.0051 | 0.0045 | -0.0013 |
| 3 | -0.0012 | -0.0007 | -0.0014 |
| 4 | -0.0044 | -0.0032 | -0.0050 |
| 5 | -0.0001 | -0.0018 | -0.0057 |
| 6 | -0.0043 | -0.0041 | -0.0079 |
| 7 | 0.0029 | -0.0042 | -0.0041 |
| 8 | -0.0008 | -0.0019 | -0.0053 |
| 9 | -0.0001 | 0.0020 | -0.0060 |
| 10 | -0.0047 | -0.0019 | -0.0042 |
| Size | | b | |
| 1 | 1.37 | 1.10 | 1.51 |
| 2 | 1.27 | 0.97 | 1.18 |
| 3 | 1.34 | 1.18 | 1.15 |
| 4 | 1.24 | 1.15 | 1.04 |
| 5 | 1.28 | 1.13 | 1.17 |
| 6 | 1.21 | 1.17 | 1.19 |
| 7 | 1.22 | 1.19 | 1.16 |
| 8 | 1.14 | 1.11 | 1.10 |
| 9 | 1.14 | 0.99 | 1.09 |
| 10 | 1.04 | 1.09 | 1.02 |
| Size | | s | |
| 1 | 1.12 | 0.85 | 1.06 |
| 2 | 0.71 | 0.56 | 0.39 |
| 3 | 0.28 | 0.63 | 0.61 |
| 4 | 0.04 | 0.48 | 0.40 |
| 5 | -0.18 | 0.29 | 0.19 |
| 6 | -0.56 | -0.02 | -0.05 |
| 7 | -0.56 | -0.36 | -0.24 |
| 8 | -0.55 | -0.71 | -0.60 |
| 9 | -0.82 | -0.73 | -0.67 |
| 10 | -0.89 | -0.88 | -0.89 |

| BTMV | High | Medium | Low |
|---|---|---|---|
| Size | | T(a) | |
| 1 | 2.05 | 1.41 | 2.19 |
| 2 | 0.94 | 1.03 | -0.25 |
| 3 | -0.35 | -0.19 | -0.39 |
| 4 | -1.19 | -1.15 | -1.39 |
| 5 | -0.03 | -0.69 | -2.49 |
| 6 | -1.62 | -1.53 | -3.41 |
| 7 | 0.90 | -1.70 | -1.35 |
| 8 | -0.33 | -0.91 | -2.18 |
| 9 | -0.05 | 0.98 | -2.35 |
| 10 | -1.23 | -0.58 | -0.97 |
| Size | | T(b) | |
| 1 | 12.27 | 13.62 | 13.54 |
| 2 | 12.47 | 11.86 | 12.00 |
| 3 | 20.36 | 16.86 | 17.14 |
| 4 | 18.24 | 22.19 | 15.72 |
| 5 | 18.87 | 23.21 | 27.68 |
| 6 | 24.44 | 23.36 | 27.54 |
| 7 | 20.45 | 25.83 | 20.85 |
| 8 | 24.00 | 28.85 | 24.39 |
| 9 | 24.21 | 26.42 | 23.20 |
| 10 | 14.51 | 17.82 | 12.75 |
| Size | | T(s) | |
| 1 | 4.99 | 5.26 | 4.75 |
| 2 | 3.47 | 3.46 | 1.98 |
| 3 | 2.13 | 4.52 | 4.52 |
| 4 | 0.28 | 4.62 | 3.01 |
| 5 | -1.35 | 3.03 | 2.26 |
| 6 | -5.65 | -0.20 | -0.58 |
| 7 | -4.68 | -3.94 | -2.19 |
| 8 | -5.78 | -9.18 | -6.68 |
| 9 | -8.66 | -9.73 | -7.13 |
| 10 | -6.21 | -7.20 | -5.52 |

## Appendix 5.2 continued

| BTMV | High | Medium | Low |
|---|---|---|---|
| Size | | h | |
| 1 | 0.14 | 0.45 | -1.39 |
| 2 | 0.26 | 0.36 | -0.09 |
| 3 | 0.24 | -0.21 | -0.46 |
| 4 | 0.27 | -0.07 | -0.19 |
| 5 | 0.16 | -0.17 | -0.34 |
| 6 | 0.61 | -0.14 | -0.18 |
| 7 | 0.35 | 0.17 | -0.29 |
| 8 | 0.34 | 0.09 | -0.08 |
| 9 | 0.27 | -0.03 | -0.24 |
| 10 | 0.15 | -0.28 | -0.18 |

| BTMV | High | Medium | Low |
|---|---|---|---|
| Size | | T(h) | |
| 1 | 0.53 | 2.38 | -5.33 |
| 2 | 1.09 | 1.90 | -0.41 |
| 3 | 1.58 | -1.30 | -2.93 |
| 4 | 1.67 | -0.60 | -1.23 |
| 5 | 1.03 | -1.51 | -3.47 |
| 6 | 5.23 | -1.19 | -1.74 |
| 7 | 2.46 | 1.54 | -2.26 |
| 8 | 3.06 | 1.04 | -0.72 |
| 9 | 2.48 | -0.36 | -2.17 |
| 10 | 0.88 | -1.96 | -0.94 |
| Size | | $R^2$ | |
| 1 | 0.60 | 0.68 | 0.60 |
| 2 | 0.60 | 0.60 | 0.55 |
| 3 | 0.79 | 0.71 | 0.71 |
| 4 | 0.75 | 0.81 | 0.67 |
| 5 | 0.76 | 0.82 | 0.86 |
| 6 | 0.86 | 0.82 | 0.86 |
| 7 | 0.80 | 0.86 | 0.79 |
| 8 | 0.85 | 0.89 | 0.85 |
| 9 | 0.86 | 0.88 | 0.84 |
| 10 | 0.69 | 0.77 | 0.63 |

## Appendix 5.3.

**Three-Factor Regressions for Simple Monthly Excess Returns on 30 Low Beta Portfolios Formed on Size and BE/ME: 1/85-12/95, 132 Months**

$$R(t)-RF(t)=a+b[RM(t)-RF(t)]+sSMB(t)+hHML(t)+e(t)$$

| BTMV | high | medium | low |
|---|---|---|---|
| Size | | a | |
| 1 | 0.0108 | 0.0081 | 0.0057 |
| 2 | 0.0002 | 0.0051 | 0.0019 |
| 3 | -0.0031 | -0.0039 | -0.0012 |
| 4 | -0.0027 | -0.0036 | -0.0019 |
| 5 | -0.0020 | -0.0016 | -0.0063 |
| 6 | -0.0003 | 0.0002 | -0.0040 |
| 7 | 0.0048 | -0.0035 | 0.0016 |
| 8 | 0.0095 | 0.0011 | 0.0073 |
| 9 | 0.0022 | 0.0056 | 0.0061 |
| 10 | 0.0016 | 0.0029 | 0.0025 |
| Size | | b | |
| 1 | 0.9 | 0.7 | 0.7 |
| 2 | 0.9 | 0.8 | 0.8 |
| 3 | 0.7 | 0.8 | 0.9 |
| 4 | 0.8 | 0.9 | 0.9 |
| 5 | 0.8 | 0.9 | 1.0 |
| 6 | 0.8 | 0.8 | 0.9 |
| 7 | 0.7 | 0.9 | 0.7 |
| 8 | 0.9 | 1.0 | 0.9 |
| 9 | 0.8 | 0.9 | 0.8 |
| 10 | 0.8 | 0.8 | 0.8 |
| Size | | s | |
| 1 | 0.59 | 0.42 | 0.81 |
| 2 | 0.45 | 0.59 | 0.63 |
| 3 | 0.38 | 0.50 | 0.79 |
| 4 | 0.40 | 0.33 | 0.63 |
| 5 | 0.03 | 0.39 | 0.41 |
| 6 | -0.04 | -0.07 | 0.27 |
| 7 | -0.50 | -0.18 | -0.19 |
| 8 | -0.82 | -0.55 | -0.63 |
| 9 | -0.71 | -0.59 | -0.70 |
| 10 | -0.70 | -0.73 | -0.69 |

| BTMV | high | medium | low |
|---|---|---|---|
| Size | | T(a) | |
| 1 | 2.19 | 1.94 | 0.92 |
| 2 | 0.08 | 2.01 | 0.67 |
| 3 | -1.26 | -1.55 | -0.43 |
| 4 | -1.23 | -1.43 | -0.63 |
| 5 | -0.64 | -0.68 | -1.86 |
| 6 | -0.09 | 0.06 | -1.07 |
| 7 | 1.34 | -1.22 | 0.45 |
| 8 | 2.41 | 0.33 | 1.90 |
| 9 | 0.69 | 1.41 | 2.08 |
| 10 | 0.79 | 1.45 | 1.09 |
| Size | | T(b) | |
| 1 | 9.43 | 8.92 | 6.16 |
| 2 | 17.84 | 16.34 | 15.39 |
| 3 | 14.68 | 17.22 | 16.63 |
| 4 | 19.18 | 18.44 | 15.91 |
| 5 | 13.83 | 20.39 | 15.13 |
| 6 | 12.94 | 13.69 | 12.68 |
| 7 | 11.25 | 16.18 | 11.65 |
| 8 | 13.00 | 15.34 | 12.87 |
| 9 | 12.96 | 12.78 | 15.22 |
| 10 | 21.02 | 20.76 | 18.95 |
| Size | | T(s) | |
| 1 | 3.25 | 2.69 | 3.50 |
| 2 | 4.61 | 6.31 | 5.92 |
| 3 | 4.21 | 5.39 | 7.36 |
| 4 | 4.82 | 3.49 | 5.70 |
| 5 | 0.25 | 4.52 | 3.28 |
| 6 | -0.31 | -0.62 | 1.95 |
| 7 | -3.76 | -1.71 | -1.50 |
| 8 | -5.60 | -4.38 | -4.41 |
| 9 | -6.17 | -3.98 | -6.43 |
| 10 | -9.36 | -10.03 | -8.17 |

## Appendix 5.3 continued

| BTMV | high | medium | low |
|---|---|---|---|
| Size | **h** | | |
| 1 | 0.70 | 0.30 | -0.53 |
| 2 | 0.62 | 0.10 | -0.56 |
| 3 | 0.41 | -0.07 | -0.14 |
| 4 | -0.04 | 0.07 | -0.28 |
| 5 | 0.23 | -0.14 | -0.20 |
| 6 | 0.33 | 0.14 | -0.43 |
| 7 | 0.64 | 0.11 | -0.03 |
| 8 | 0.19 | -0.09 | -0.10 |
| 9 | 0.40 | -0.49 | -0.11 |
| 10 | -0.02 | -0.11 | -0.33 |

| BTMV | high | medium | low |
|---|---|---|---|
| Size | **T(h)** | | |
| 1 | 3.26 | 1.64 | -1.95 |
| 2 | 5.38 | 0.95 | -4.46 |
| 3 | 3.88 | -0.65 | -1.12 |
| 4 | -0.44 | 0.62 | -2.13 |
| 5 | 1.65 | -1.39 | -1.37 |
| 6 | 2.14 | 1.01 | -2.65 |
| 7 | 4.12 | 0.84 | -0.21 |
| 8 | 1.13 | -0.60 | -0.59 |
| 9 | 2.98 | -2.83 | -0.86 |
| 10 | -0.21 | -1.27 | -3.32 |
| Size | $R^2$ | | |
| 1 | 0.54 | 0.46 | 0.26 |
| 2 | 0.79 | 0.73 | 0.66 |
| 3 | 0.71 | 0.73 | 0.72 |
| 4 | 0.76 | 0.75 | 0.69 |
| 5 | 0.64 | 0.78 | 0.66 |
| 6 | 0.62 | 0.63 | 0.56 |
| 7 | 0.61 | 0.70 | 0.54 |
| 8 | 0.65 | 0.69 | 0.62 |
| 9 | 0.67 | 0.61 | 0.71 |
| 10 | 0.83 | 0.83 | 0.79 |

# Chapter 6

# Markov Chain Model and the Size Effect

## 6.1. Introduction

It is well known that economic time series often exhibit dependence in their successive observations. There are many models which attempt to capture such autoregressive behaviour either at a univariate or multivariate level. Examples of such models are the Random Walk, the AR process, and the VAR. These models are an application of Markov processes in the sense that current values of economic variables are assumed to be dependent on earlier values of the same variables. Markov processes assume that the transition of "objects" from one state to another are governed by a probabilistic mechanism or structure. More precisely, Markov processes or chains can be described as follows: assume there are $n$ states of possible outcomes or events that cover all possible contingencies. Let these outcomes be defined as $E_i$ ($i$= 1, 2, ......$n$). The probability that a state $i$ occurs on trial $t$ is denoted by

$$P(E_{it}) = p_{it} \tag{6.1}$$

If the states occur unconditionally on successive trials, then the probability of a sequence of states is the product of the probabilities of these states taking place at particular moments in time. Thus, assuming independence, the probability of the sequence $E_i$ in trial $t$ and $E_j$ in trial $t+1$ is given by

$$P(E_{it}, E_{jt+1}) = P(E_{it})P(E_{jt+1}) = p_{it}p_{jt+1} \tag{6.2}$$

A situation in which events occur independently in successive trials is a special case of a Markov process called a zero-order Markov process. In a first order Markov chain the probability of an event in a trial is conditional on which trial preceded it. Thus, denoting the probability of state $j$ on trial $t+1$ conditional on state $i$ in trial $t$ as $p_{ij}$ we have:

$$P(E_{jt+1} / E_{it}) = p_{ij} \tag{6.3}$$

The absence of $t$ subscripts on $p_{ij}$ indicates that the probability of transition from $i$ to $j$ is the same for all trials, providing the event $i$ is realised in trial $t$. Therefore, the conditional probability of the sequence $E_i$ in trial $t$ and $E_j$ in trial $t+1$ is:

$$P(E_{jt+1} / E_{it}) = P(E_{it}, E_{jt+1}) / P(E_{it}) = p_{ij} \tag{6.4}$$

Although equations' (6.2) and (6.4) left hand sides are similar, they have quite different right hand sides. As equation (6.4) is arrived at by replacing the probability of $E_{jt+1}$ in equation (6.2) with the conditional probability of $E_{jt+1}$ in equation (6.3), equation (6.4) implies the existence of structure. The key element of this structure is the conditional probability $p_{ij}$. In contrast to (6.2), the knowledge of which state occurred in trial $t$ affects the expectation of which state will occur in trial $t+1$. Under the zero-order chain characterised by (6.2), the expectation in trial $t+1$ is the same for all possible sequences of events preceding trial $t+1$. Even if we knew which event was realised on trial $t$, that should not change our expectation of the outcome on trial $t+1$. The conditional probability of $E_j$ in trial $t+1$ is the same as the unconditional probability of $E_j$ in trial $t+1$. A zero-order process requires $p_{ij}$ to be the same for all $i$. That condition, however, is not obeyed in a first-order process, where $p_{ij}$ is not equal to, say, $p_{ik}$. Thus, the probability of moving to state $i$ is different, depending upon which preceding event (state) has materialised. Second or higher order processes allow the transition probabilities to vary according to the outcome of two or more preceding trials.

A simple example might be helpful in clarifying the Markov process. Let's take the trivial example of tossing a coin. Every time the coin is flipped, there are two possible outcomes - head or tail. The probability of having a head is equal to the probability of having a tail on each trial, i.e., 0.5, and the probability on each trial is not affected by the outcome of the previous trial. These are presented in the contingency table below:

| | | trial $t+1$ | |
|---|---|---|---|
| | | $E_i$ =heads | $E_j$ =tails |
| trial $t$ | $E_i$ | 0.5 | 0.5 |
| | $E_j$ | 0.5 | 0.5 |

Of course, the practical realisation of these probabilities would require a great deal of repetition of trial $t$ and trial $t+1$, so that the Large Numbers Law is obeyed. If the outcome of coin tossing followed a first order Markov chain, then the probability of heads and tails in trial $t+1$ would be different from the above zero-order Markov process. Now the probability of heads and tails on trial $t+1$ differs depending upon whether heads or tails are observed in trial $t$.

| | | trial $t+1$ | |
|---|---|---|---|
| | | $E_i$=heads | $E_j$=tails |
| trial $t$ | $E_i$ | 0.8 | 0.2 |
| | $E_j$ | 0.3 | 0.7 |

The probability structure shown above is purely artificial, and it does not adequately reflect the true probabilistic structure of tossing a coin. If it existed, then the process would be described as a first order Markov chain. Whatever the process order is, the probability contingency table should be constrained by the following equation:

$$\sum p_{ij} = 1, j = 1....n \tag{6.5}$$

This equation says that whatever event took place in trial $t$, one of the $n$ possible events must take place in trial $t+1$. In a *nxn* probability matrix (contingency table), the row $i$ sum must be one, as columns $j$ list all possible $n$ events to take place in trial $t+1$.

## 6.2. Using the Markov Chain Model to test for the Random Walk Hypothesis of Size Portfolios' Returns

The purpose of this experiment is to test the Random Walk Hypothesis for different size portfolios' returns. Rejection of the RW hypothesis would imply the existence of a structure in the sequence of returns and possibly speculative bubbles as a special case of the former.

In this chapter the Markov chain methodology is applied to monthly size portfolios' returns from 1/01/1985 to 30/12/1995. Each month's return is designated as state 0 or 1. State 0 exists if the observed month's return is lower than the average monthly return $\overline{R}$ for the previous three calendar years. The choice of the previous three calendar years was made for three main reasons. Firstly, it is consistent with the period for which betas of the Market Model are estimated. Secondly, technical precision would require $\overline{R}$ to be estimated for the whole period returns. That however, implies *ex-ante* knowledge of $\overline{R}$ and therefore would not allow trading strategies to be applied. Thirdly, a period similar to this has been applied in many other studies using Markov Chains in both the Stock and Foreign Exchange markets. If the current month's return is higher than $\overline{R}$, it is assigned state 1. Let $R_t$ denote the *t*th return in a stationary time series of T returns, and let $I_n$ be a sequence of $n$=2 transitional Markovian states. These states are defined as follows:

$$I_n = \begin{cases} 1, R_t > \overline{R} \\ 0, R_t < \overline{R} \end{cases}$$

Thus, the observed return time series $R_t$ is transformed into a dichotomous sequence of two Markovian states $I_n$. The derived series $I_n$ is calculated for 10 size portfolios' monthly returns, which are a transformation of the size portfolios' observed return. In comparison to other approaches, such as the variance ratio and regression tests, which assume linearity in return series, the Markov chain approach allows for non-linearity of the return series. Furthermore, the Markov chain approach can detect patterns of non-randomness; it does not require a normal distribution of returns, although return series must be stationary in terms of constant transition probabilities. Thus, for each size portfolios' $I_n$ series, a two-state second order[1] Markov chain model is applied. The first stage is to estimate the transitional counts, i.e., the number of occurrences of state $n$ (0,1), when the previous two states were 00, for instance. The combination of the two states 0 and 1 for the prior two periods produces 4 combinations - 00, 01, 10, 11. For the current period there are only two possibilities that cover all possible contingencies - 0 and 1. Thus, the transitional counts and associated transitional probabilities can be presented in a 4 by 2 matrix form:

Transition Count Matrix

| Prior States | | Current State 0 | Current State 1 |
|---|---|---|---|
| 0 | 0 | $N_{00}$ | $M_{00}$ |
| 0 | 1 | $N_{01}$ | $M_{01}$ |
| 1 | 0 | $N_{10}$ | $M_{10}$ |
| 1 | 1 | $N_{11}$ | $M_{11}$ |

Transition Probability Matrix

| Prior States | | Current State 0 | Current State 1 |
|---|---|---|---|
| 0 | 0 | $\lambda_{00}$ | $1-\lambda_{00}$ |
| 0 | 1 | $\lambda_{01}$ | $1-\lambda_{01}$ |
| 1 | 0 | $\lambda_{10}$ | $1-\lambda_{10}$ |
| 1 | 1 | $\lambda_{11}$ | $1-\lambda_{11}$ |

[1]See arguments for second order below.

$N_{ij}$, $M_{ij}$ stand for the number of occurrences of transitions from one state to another. Thus $N_{00}$ is the number of observed 0, when the previous state sequence is 00 and $M_{00}$ is the number of observed 1, when the previous sequence of states is 00. Corresponding transition probabilities can be defined as:

$$\lambda_{00} = P[I_{0t}|I_{0t-2}, I_{0t-1}]$$
$$\lambda_{01} = P[I_{0t}|I_{0t-2}, I_{1t-1}]$$
$$\lambda_{10} = P[I_{0t}|I_{1t-2}, I_{0t-1}]$$
$$\lambda_{11} = P[I_{0t}|I_{1t-2}, I_{1t-1}]$$

where $I_{nt}$ is a realisation of state $n$ ($n$=0,1), at period $t$.

Using the likelihood function[2] $L(S_t, \Lambda', \pi)$, the value of the four unknown parameters $\Lambda = [\lambda_{00}\lambda_{01}\lambda_{10}\lambda_{11}]'$ is found by setting the partial derivatives of the log-likelihood function equal to zero and solving them for the four parameters in terms of transitional counts. There is, however, a difficulty, caused by the presence of the initial state $\pi$ in the log-likelihood function, i.e.,:

$$L(S_t, \Lambda', \pi) = \log \pi + \sum_{ij=00}^{11} N_{ij} \log \lambda_{ij} + M_{ij} \log(1-\lambda_{ij}), \quad I_1 = I_2 = 1 \tag{6.6}$$

where $S_t$ is the realisation of $\{I_{nt}\}$ and $\pi$ is the probability of the initial states. The incorporation of the initial state requires an iterative solution to $\Lambda$, since ignoring $\pi$ allows a solution of the first order conditions in a standard way as the sample's estimates of the maximum likelihood of the transition probabilities.

There are two conditions under which $\pi$ can be treated as a nuisance parameter and thus can be ignored; one of these cases occurs when the sample size T is large enough. Then, as Feller (1971) proves mathematically, the basic facts concerning stationary distributions are the same for both discrete and continuous Markov chains. Under mild regularity conditions on the transitional probabilities, there exists a unique stationary distribution which represents the asymptotic distribution of the event sequence under any initial distribution. In other words, the influence of the initial state fades away and the system tends towards a steady state governed by a stationary solution. In the second case one can assume that the process $\{I_{nt}\}$ indeed started at time $t = 1$.

As the number of observations used for this study are more than 100 and this figure is considered sufficiently large to approximate the asymptotic distribution by many authors, the maximum likelihood estimates for $\lambda_{ij}$ are calculated from the trimmed likelihood function, i.e., without consideration of the argument $\pi$. Thus, the maximum likelihood estimate of $\lambda_{ij}$, $N_{ij} / (N_{ij} + M_{ij})$, and its asymptotic variance $\sigma^2(\lambda_{ij}) = \lambda_{ij}(1 - \lambda_{ij}) / (N_{ij} + M_{ij})$, are associated with the mean and variance of the binomial distribution. In this way, for instance, the maximum likelihood estimate and asymptotic variance of $\lambda_{00}$ will be, respectively: $\hat{\lambda}_{00} = N_{00} / (N_{00} + M_{00})$ and $\hat{\sigma}^2(\lambda_{00}) = \hat{\lambda}_{00}(1 - \hat{\lambda}_{00}) / (N_{00} + M_{00})$.

## 6.3. Hypotheses and their Tests

The Random Walk Hypothesis requires two important conditions in order to hold. One condition is that the expected payoff of a "game" must be zero. In terms of the size portfolios' return series that condition has been forced by subtracting the prior three years' mean return from the original gross return. The second condition concerns the prospects of the market prices predictability from historic prices. The market is weak form efficient if no one can use the past prices to earn excess returns. Thus, the subject of the test here is the size portfolios' return path, which determines the second moments of the return series. Under the Random Walk Hypothesis, this path should be purely random, so that no

[2]See Chaw (1983), Poirier (1995) and Azzalini (1996).

structure or pattern associating previous returns to current and future returns should appear. The conventional econometric approach to detecting association between past and current returns is by estimating the autocorrelation coefficients of the return series. This approach, however, averages the association of the present return level with a discrete distance return, say 2 months before, which is an autocorrelation coefficient with lag 2.

The advantage of this method is the precise quantification of the process. We learn for instance that the current expected return must be say, -12% of the lag 2 returns. We do not know, however, anything about the return path from lag 2 to lag 0, which counts as a disadvantage of the common econometrics approach. The Markov Chain method deals with this impediment, by showing the path, its branches and allied probabilities two stages back in the present experiment.

The question of why a two-state second-order Markov chain is chosen may arise. It is true that various combinations of the number of states and order of degree exist in the literature. Thus Dryden (1969) uses a three-state first-order Markov chain to test for stock indices' patterns. The three states are I (increase), D (decrease), N (no change). Such a structure makes sense in his investigation, as he uses daily price series, and it is more likely for the prices to stay unchanged on a daily, rather than a longer basis. Mills (1995b) uses a three states second order Markov chain to test for business cycle asymmetries. Other authors construct higher and lower bounds and count only the break-outs as ups or downs. That is solely to show the diverse possibilities one can explore. The approach that is adopted here follows the McQueen and Thorley (1991) structure. A two-state Markov Chain is chosen because it relates closely to the spirit of the Random Walk, and also because of the lack of the U (unchanged) state in the monthly portfolios' return series, after deducting the rolling mean. A second order is chosen because it allows one to test also for the presence of speculative bubbles. The first-order Markov chain has limited abilities in this area. The third and higher orders of Markov chains will introduce an unwanted multiplication of prior states as well as the number of observations from which the marginal probabilities are drawn. In addition, the experiment carried out by Kroll, Levy and Rapoport (1988) finds that investors behave as if stock returns have a two-period memory.

Last, but not least, is the argument that whatever the Markov chain order is, a given return series should have an equal probability structure if it follows a Random Walk. That is because the Random Walk hypothesis requires that state 0 or 1 has the same probability of occurring, no matter what the previous state sequence is. Hence, the null hypothesis of a random walk is that all transition probabilities are equal. Testing for all possible combinations of transition probabilities is a tiresome and pointless task, and thus the second hypothesis test aims at the fad and rational bubbles options. The rational bubbles hypothesis of asset pricing and the Markov chain test are suggested by Blanchard and Watson (1982), who provide a middle ground between the rational and irrational behaviour of investors. Their idea is that investors who hold assets whose value is above the fundamental value and who are aware of that, do not sell their assets because they anticipate further price increases. It is implied, however, that there will be uninformed buyers so that this strategy can succeed. Sooner or later, the inflation of the overpriced asset must come to an end. That is the moment of fundamental value realisation, or the "judgement day", when the bubble bursts and the asset's price falls sharply, in many instances below the fundamental value. This alternative is harmonious with the bounded rationality assumption in the transaction cost economy.

The initial supposition for rational bubbles is that they are more likely to occur in the prices of assets with less information or less reliable information. A large number of studies finds that these are the shares of firms with lower market capitalisation, i.e., the small size firms, which are also less followed by analysts. If there is no rational bubble, then the equality $\lambda_{00} = \lambda_{11}$ must be obeyed. According to the supposition already made, we are more likely to observe the inequality $\lambda_{00} < \lambda_{11}$ for the smaller market value portfolios, as the probability of state 0 should be higher for the prior state 11 than 00. Therefore, Hypothesis 1 is $\lambda_{00} = \lambda_{11}$, and Hypothesis 2 is $\lambda_{00} = \lambda_{01} = \lambda_{10} = \lambda_{11}$. The hypotheses' significance is evaluated by the likelihood ratio test (LRT):

$$LRT = 2\left[L(\Lambda_u) - L(\Lambda_c)\right] \sim \chi_n^2 \tag{6.7}$$

where $L(\Lambda_u)$ is the log likelihood function evaluated at the unconstrained MLE of the parameters, and $L(\Lambda_c)$ is the log likelihood obtained from the MLE of the constrained parameters. The likelihood ratio test is asymptotically distributed $\chi_n^2$, where $n$ equals the number of restrictions. Thus, Hypothesis 1 has 2 and Hypothesis 2 has 4 restrictions.

## 6.4. Test Results

Table 6.1 shows the summary statistics for the monthly size portfolios' returns. All size portfolios' returns exhibit positive one period autocorrelations, which are most pronounced for the smaller size portfolios, with autocorrelations in the range 0 to 0.3. The magnitude of the higher lag autocorrelations decays for all size portfolios.

## Table 6.1.
## Summary Statistics of 10 Size Portfolios' Monthly Equally Weighted Returns from January 1985 to December 1995.

Mean, Median and SD are size portfolios' sample mean, median and standard deviation of portfolios' return series formed and evaluated as explained in Chapter 4. $\rho t$ is portfolios' autocorrelation at lag $t$ and s(r) is the asymptotic standard error of the autocorrelations under the null hypothesis of a random walk.
Q(6) is the Box-Ljung (1978) portmanteau test statistics for 6 autocorrelations, distributed chi-squared with 6 degree of freedom, and M.S. is the marginal significance level of the Box-Ljung test.

| Variable | Mean | Median | SD | ρ1 | ρ2 | ρ3 | ρ4 | ρ5 | ρ6 | s(r) | Q(6) | M.S. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| pf1 | 0.0309 | 0.0278 | 0.0651 | 0.304 | -0.056 | -0.045 | -0.03 | 0.014 | 0.011 | 0.085 | 13.11 | 0.012 |
| pf2 | 0.0199 | 0.0237 | 0.0548 | 0.315 | -0.071 | -0.045 | 0.068 | -0.061 | -0.072 | 0.085 | 14.77 | 0.005 |
| pf3 | 0.0155 | 0.0131 | 0.0567 | 0.372 | -0.039 | -0.047 | -0.007 | -0.028 | -0.047 | 0.085 | 19.20 | 0.001 |
| pf4 | 0.0129 | 0.0143 | 0.0547 | 0.277 | -0.144 | -0.117 | -0.064 | -0.056 | -0.003 | 0.085 | 14.37 | 0.005 |
| pf5 | 0.0127 | 0.0156 | 0.0584 | 0.186 | -0.098 | -0.089 | -0.023 | -0.033 | -0.061 | 0.085 | 6.64 | 0.123 |
| pf6 | 0.0102 | 0.0134 | 0.0603 | 0.158 | -0.187 | -0.064 | -0.008 | -0.031 | -0.040 | 0.085 | 7.80 | 0.079 |
| pf7 | 0.0115 | 0.0169 | 0.0622 | 0.128 | -0.17 | -0.065 | -0.013 | -0.04 | -0.031 | 0.085 | 5.98 | 0.158 |
| pf8 | 0.0096 | 0.0163 | 0.0616 | 0.100 | -0.212 | -0.088 | -0.044 | -0.023 | -0.025 | 0.085 | 7.31 | 0.111 |
| pf9 | 0.0102 | 0.0114 | 0.0590 | 0.079 | -0.232 | -0.032 | -0.002 | -0.038 | -0.074 | 0.085 | 7.24 | 0.131 |
| pf10 | 0.0095 | 0.0142 | 0.0525 | 0.015 | -0.177 | -0.058 | -0.012 | 0.017 | -0.085 | 0.085 | 4.09 | 0.392 |

Table 6.2 displays the Markov chain transitional counts for the 10 size portfolios as well as the MLE of the transition probabilities and related statistics. The outcome is high (low) returns when the monthly gross return, estimated from the shares' price, is greater (lower) than the average monthly return of the previous three calendar years. That means, for instance, that for January 1990 say, $\overline{R}$ is the average monthly return for 1987, 1988 and 1989, and so remains $\overline{R}$ for the remaining eleven months of 1990. The unconstrained point estimates for $\lambda_{00}$ and $\lambda_{11}$ show precisely the existence of positive serial dependence in portfolios 1 through 4 monthly returns. From portfolio 5 to portfolio 8 this tendency disappears, and it turns into a weak negative serial dependence in portfolios 9 and 10. This interesting evidence highlights the regularity obtained in estimating beta (Chapter 4). The reader will recall that in applying one lag and one lead to the contemporary market index in the Market Model, the lead market index turns out to be insignificant in most of the regressions. The lagged index is significant, and increases the smaller size portfolios' beta and decreases the larger size portfolios' beta. For the middle size portfolios (e.g., portfolio 5) this correction is zero. Looking at the transition counts, one can see that portfolio 1 has 24 low and 14 high returns when the previous two period returns were also low. Portfolio 10 exhibits a reverse relation, 13 low and 18 high counts when the prior two states were 00. When the previous state 11 is considered, the situation alters; now it is more likely after observing states 11 for a state 1 to occur for portfolio 1, whereas the state 0 is more likely for portfolio 10. That explains the phenomena associated with the Market Model, when Dimson's estimator is applied; the question of why smaller size portfolios exhibit positive serial dependence still remains. A clue to the answer may be provided by the bubbles, or rational bubbles Hypothesis 1 test.

It is, however, worth looking at the intermediate transition counts with prior states 01 and 10, before examining the test results; For both 0 and 1 current states portfolio 1 has only 49 transition counts out of 131 counts. Going through the size portfolios the amount of these counts gradually increases to reach 67 at portfolio 10. That is to say, most of the transitional counts are concentrated at the extreme prior states 00 and 11 of the smaller firms, and evenly spread between all prior states for the larger size firms.

Reestimating the parameters of the log-likelihood function (6.6) under the restrictions imposed by H1 $\lambda_{00} = \lambda_{11}$, and substituting for both the constrained and unconstrained likelihoods in equation (6.7), yields the LRT test value for different size portfolios. The likelihood ratio test (LRT) follows a Chi-square distribution, whose critical value for 2 degrees of freedom at 0.1 level of significance is 4.60. From Table 6.2 it becomes obvious that Hypothesis 1 can be rejected for portfolio 2 at 10 percent significance and portfolio 1 follows closely. Although not exceptionally high, portfolios' 1 and 2 LRT values discriminate them from the remaining portfolios 3 through 10. Having in mind that the portfolios' return series are equally weighted averages of individual company return series, the test results for Hypothesis 1 imply common factors that associate the aggregate returns of the small firms with bubbles. In addition to the LRT test, the Wald test is also performed for the bubbles hypothesis and the results of this test support the LRT conclusions.

Hypothesis 2 imposes the restriction that all transition probabilities are equal, i.e., $\lambda_{00} = \lambda_{01} = \lambda_{10} = \lambda_{11}$. At the 5 percent significance for portfolio 1 and the 10 percent significance for portfolio 2, Hypothesis 1 can be rejected, whereas this is not possible for the remaining portfolios. Therefore, the test offered here cannot reject the Random Walk Hypothesis for the bulk of firms, and does so only for the two deciles of the smallest firms.

Figure 6.1 provides a scatter diagram using the estimated transition probabilities $\lambda_{00}$ and $\lambda_{11}$ for the 10 size portfolios, to support the findings of Hypothesis 1.

## Table 6.2.

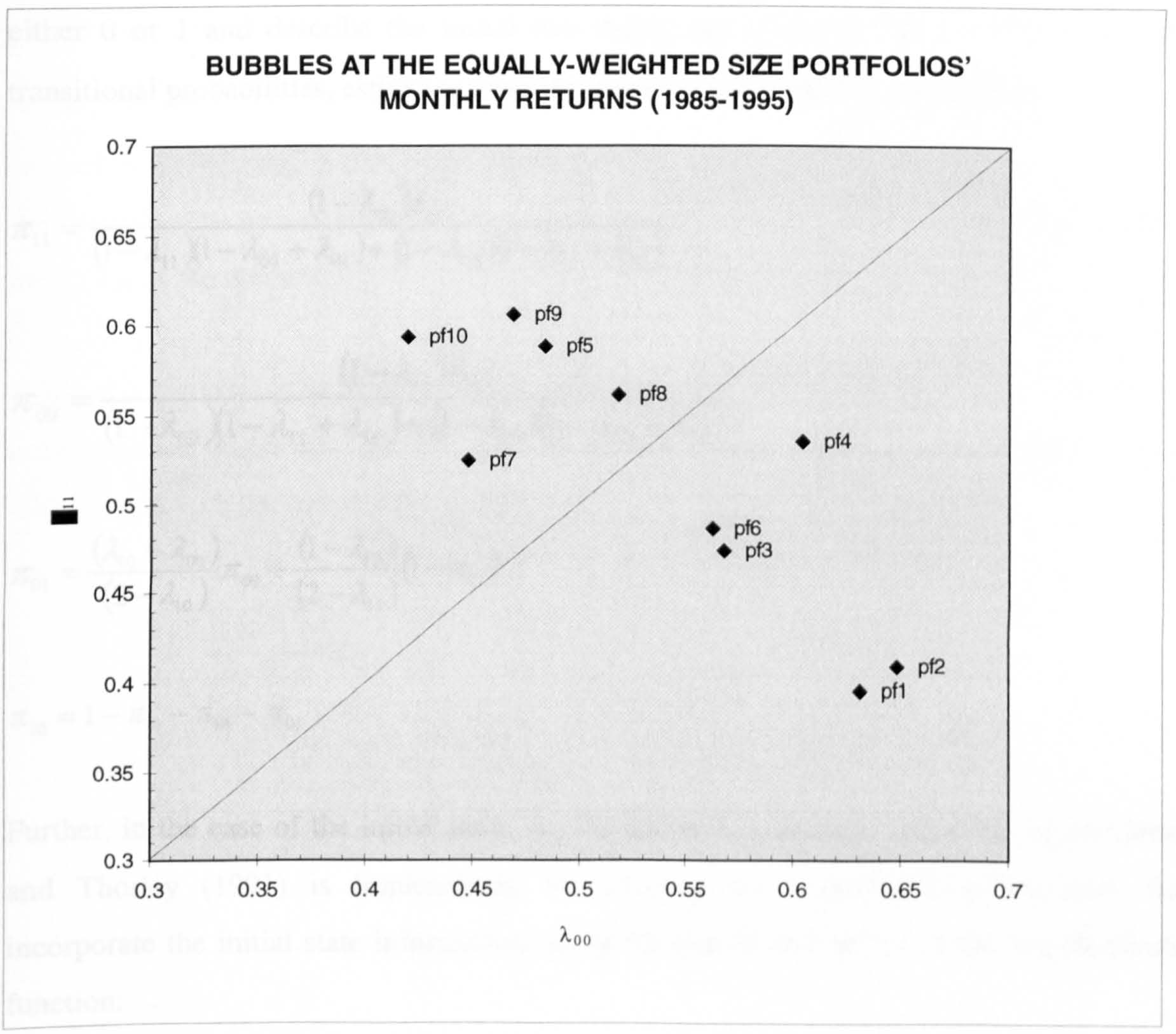
## Maximum Likelihood Estimates and Likelihood Ratio Test for Monthly Returns (1985-1995) of Ten Size Portfolios

| Transition Counts | Size Portf. 1 Current State | | Size Portf. 2 Current State | | Size Portf. 3 Current State | | Size Portf. 4 Current State | | Size Portf. 5 Current State | | Size Portf. 6 Current State | | Size Portf. 7 Current State | | Size Portf. 8 Current State | | Size Portf. 9 Current State | | Size Portf. 10 Current State | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Prior States | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| 00 | 24 | 14 | 24 | 13 | 21 | 16 | 26 | 17 | 15 | 16 | 18 | 14 | 13 | 16 | 14 | 13 | 15 | 17 | 13 | 18 |
| 01 | 7 | 17 | 7 | 17 | 10 | 17 | 15 | 14 | 13 | 19 | 12 | 18 | 10 | 20 | 8 | 23 | 13 | 19 | 14 | 19 |
| 10 | 15 | 10 | 13 | 12 | 17 | 11 | 18 | 12 | 17 | 16 | 15 | 16 | 16 | 15 | 14 | 17 | 17 | 16 | 18 | 16 |
| 11 | 17 | 26 | 18 | 26 | 18 | 20 | 15 | 13 | 20 | 14 | 18 | 19 | 21 | 19 | 23 | 18 | 20 | 13 | 19 | 13 |
| Initial State | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| <u>MLE Estimates</u> | | | | | | | | | | | | | | | | | | | | |
| $\lambda_{00}$ | 0.632 | | 0.649 | | 0.568 | | 0.605 | | 0.484 | | 0.563 | | 0.448 | | 0.519 | | 0.469 | | 0.419 | |
| $\sigma(\lambda_{00})$ | (.078) | | (.078) | | (.081) | | (.075) | | (.090) | | (.088) | | (.092) | | (.096) | | (.088) | | (.089) | |
| $\lambda_{11}$ | 0.395 | | 0.409 | | 0.474 | | 0.536 | | 0.588 | | 0.486 | | 0.525 | | 0.561 | | 0.606 | | 0.594 | |
| $\sigma(\lambda_{11})$ | (.075) | | (.074) | | (.081) | | (.094) | | (.084) | | (.082) | | (.079) | | (.078) | | (.085) | | (.087) | |
| <u>Hypothesis Tests</u> | | | | | | | | | | | | | | | | | | | | |
| $H_1: \lambda_{00} = \lambda_{11}$ | | | | | | | | | | | | | | | | | | | | |
| WT | 4.78 | | 4.92 | | 0.67 | | 0.33 | | 0.72 | | 0.40 | | 0.40 | | 0.12 | | 1.26 | | 1.98 | |
| LRT | 4.57 | | 4.71 | | 0.66 | | 0.34 | | 0.71 | | 0.40 | | 0.41 | | 0.12 | | 1.24 | | 1.93 | |
| $H_2: \lambda_{00}=\lambda_{11}=\lambda_{01}=\lambda_{10}$ | | | | | | | | | | | | | | | | | | | | |
| LRT | 9.75 | | 8.89 | | 3.89 | | 0.80 | | 2.26 | | 1.65 | | 3.09 | | 7.42 | | 2.78 | | 2.79 | |

The plane is split in two by a 45 degree line which represents the Random Walk locus of combinations for which $\lambda_{00} = \lambda_{11}$. In the case of H1, the portfolios' location should be along the diagonal, i.e. $\lambda_{00} = \lambda_{11}$ if no bubble behaviour occurs. As becomes obvious from Figure 6.1, none of the portfolios lies on the diagonal. This is particularly true for portfolio 2 and to some extent portfolio 1, for which the LRT establishes H1 rejection at 0.10 significance. It is also obvious that portfolios above the diagonal exhibit negative autocorrelations, whereas those below the diagonal have positive autocorrelation patterns. It is fascinating, indeed, that these patterns relate to the firms' size; It is only portfolios 5 and 6 that do not follow the pattern, by "swapping" their places.

**Figure 6.1.**

Equally weighted size portfolios' monthly returns (1985-1995) $\lambda_{00}$ = the transition probability that two low return years are followed by a low return year, $\lambda_{11}$= the transition probability that two high return years are followed by a high return year. The 45 degree line is the locus of points representing all possible combinations between $\lambda_{00}$ and $\lambda_{11}$, such that $\lambda_{00} = \lambda_{11}$,




## 6.5. Incorporating the Initial State Information

The Maximum Likelihood estimates reported in Table 6.2 do not take into account the initial state information, denoted by $\pi$ in the log likelihood function (6.6). The reasons for ignoring $\pi$ have been stated already, but it is worthwhile showing that the sample used here is large enough for $\pi$ to be ignored. In addition, a methodology for incorporating the initial state information may prove necessary in the smaller sample experiments.

It can be shown that the probability of the initial state values depend on the transitional probabilities. Thus, following Neftci (1984), analytical values of $\pi_{ab}$, where a and b are either 0 or 1 and describe the initial two states, can be calculated by utilising the λs' transitional probabilities, estimated from the incomplete log-likelihood function:

$$\pi_{11} = \frac{(1-\lambda_{00})\lambda_{10}}{(1-\lambda_{11})(1-\lambda_{00}+\lambda_{01})+(1-\lambda_{00})(1-\lambda_{11}+\lambda_{10})}$$

$$\pi_{00} = \frac{(1-\lambda_{11})\lambda_{01}}{(1-\lambda_{00})(1-\lambda_{11}+\lambda_{10})+(1-\lambda_{11})(1-\lambda_{00}+\lambda_{01})}$$

$$\pi_{01} = \frac{(\lambda_{10}-\lambda_{00})}{(2-\lambda_{10})}\pi_{00} + \frac{(1-\lambda_{10})}{(2-\lambda_{11})}(1-\pi_{11})$$

$$\pi_{10} = 1-\pi_{11}-\pi_{00}-\pi_{01}$$

Further, in the case of the initial state, $\pi_{11}$ for instance, a solution suggested by McQueen and Thorley (1991) is implemented for deriving the transitional probabilities that incorporate the initial state information, using the partial derivatives of the log-likelihood function:

$$\lambda_{ij} = \frac{N_{ij}}{N_{ij}+M_{ij}} + \frac{\partial \log \pi_{11}}{\partial \lambda_{ij}} \frac{\lambda_{ij}(1-\lambda_{ij})}{(N_{ij}+M_{ij})} \tag{6.8}$$

As can be seen, the rebuilt transition probabilities are equal to the Maximum Likelihood Estimates, i.e., the first term in the equation, plus the first partial derivative of the initial state multiplied by the asymptotic variance of $\lambda_{ij}$. Notice that, as the number of observations grows, so does the denominator of the asymptotic variance $(N_{ij} + M_{ij})$, thus leading to the smaller importance of the initial state. The first partial derivative of the initial state in the above equation (6.8) is replaced by its analytical form, as calculated from the incomplete ML transition probabilities. In order to arrive at the *correct* transition probabilities, equation (6.8) ought to be estimated by substituting the previous $\lambda_{ij}$ estimates in the right hand side with the left hand side estimates until $\lambda_{ij}$ estimates converge. In the case of the series used in this study, convergence is achieved after one iteration, and further iterations lead to an unjustifiable diversion of the transition probabilities from their MLE if initial states are ignored.

Table 6.3 provides a comparison between the transitional probabilities, constrained and unconstrained MLE and the H1 test when the transitional probabilities are estimated without and with the initial state information.

## Table 6.3.
## Maximum Likelihood Estimates and Lilkelihood Ratio Tests Results' Comparison with and without Incorporating the Initial State Information for Monthly Equally Weighted Returns of 10 Size Portfolios (1985-1995)

The log likelihood function is: $L(S_t, \Lambda', \pi) = \log \pi + \sum_{ij=00}^{11} N_{ij} \log \lambda_{ij} + M_{ij} \log(1-\lambda_{ij})$. $\lambda_{ij}$ is the estimated transition probability of going from a state sequence of $I_{nt-2}$ and $I_{nt-1}$ to $I_t = 0$, where n equals 1 for high-return months and 0 for low return months. $\pi_{11}$ = the probability of initial state values of $I_1 = I_2 = 1$. LRT = the likelihood ratio test under the null hypothesis H1: $\lambda_{00} = \lambda_{11}$

| | Portfolio 1 | | Portfolio 2 | | Portfolio 3 | | Portfolio 4 | | Portfolio 5 | | Portfolio 6 | | Portfolio 7 | | Portfolio 8 | | Portfolio 9 | | Portfolio 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | without | with | Without | with | without | with | without | with | without | with | without | With | without | with | without | with | without | with | without | with |
| Unconstrained MLE | | | | | | | | | | | | | | | | | | | | |
| $\lambda_{00}$ | 0.632 | 0.634 | 0.649 | 0.650 | 0.568 | 0.569 | 0.605 | 0.606 | 0.484 | 0.486 | 0.563 | 0.565 | 0.448 | 0.451 | 0.519 | 0.521 | 0.469 | 0.471 | 0.419 | 0.421 |
| $\lambda_{01}$ | 0.292 | 0.294 | 0.292 | 0.294 | 0.370 | 0.373 | 0.517 | 0.520 | 0.406 | 0.409 | 0.400 | 0.402 | 0.333 | 0.336 | 0.258 | 0.260 | 0.406 | 0.409 | 0.424 | 0.426 |
| $\lambda_{10}$ | 0.600 | 0.603 | 0.520 | 0.522 | 0.607 | 0.610 | 0.600 | 0.602 | 0.515 | 0.517 | 0.484 | 0.486 | 0.516 | 0.519 | 0.452 | 0.454 | 0.515 | 0.518 | 0.529 | 0.531 |
| $\lambda_{11}$ | 0.395 | 0.397 | 0.409 | 0.410 | 0.474 | 0.476 | 0.536 | 0.538 | 0.588 | 0.590 | 0.486 | 0.488 | 0.525 | 0.527 | 0.561 | 0.562 | 0.606 | 0.608 | 0.594 | 0.596 |
| $L_U$ | -85.18 | -85.18 | -85.55 | -85.55 | -88.15 | -88.15 | -88.47 | -88.47 | -88.98 | -88.98 | -89.22 | -89.23 | -88.19 | -88.19 | -85.85 | -85.85 | -88.72 | -88.72 | -88.70 | -88.70 |
| Constrained MLE | | | | | | | | | | | | | | | | | | | | |
| $\lambda_{00}$ | 0.513 | 0.515 | 0.529 | 0.530 | 0.521 | 0.523 | 0.570 | 0.572 | 0.536 | 0.538 | 0.524 | 0.526 | 0.487 | 0.489 | 0.540 | 0.542 | 0.537 | 0.540 | 0.507 | 0.509 |
| $\lambda_{01}$ | 0.292 | 0.294 | 0.292 | 0.294 | 0.370 | 0.373 | 0.517 | 0.520 | 0.406 | 0.409 | 0.400 | 0.402 | 0.333 | 0.336 | 0.258 | 0.260 | 0.406 | 0.409 | 0.424 | 0.426 |
| $\lambda_{10}$ | 0.600 | 0.603 | 0.520 | 0.522 | 0.607 | 0.610 | 0.600 | 0.602 | 0.515 | 0.517 | 0.484 | 0.486 | 0.516 | 0.519 | 0.452 | 0.454 | 0.515 | 0.518 | 0.529 | 0.531 |
| $\lambda_{11}$ | 0.513 | 0.515 | 0.529 | 0.530 | 0.521 | 0.523 | 0.570 | 0.572 | 0.536 | 0.538 | 0.524 | 0.526 | 0.487 | 0.489 | 0.540 | 0.542 | 0.537 | 0.540 | 0.507 | 0.509 |
| $L_C$ | -87.46 | -87.47 | -87.90 | -87.91 | -88.48 | -88.49 | -88.64 | -88.64 | -89.34 | -89.34 | -89.42 | -89.43 | -88.39 | -88.39 | -85.92 | -85.91 | -89.34 | -89.34 | -89.66 | -89.66 |
| LRT | 4.57 | 4.57 | 4.71 | 4.72 | 0.66 | 0.66 | 0.34 | 0.34 | 0.71 | 0.71 | 0.40 | 0.40 | 0.41 | 0.40 | 0.12 | 0.12 | 1.24 | 1.24 | 1.93 | 1.92 |

As Table 6.3 shows, there is a slight deviation between the transition probability values estimated without and with the initial state values. The same applies to the log-likelihood ratio test (LRT), where the differences are observed after the third digit. Table 6.3 provides an excellent opportunity for a comparison between the transitional probabilities of different size portfolios. It is seen that the two extreme cases of $\lambda_{00}$ and $\lambda_{11}$ take high and low values at the lower size portfolios 1-3, and then moderate and slightly reverse their subordination as they approach the largest size portfolios 9 and 10. For the intermediary cases $\lambda_{01}$ and $\lambda_{10}$ there is no discernible pattern across size portfolios, but their values consolidate around 0.5 at the largest size portfolios 9 and 10.

## 6.6. Stationarity of the transition probabilities

One question that remains after the reporting of the above results is how sound the estimated transition probabilities are. The problem of the stability of the transition probabilities is the Markov Chain equivalent to the stationarity problem in time series econometrics. Econometrics defines the observed time series as stationary when their mean, variance and covariance do not depend on time (weak stationarity). Markov Chain stationarity is defined as constant transition probabilities over time. An advantage of working with the Markov Chain is that a normal distribution is not required to test for the random walk, as is the case with observed return series. On the other hand, the cost that must be paid is the loss of information by using dichotomous instead of observed series. In brief, the Markov Chain test does not require a normal distribution of returns, but it does require stationary returns.

As there is not a formal methodology developed to test for stationarity of dichotomous time series, one rough-and-ready way to consider the problem of the stability of the transition probabilities is to repeat the analysis on sub-sets of the data.

Hence, the same 10 size portfolio series are split into two sub-sets. As the whole period is 11 years, it is impossible for the series to be split into two even sub-periods. Dividing initial series into two equal length sub-periods will lead to one sub-period series starting from January, and the other starting from July. This is not a suitable solution in so far as the series may have a seasonal component. That is why the original series are split into two sub-series so that the first sub-series begins at January 1985 and ends at December 1990. The second sub-series starts at January 1991 and ends at December 1995.

The same procedure applied for the whole length series is repeated for the two sub-series and the results are given in Table 6.4.

It is obvious from Table 6.4 that the transitional probabilities for the two sub-periods differ slightly from the whole period ones. The differences, however, are within the acceptable tolerance and, what is more important, the dominance pattern observed in the whole period across size portfolios is valid. Thus, portfolios 1-3 exhibit a substantial contrast between $\lambda_{00}$ and $\lambda_{11}$ in the domain of positive autocorrelations. The difference slowly decays as portfolio size grows, to switch into a mild difference for portfolios 9 and 10 in the negative autocorrelation domain. Notice that the size portfolios are rebalanced each calendar year, and the list of firm-participants is up-dated, so that individual firm specificity plays no significant role in determining size portfolios' return behaviour. That is to say, the pattern found in Table 6.2 does not belong to different groups of firms assigned to portfolios according to their market capitalisation and other non-controlled factors, but this pattern is exclusively inherent to portfolios of firms with a different market capitalisation.

# Table 6.4

PERIOD 1985 - 1990

| Transition Counts | Size Portf. 1 | | Size Portf. 2 | | Size Portf. 3 | | Size Portf. 4 | | Size Portf. 5 | | Size Portf. 6 | | Size Portf. 7 | | Size Portf. 8 | | Size Portf. 9 | | Size Portf. 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | |
| Prior States | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| 00 | 13 | 7 | 12 | 7 | 9 | 9 | 14 | 11 | 7 | 9 | 8 | 9 | 5 | 8 | 4 | 7 | 9 | 11 | 7 | 10 |
| 01 | 4 | 10 | 5 | 9 | 10 | 7 | 9 | 6 | 10 | 9 | 9 | 9 | 7 | 11 | 7 | 13 | 9 | 9 | 9 | 10 |
| 10 | 8 | 7 | 8 | 7 | 9 | 8 | 12 | 4 | 9 | 10 | 9 | 9 | 8 | 10 | 7 | 12 | 11 | 8 | 10 | 10 |
| 11 | 10 | 11 | 10 | 12 | 8 | 10 | 7 | 7 | 10 | 6 | 8 | 9 | 11 | 10 | 12 | 8 | 10 | 3 | 10 | 4 |
| Initial State | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |

MLE Estimates

| | Size Portf. 1 | Size Portf. 2 | Size Portf. 3 | Size Portf. 4 | Size Portf. 5 | Size Portf. 6 | Size Portf. 7 | Size Portf. 8 | Size Portf. 9 | Size Portf. 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\lambda_{00}$ | 0.65 | 0.632 | 0.5 | 0.56 | 0.438 | 0.471 | 0.385 | 0.364 | 0.45 | 0.419 |
| $\lambda_{01}$ | 0.107 | 0.111 | 0.118 | 0.099 | 0.124 | 0.121 | 0.135 | 0.145 | 0.111 | 0.12 |
| $\lambda_{10}$ | 0.476 | 0.455 | 0.444 | 0.5 | 0.625 | 0.471 | 0.524 | 0.6 | 0.769 | 0.594 |
| $\lambda_{11}$ | 0.109 | 0.106 | 0.117 | 0.134 | 0.121 | 0.121 | 0.109 | 0.11 | 0.117 | 0.131 |

PERIOD 1991 - 1995

| Transition Counts | Size Portf. 1 | | Size Portf. 2 | | Size Portf. 3 | | Size Portf. 4 | | Size Portf. 5 | | Size Portf. 6 | | Size Portf. 7 | | Size Portf. 8 | | Size Portf. 9 | | Size Portf. 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | | Current State | |
| Prior States | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| 00 | 9 | 7 | 10 | 6 | 11 | 7 | 12 | 5 | 7 | 7 | 10 | 5 | 8 | 8 | 10 | 6 | 6 | 6 | 6 | 8 |
| 01 | 3 | 7 | 2 | 8 | 0 | 10 | 5 | 8 | 3 | 10 | 3 | 9 | 3 | 9 | 1 | 10 | 3 | 10 | 4 | 9 |
| 10 | 7 | 3 | 5 | 5 | 7 | 3 | 6 | 8 | 7 | 6 | 6 | 7 | 7 | 5 | 6 | 5 | 5 | 8 | 8 | 5 |
| 11 | 7 | 15 | 8 | 14 | 10 | 10 | 8 | 6 | 10 | 8 | 9 | 9 | 9 | 9 | 11 | 9 | 10 | 10 | 9 | 9 |
| Initial State | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

MLE Estimates

| | Size Portf. 1 | Size Portf. 2 | Size Portf. 3 | Size Portf. 4 | Size Portf. 5 | Size Portf. 6 | Size Portf. 7 | Size Portf. 8 | Size Portf. 9 | Size Portf. 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\lambda_{00}$ | 0.563 | 0.625 | 0.611 | 0.706 | 0.5 | 0.667 | 0.5 | 0.625 | 0.5 | 0.429 |
| $\lambda_{01}$ | 0.124 | 0.121 | 0.115 | 0.111 | 0.134 | 0.122 | 0.125 | 0.121 | 0.144 | 0.132 |
| $\lambda_{10}$ | 0.318 | 0.364 | 0.5 | 0.571 | 0.556 | 0.5 | 0.5 | 0.55 | 0.5 | 0.5 |
| $\lambda_{11}$ | 0.099 | 0.103 | 0.112 | 0.132 | 0.117 | 0.118 | 0.118 | 0.111 | 0.112 | 0.118 |

## 6.7. Market Model and the Random Walk Hypothesis

Another way of testing for the Bubbles and Random Walk hypotheses is by applying the Markov Chain model to the residuals from the Market Model. By doing so, both concepts of market efficiency and risk are introduced into the analysis of the above hypotheses.

In the last few years it became fashionable for large numbers of market analysts to apply the so called technical analysis. Technical analysis attracts wide academic attention as well. Testing for bubbles and Random Walks in the Market Model residuals, therefore, may prove whether or not technical analysis strategies and "noise" traders have a sound basis for their experiments. It can also affirm the applicability of the Market Model as a means of establishing a correct risk-return relationship.

There appears to be a problem when the residuals are considered; If the original 3 years rolling regression residuals are to be considered, that may involve unequilibrated residuals, e.g., not summing up to zero, due to a changing risk parameter. For this reason, the 10 size portfolios' Market Model is estimated for the whole period 1985-1995, as the specific information obtained under the original beta estimation (Chapter 4) are taken into account. The estimation results are consistent with the 3-year rolling regression results, which are available on request. Estimated in such a manner, the residuals from the market model fulfil the basic condition required by the Markov Chain Model, i.e., they sum up to zero. Then, the same analysis carried out with the gross returns of the size portfolios is carried out with respect to the size portfolios' Market Model residuals. The result are shown in Table 6.5.

Table 6.5 tells a story that is quite different from the previous experiment. The transition probabilities across the size portfolios show nearly equal lambdas. Hypothesis 1, $\lambda_{00} = \lambda_{11}$ cannot be rejected for any size portfolio. The same is true for Hypothesis 2, testing for the Random Walk.

Thus, there are neither bubbles nor predictable components stemming from the residuals of the Market model. This is in contrast to the results reported in Table 6.3, which are based on 3-year average monthly gross returns.

## Table 6.5.

| Transition Counts | Size Portf. 1 Current State | | Size Portf. 2 Current State | | Size Portf. 3 Current State | | Size Portf. 4 Current State | | Size Portf. 5 Current State | | Size Portf. 6 Current State | | Size Portf. 7 Current State | | Size Portf. 8 Current State | | Size Portf. 9 Current State | | Size Portf. 10 Current State | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Prior States | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| 00 | 8 | 12 | 14 | 16 | 20 | 17 | 14 | 16 | 16 | 20 | 39 | 16 | 27 | 21 | 14 | 18 | 14 | 19 | 15 | 17 |
| 01 | 15 | 19 | 19 | 16 | 14 | 18 | 19 | 16 | 24 | 11 | 16 | 13 | 21 | 10 | 20 | 16 | 20 | 15 | 15 | 17 |
| 10 | 12 | 22 | 16 | 19 | 17 | 14 | 16 | 19 | 21 | 15 | 16 | 13 | 20 | 11 | 19 | 17 | 19 | 17 | 17 | 16 |
| 11 | 18 | 24 | 16 | 14 | 17 | 13 | 16 | 14 | 12 | 11 | 13 | 4 | 10 | 10 | 16 | 10 | 16 | 10 | 17 | 16 |
| Initial State | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |
| <u>MLE Estimates</u> | | | | | | | | | | | | | | | | | | | | |
| $\lambda_{00}$ | 0.400 | | 0.467 | | 0.541 | | 0.467 | | 0.444 | | 0.709 | | 0.563 | | 0.438 | | 0.424 | | 0.469 | |
| $\sigma(\lambda_{00})$ | 0.110 | | 0.091 | | 0.082 | | 0.091 | | 0.083 | | 0.061 | | 0.072 | | 0.088 | | 0.086 | | 0.088 | |
| $\lambda_{11}$ | 0.429 | | 0.533 | | 0.567 | | 0.533 | | 0.522 | | 0.765 | | 0.500 | | 0.615 | | 0.615 | | 0.515 | |
| $\sigma(\lambda_{11})$ | 0.076 | | 0.091 | | 0.090 | | 0.091 | | 0.104 | | 0.103 | | 0.112 | | 0.095 | | 0.095 | | 0.087 | |
| <u>Hypothesis Tests</u> | | | | | | | | | | | | | | | | | | | | |
| $H_1: \lambda_{00} = \lambda_{11}$ | | | | | | | | | | | | | | | | | | | | |
| WT | 0.05 | | 0.27 | | 0.05 | | 0.27 | | 0.36 | | 0.31 | | 0.25 | | 1.86 | | 2.18 | | 0.14 | |
| LRT | 0.05 | | 0.27 | | 0.05 | | 0.27 | | 0.34 | | 0.22 | | 0.22 | | 1.88 | | 2.21 | | 0.14 | |
| $H_2: \lambda_{00}=\lambda_{11}=\lambda_{01}=\lambda_{10}$ | | | | | | | | | | | | | | | | | | | | |
| LRT | 0.66 | | 0.78 | | 1.29 | | 0.78 | | 4.46 | | 4.28 | | 2.15 | | 1.97 | | 2.51 | | 0.28 | |

## 6.8. Conclusion

The Markov Chain methodology applied here shows that different size firms' returns follow different patterns; Small size firms are prone to bubbles and positive autocorrelation that stretches 2 lags at minimum. In addition, the test of the Random Walk hypothesis fails to accept randomness of the smallest market capitalisation portfolios 1 and 2.

Having in mind that portfolio returns series are composed of multiple firms, any such dependence as that stated above is evidence of company size dependent factors that affect share prices.

A test of stationarity shows that return series are stationary, implying a stable process during the period 1985-1995.

Tests using the residuals of the Market Model find neither bubbles nor deviation from the Random Walk across all size portfolios. This indicates a proper alteration and adjustment in the Market Model, estimated in Chapter 4. Individual size portfolios' allowances for infrequent trades and autocorrelation error obviously play an important role in achieving the Market Model's good fit.

The fact that Market Model residual series are random and do not exhibit bubbles should not be taken as an indication that the actual series are white noise. Portfolios' residual series are produced by the relation of portfolios' returns to the market return, and the direction and magnitude of their deviation has nothing to do with the portfolios' gross return deviations. In the Market Model, for instance, a positive residual may be associated with a portfolio's relative outperformance of the market, although the portfolio's absolute gross return may be negative, for a particular period. This asks the question of whether the deviations from the average, moving average respectively, or the Market Model residuals should be used for a case study of the "news" impact on the market prices. In my opinion the series used for "news" impact on market prices ought to be firms' own, rather that Market Model residuals.

## Appendix 6.1.

It may be possible for a higher return to be earned by using the information about the sequential relation of the size portfolios' returns. A formal test of a strategy, based on the portfolios 1 and 10 return series is shown below. The strategy relates to the results shown in Table 6.2, and for consistency reasons no change in the return series is made.

The strategy consists of signals "buy" and "sell" which are based on the transition probability matrices of portfolios 1 and 10.

The signal-extraction process has a two period memory; for portfolio 1, the signal extraction function looks as follows:

| Observed last two periods | Action applied in the current period |
|---|---|
| uu | buy or hold the investment |
| ud | sell or stay out of market |
| du | buy or hold the investment |
| dd | sell or stay out of market |

*Note:*

*u* stands for up, or higher than average returns

*d* stands for down, or lower than average returns

To sum up, the strategy for portfolio 1 is:

buy if the observed last two periods are *uu* or *du*

sell if the observed last two periods are *ud* or *dd*

This simple strategy however, is based on the observed transition probabilities for portfolio 1. In the case of the buy (hold) signal, the probability of the current state *u* after prior states *uu* is 0.605 and the probability of the current state *u* after prior states *du* is 0.708. This gives the basic idea that the small size portfolio return is more likely to go up when previous states *uu* or *du* are observed, which is consistent with the positive autocorrelation and the bubbles ascertained earlier.

As size portfolios' transition probabilities differ, an altered strategy ought to be applied for portfolio 10. In a similar manner to portfolio 1, following the probability dominance, the investment strategy for portfolio 10 is:

| Observed last two periods | Action applied in the current period |
|---|---|
| uu | sell or stay out of market |
| ud | stay where you are (do nothing) |
| du | buy or hold the investment |
| dd | buy or hold the investment |

As is seen from the above formalisation, the portfolio 10 strategy is nearly opposite to the portfolio 1 strategy. This is a manifestation of the opposite sign autocorrelation. Besides, because of its marginal probabilistic structure it is not a straightforward procedure to establish the portfolio 10 trading strategy; This is especially pronounced for the prior state *ud*, where current states *u* and *d* have almost the same probability of occurring. In this case, the transaction costs of a trade are a paramount consideration, and thus a "do nothing" strategy is suggested.

Hence, if an imaginary investor starts at a particular point of time to invest by using the proposed strategy, he or she will not be in the market all the time. The investor will switch in/out according to the market signals transformed to buy/sell orders by the described strategy.

The following table summarises the results of the strategy applied to portfolios 1 and 10:

**Table Appendix 6.1.**

**Results of applying the trading strategy based on transition probabilities for portfolios 1 and 10 (1985-1995)**

| Item | Portfolio 1 | | | Portfolio 10 | | |
|---|---|---|---|---|---|---|
| | whole | in | out | whole | in | out |
| No of months | 130 | 67 | 63 | 129 | 78 | 51 |
| No unsuccessful in/out predictions | | 21 | 24 | | 34 | 22 |
| Average monthly profit (gross) | 0.0309 | 0.0441 | 0.0169 | 0.0095 | 0.0136 | 0.0031 |
| No of buy/sell | | 48 | | | 38 | |

As Appendix 6.1 shows, applying a trading strategy based on transition probabilities brings about 50% higher return, compared to the average portfolios' gross return. In absolute terms the difference between buy and hold and in/out strategy is much more pronounced for the smallest size portfolio 1, whose whole period return is quite impressive anyway. For a holding period of 67 months the total portfolio 1 extra return is 88.44%, allowing for up to 1.84% per transaction. Clearly, that is not enough to cover the transaction costs and make such a strategy profitable *per se.* Therefore, it is not possible to earn a profit on the trading rule. Considering the higher small size firms' return in general, this strategy may be a helpful tool, so that a temporary allocation of free financial resources to be timed properly by the small size firms.

# Chapter 7

# The Relationship Between Size Portfolios Returns and Economy-Wide Variables in the Vector Autoregression (VAR) Framework

## 7.1. Introduction

The results of Chapter 4 confirm the existence of the size effect in the LSE from 1985 to 1995. Furthermore, the excess returns of small and large firms exhibit a reverse cyclical pattern; when there is a positive small size excess return, the large size excess return is negative and *vice versa*. This pattern is apparent on a yearly and monthly return basis.

A tentative approach for a further test of the return behaviour across the size portfolios (Campbell and MacKinlay (1997)) tests the cross-autocorrelations matrices $\hat{Y}_k$ of the vector of weekly returns of the size-sorted portfolios, for a sample of NYSE-AMEX stock from July 1962 to December 1994. A study of these finds an interesting pattern demonstrating almost always positive autocorrelation below and negative autocorrelation above the diagonal of the matrices formed using current and lagged size returns. The pattern is most prominent at lag one, but similar patterns can be seen in the higher order autocorrelation matrices, although the magnitudes are smaller, due to the higher order cross-autocorrelation diminution.

An investigation similar to Campbell and MacKinlay is carried out, using the return series of ten size-portfolios formed as explained in Chapter 4. Matrix $\hat{Y}_0$ in Table 7.1 shows the contemporaneous cross-autocorrelation for 10 size-sorted portfolio returns. It is evident from $\hat{Y}_0$ that the closer size portfolios (by size) are, the more they are correlated and *vice versa*. More of a puzzle, however, is $\hat{Y}_1$ where

**Table 7.1.**

$\hat{Y}_0$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.00 | 0.90 | 0.87 | 0.89 | 0.85 | 0.82 | 0.78 | 0.72 | 0.67 | 0.62 |
| 2 | 0.90 | 1.00 | 0.91 | 0.91 | 0.89 | 0.87 | 0.82 | 0.76 | 0.72 | 0.64 |
| 3 | 0.87 | 0.91 | 1.00 | 0.94 | 0.92 | 0.90 | 0.87 | 0.80 | 0.77 | 0.70 |
| 4 | 0.89 | 0.91 | 0.94 | 1.00 | 0.94 | 0.93 | 0.90 | 0.85 | 0.80 | 0.75 |
| 5 | 0.85 | 0.89 | 0.92 | 0.94 | 1.00 | 0.95 | 0.93 | 0.89 | 0.86 | 0.81 |
| 6 | 0.82 | 0.87 | 0.90 | 0.93 | 0.95 | 1.00 | 0.96 | 0.93 | 0.90 | 0.84 |
| 7 | 0.78 | 0.82 | 0.87 | 0.90 | 0.93 | 0.96 | 1.00 | 0.95 | 0.92 | 0.88 |
| 8 | 0.72 | 0.76 | 0.80 | 0.85 | 0.89 | 0.93 | 0.95 | 1.00 | 0.96 | 0.93 |
| 9 | 0.67 | 0.72 | 0.77 | 0.80 | 0.86 | 0.90 | 0.92 | 0.96 | 1.00 | 0.94 |
| 10 | 0.62 | 0.64 | 0.70 | 0.75 | 0.81 | 0.84 | 0.88 | 0.93 | 0.94 | 1.00 |

$\hat{Y}_1$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1(-1) | 0.30 | 0.24 | 0.25 | 0.18 | 0.08 | 0.00 | -0.03 | -0.11 | -0.14 | -0.16 |
| 2(-1) | 0.37 | 0.32 | 0.33 | 0.25 | 0.16 | 0.06 | 0.02 | -0.06 | -0.09 | -0.12 |
| 3(-1) | 0.43 | 0.37 | 0.37 | 0.31 | 0.20 | 0.12 | 0.06 | -0.03 | -0.07 | -0.10 |
| 4(-1) | 0.40 | 0.35 | 0.35 | 0.28 | 0.18 | 0.09 | 0.04 | -0.04 | -0.07 | -0.10 |
| 5(-1) | 0.40 | 0.37 | 0.36 | 0.30 | 0.19 | 0.11 | 0.06 | -0.01 | -0.06 | -0.11 |
| 6(-1) | 0.43 | 0.39 | 0.40 | 0.34 | 0.23 | 0.16 | 0.11 | 0.03 | -0.01 | -0.06 |
| 7(-1) | 0.42 | 0.40 | 0.41 | 0.35 | 0.24 | 0.17 | 0.13 | 0.05 | 0.01 | -0.05 |
| 8(-1) | 0.44 | 0.41 | 0.43 | 0.38 | 0.27 | 0.22 | 0.18 | 0.10 | 0.05 | 0.00 |
| 9(-1) | 0.43 | 0.43 | 0.46 | 0.40 | 0.30 | 0.24 | 0.22 | 0.13 | 0.08 | 0.03 |
| 10(-1) | 0.39 | 0.38 | 0.43 | 0.37 | 0.28 | 0.22 | 0.21 | 0.11 | 0.07 | 0.02 |

$\hat{Y}_2$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1(-2) | -0.06 | -0.08 | -0.09 | -0.13 | -0.15 | -0.18 | -0.18 | -0.21 | -0.21 | -0.15 |
| 2(-2) | -0.04 | -0.07 | -0.08 | -0.13 | -0.15 | -0.18 | -0.19 | -0.23 | -0.22 | -0.16 |
| 3(-2) | 0.00 | -0.04 | -0.04 | -0.10 | -0.13 | -0.15 | -0.19 | -0.22 | -0.22 | -0.15 |
| 4(-2) | -0.07 | -0.08 | -0.08 | -0.14 | -0.17 | -0.20 | -0.22 | -0.25 | -0.25 | -0.18 |
| 5(-2) | 0.00 | -0.02 | -0.03 | -0.07 | -0.10 | -0.14 | -0.17 | -0.19 | -0.19 | -0.12 |
| 6(-2) | -0.04 | -0.07 | -0.06 | -0.11 | -0.16 | -0.19 | -0.22 | -0.25 | -0.25 | -0.20 |
| 7(-2) | -0.01 | -0.03 | -0.02 | -0.06 | -0.10 | -0.14 | -0.17 | -0.20 | -0.21 | -0.15 |
| 8(-2) | -0.01 | -0.02 | -0.01 | -0.05 | -0.11 | -0.14 | -0.18 | -0.21 | -0.22 | -0.18 |
| 9(-2) | -0.01 | -0.01 | 0.00 | -0.03 | -0.10 | -0.13 | -0.19 | -0.22 | -0.23 | -0.19 |
| 10(-2) | 0.01 | -0.01 | -0.02 | -0.04 | -0.11 | -0.14 | -0.18 | -0.21 | -0.23 | -0.18 |

$\hat{Y}_3$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1(-3) | -0.05 | -0.06 | -0.07 | -0.14 | -0.10 | -0.14 | -0.12 | -0.13 | -0.12 | -0.13 |
| 2(-3) | -0.04 | -0.05 | -0.04 | -0.11 | -0.08 | -0.11 | -0.09 | -0.10 | -0.08 | -0.08 |
| 3(-3) | -0.02 | -0.06 | -0.05 | -0.11 | -0.08 | -0.12 | -0.09 | -0.12 | -0.11 | -0.10 |
| 4(-3) | -0.05 | -0.07 | -0.06 | -0.12 | -0.09 | -0.12 | -0.09 | -0.11 | -0.11 | -0.10 |
| 5(-3) | -0.05 | -0.07 | -0.06 | -0.12 | -0.09 | -0.12 | -0.11 | -0.13 | -0.12 | -0.14 |
| 6(-3) | -0.01 | -0.02 | -0.02 | -0.07 | -0.03 | -0.06 | -0.06 | -0.07 | -0.07 | -0.07 |
| 7(-3) | 0.00 | -0.03 | 0.00 | -0.06 | -0.03 | -0.06 | -0.07 | -0.07 | -0.08 | -0.08 |
| 8(-3) | -0.01 | -0.05 | -0.03 | -0.09 | -0.05 | -0.09 | -0.09 | -0.09 | -0.10 | -0.10 |
| 9(-3) | 0.05 | 0.02 | 0.02 | -0.02 | 0.02 | -0.02 | -0.02 | -0.02 | -0.03 | -0.04 |
| 10(-3) | 0.00 | -0.04 | -0.02 | -0.06 | -0.01 | -0.05 | -0.05 | -0.05 | -0.06 | -0.06 |

$\hat{Y}_4$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1(-4) | -0.03 | -0.02 | -0.06 | -0.12 | -0.10 | -0.05 | -0.07 | -0.09 | -0.08 | -0.09 |
| 2(-4) | 0.04 | 0.07 | 0.03 | -0.04 | -0.01 | 0.03 | 0.01 | -0.03 | -0.01 | -0.02 |
| 3(-4) | 0.02 | 0.00 | -0.01 | -0.09 | -0.05 | -0.03 | -0.04 | -0.07 | -0.05 | -0.05 |
| 4(-4) | 0.05 | 0.03 | 0.01 | -0.06 | -0.01 | 0.00 | -0.01 | -0.03 | -0.02 | -0.02 |
| 5(-4) | 0.04 | 0.05 | 0.02 | -0.06 | -0.02 | -0.01 | -0.02 | -0.05 | -0.03 | -0.04 |
| 6(-4) | 0.05 | 0.07 | 0.03 | -0.04 | -0.01 | -0.01 | -0.02 | -0.05 | -0.03 | -0.05 |
| 7(-4) | 0.07 | 0.07 | 0.03 | -0.04 | 0.00 | -0.01 | -0.01 | -0.04 | -0.03 | -0.04 |
| 8(-4) | 0.06 | 0.05 | 0.04 | -0.04 | -0.01 | -0.01 | -0.02 | -0.04 | -0.03 | -0.03 |
| 9(-4) | 0.09 | 0.08 | 0.07 | 0.00 | 0.01 | 0.00 | -0.01 | -0.03 | 0.00 | -0.01 |
| 10(-4) | 0.05 | 0.04 | 0.03 | -0.02 | -0.01 | -0.02 | -0.01 | -0.03 | -0.01 | -0.01 |

cross-autocorrelations between the portfolios' contemporaneous and lag (1) return are displayed. As in Campbell *et al* (1997), the cross-autocorrelations below the diagonal are larger than those above the diagonal. This seems to be valid in the prevailing number of cases not only for $\hat{Y}_1$, but also for $\hat{Y}_2$ through $\hat{Y}_4$, although the magnitude diminishes slightly.

This fascinating lead-lag pattern, where the larger capitalisation stocks lead and the smaller capitalisation stocks lag, is clearer in Table 7.2, where the differences between autocorrelation matrices and their transposes are reported. For $\hat{Y}_1 - \hat{Y}_1'$ all values below the diagonal are positive and *vice versa*, implying that the correlation between the current returns of smaller firms and past returns of larger stocks is always bigger than the correlation between the current returns of larger firms and past returns of smaller firms. In relation to this study, the above assertion, although puzzling, is in line with the findings in the previous chapters. Thus the estimation of beta, (Chapter 4) carried out on the lagged, contemporary and led Market Index reveals a lagged market contribution of 0.19 for portfolio 1 (smallest), and -0.23 to portfolio 10 (biggest) for the period 1985-1995. Clearly, this regularity is confirmed by the correlation matrices in Table 7.1. Chapter 6 provides evidence on the positive autocorrelation in the small size returns and negative autocorrelation in the large size returns, using the two-state second-order Markov Chain.

Lo and MacKinlay (1990) argue that the existence of cross-effects can explain the apparent profitability of contrarian investment strategies, which are successful in the presence of negative serial autocorrelation. These strategies revolve on the notion that investors tend to overreact to information. Thus, if asset returns are negatively correlated, selling "winners" and buying "losers" will earn positive excess returns. If there are positive cross-effects, another profitable scheme can be applied; a higher than average market return of an asset A today, whose lagged return correlates positively with the return of an asset B, will imply a higher return on asset B tomorrow. A long position on B may then turn profitable.

# Table 7.2.

$\hat{Y}_1 - \hat{Y}_1'$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1(-1) | 0.00 | -0.12 | -0.18 | -0.22 | -0.31 | -0.43 | -0.46 | -0.55 | -0.57 | -0.55 |
| 2(-1) | 0.12 | 0.00 | -0.04 | -0.09 | -0.21 | -0.33 | -0.38 | -0.48 | -0.52 | -0.51 |
| 3(-1) | 0.18 | 0.04 | 0.00 | -0.04 | -0.16 | -0.28 | -0.35 | -0.46 | -0.53 | -0.52 |
| 4(-1) | 0.22 | 0.09 | 0.04 | 0.00 | -0.12 | -0.26 | -0.31 | -0.42 | -0.47 | -0.47 |
| 5(-1) | 0.31 | 0.21 | 0.16 | 0.12 | 0.00 | -0.12 | -0.18 | -0.28 | -0.36 | -0.39 |
| 6(-1) | 0.43 | 0.33 | 0.28 | 0.26 | 0.12 | 0.00 | -0.06 | -0.19 | -0.26 | -0.29 |
| 7(-1) | 0.46 | 0.38 | 0.35 | 0.31 | 0.18 | 0.06 | 0.00 | -0.13 | -0.21 | -0.26 |
| 8(-1) | 0.55 | 0.48 | 0.46 | 0.42 | 0.28 | 0.19 | 0.13 | 0.00 | -0.08 | -0.11 |
| 9(-1) | 0.57 | 0.52 | 0.53 | 0.47 | 0.36 | 0.26 | 0.21 | 0.08 | 0.00 | -0.05 |
| 10(-1) | 0.55 | 0.51 | 0.52 | 0.47 | 0.39 | 0.29 | 0.26 | 0.11 | 0.05 | 0.00 |

$\hat{Y}_2$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1(-2) | 0.00 | -0.04 | -0.08 | -0.06 | -0.15 | -0.14 | -0.17 | -0.20 | -0.20 | -0.16 |
| 2(-2) | 0.04 | 0.00 | -0.04 | -0.04 | -0.13 | -0.12 | -0.17 | -0.21 | -0.21 | -0.16 |
| 3(-2) | 0.08 | 0.04 | 0.00 | -0.02 | -0.11 | -0.09 | -0.17 | -0.21 | -0.22 | -0.14 |
| 4(-2) | 0.06 | 0.04 | 0.02 | 0.00 | -0.10 | -0.09 | -0.16 | -0.20 | -0.22 | -0.14 |
| 5(-2) | 0.15 | 0.13 | 0.11 | 0.10 | 0.00 | 0.02 | -0.06 | -0.08 | -0.09 | -0.02 |
| 6(-2) | 0.14 | 0.12 | 0.09 | 0.09 | -0.02 | 0.00 | -0.09 | -0.11 | -0.12 | -0.06 |
| 7(-2) | 0.17 | 0.17 | 0.17 | 0.16 | 0.06 | 0.09 | 0.00 | -0.01 | -0.02 | 0.03 |
| 8(-2) | 0.20 | 0.21 | 0.21 | 0.20 | 0.08 | 0.11 | 0.01 | 0.00 | 0.00 | 0.03 |
| 9(-2) | 0.20 | 0.21 | 0.22 | 0.22 | 0.09 | 0.12 | 0.02 | 0.00 | 0.00 | 0.04 |
| 10(-2) | 0.16 | 0.16 | 0.14 | 0.14 | 0.02 | 0.06 | -0.03 | -0.03 | -0.04 | 0.00 |

$\hat{Y}_3 - \hat{Y}_3'$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1(-3) | 0.00 | -0.02 | -0.05 | -0.09 | -0.05 | -0.13 | -0.11 | -0.12 | -0.16 | -0.13 |
| 2(-3) | 0.02 | 0.00 | 0.02 | -0.05 | -0.01 | -0.08 | -0.06 | -0.04 | -0.10 | -0.04 |
| 3(-3) | 0.05 | -0.02 | 0.00 | -0.05 | -0.01 | -0.10 | -0.09 | -0.09 | -0.14 | -0.08 |
| 4(-3) | 0.09 | 0.05 | 0.05 | 0.00 | 0.03 | -0.05 | -0.04 | -0.03 | -0.09 | -0.04 |
| 5(-3) | 0.05 | 0.01 | 0.01 | -0.03 | 0.00 | -0.09 | -0.08 | -0.08 | -0.14 | -0.13 |
| 6(-3) | 0.13 | 0.08 | 0.10 | 0.05 | 0.09 | 0.00 | 0.01 | 0.02 | -0.05 | -0.02 |
| 7(-3) | 0.11 | 0.06 | 0.09 | 0.04 | 0.08 | -0.01 | 0.00 | 0.02 | -0.06 | -0.03 |
| 8(-3) | 0.12 | 0.04 | 0.09 | 0.03 | 0.08 | -0.02 | -0.02 | 0.00 | -0.08 | -0.05 |
| 9(-3) | 0.16 | 0.10 | 0.14 | 0.09 | 0.14 | 0.05 | 0.06 | 0.08 | 0.00 | 0.02 |
| 10(-3) | 0.13 | 0.04 | 0.08 | 0.04 | 0.13 | 0.02 | 0.03 | 0.05 | -0.02 | 0.00 |

$\hat{Y}_4 - \hat{Y}_4'$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1(-4) | 0.00 | -0.06 | -0.08 | -0.17 | -0.14 | -0.10 | -0.14 | -0.14 | -0.17 | -0.14 |
| 2(-4) | 0.06 | 0.00 | 0.02 | -0.07 | -0.05 | -0.03 | -0.06 | -0.07 | -0.09 | -0.07 |
| 3(-4) | 0.08 | -0.02 | 0.00 | -0.10 | -0.07 | -0.06 | -0.06 | -0.10 | -0.12 | -0.09 |
| 4(-4) | 0.17 | 0.07 | 0.10 | 0.00 | 0.06 | 0.04 | 0.03 | 0.01 | -0.01 | 0.01 |
| 5(-4) | 0.14 | 0.05 | 0.07 | -0.06 | 0.00 | 0.00 | -0.02 | -0.04 | -0.05 | -0.03 |
| 6(-4) | 0.10 | 0.03 | 0.06 | -0.04 | 0.00 | 0.00 | -0.01 | -0.03 | -0.03 | -0.03 |
| 7(-4) | 0.14 | 0.06 | 0.06 | -0.03 | 0.02 | 0.01 | 0.00 | -0.02 | -0.02 | -0.03 |
| 8(-4) | 0.14 | 0.07 | 0.10 | -0.01 | 0.04 | 0.03 | 0.02 | 0.00 | 0.00 | -0.01 |
| 9(-4) | 0.17 | 0.09 | 0.12 | 0.01 | 0.05 | 0.03 | 0.02 | 0.00 | 0.00 | 0.00 |
| 10(-4) | 0.14 | 0.07 | 0.09 | -0.01 | 0.03 | 0.03 | 0.03 | 0.01 | 0.00 | 0.00 |

Boudoukh, Richardson, and Whitelaw (1994) classify the explanations into three groups; Loyalist, Revisionists and Heretics. Loyalists resist the efficiency of stock markets by stressing data mismeasurement and market imperfections as the sources for predictability. Revisionists attribute the predictability of small stock returns to time-varying risk premiums. Finally, Heretics attribute the predictability to market fads, bubbles, or overreaction.

The cross-correlation pattern across size portfolio returns, alongside the other evidence of return-regularities based on differences in market capitalisation, suggest contrariety in accommodating the economy-wide signals. Economy-wide factors are here envisaged as those macroeconomic variables common to all stocks, although their fluctuation may affect stocks differently depending on their market capitalisation. Thus, market capitalisation in itself may not be responsible for the observed discrepancies in returns based on size, but it may well proxy for different patterns in accommodating the information in security prices.

Balduzzi, Bertola, and Foresi's (BBF) (1995) article combines the continuous arrival of information and the infrequency of trade, and investigates the effects on asset price dynamics of positive and negative feedback trading.

The strategy applied to portfolio rebalancing determines the difference between positive and negative feedback trading. Traders applying a negative (contrarian) feedback strategy would buy losers and sell winners. Positive feedback traders would buy winners and sell losers. In the presence of transaction costs, investors may find it optimal to rebalance their portfolios only occasionally, and then by discrete amounts. In fact, if the transaction costs are proportional, trades will occur only when the portfolio is sufficiently far "out of line", and if part of the transaction costs is fixed, it then becomes optimal to trade discrete amounts of assets.

According to BBF, the type of feedback trader determines the variability of stock prices. The presence of negative feedback traders leads to lower price variability, as their strategy is the converse of price movements - sell at a price increase, buy at a price decrease. The positive feedback traders increase stock price variability, as their strategy is to follow the existing trend (self-fulfilment). The standard deviations of size portfolios provided in Table 4.1 confirm this conjecture with respect to portfolios 1, 9 and 10.

It might be deemed easier to induce stock price movements by buying or selling the shares of small capitalisation firms as they are not frequently traded, and therefore have less certain intrinsic value.

The higher volatility of small size firms may be due to the scarce availability of information about these firms. Information gathering is a costly activity. It can be argued that the cost of making inquiries about a firm are roughly the same, no matter how large the firm is. Therefore, it is more efficient if frequent information is provided for the larger firms, since this information will be sought by more investors. As small firm information is not as frequently available as that for bigger firms, the 'neglected firms' explanation of the Small size Anomaly has to be acknowledged.

When information relating to small firms becomes available to the market, small firm investors tend to overreact more than the larger firm investors, because of the information vacuum, implying the existence of positive feedback investors. Therefore, it is quite possible for small and large firms to have different return distributions. One may expect more leptokurtic distributions of small companies' returns. A glance at Figure 4.1 justifies this assumption in relation to portfolios 1 and 10.

It can be hypothesised that, due to their thin trading, small capitalisation firms react with a delay to changes in economy-wide indicators compared to larger firms. The model proposed here attempts to detect whether those factors which are common to all affect different share prices and returns with different magnitudes and lags. By different share prices and returns is meant a difference in market capitalisation. The model's aim is to detect possible delayed reactions of small firms which are of lesser magnitude than the large firm reaction to the common factors influencing stock prices.

There are various papers alleging different behaviour of small and large firm prices, which stems from the idiosyncracy of transmission of the firms' specific information. Thus, in relation to the reporting of firms' accounts, (i) Mendenhall and Nichols (1988) find a larger per-unit market response to interim quarter bad news than to fourth quarter bad news; (ii) Dye (1988) makes claims for managerial incentives for income increasing biases; (iii) Mendenhall and Nichols (1988) reveal that there are opportunities provided for managers to engage in such biases for non-audited quarterly reports.

As a result of the above, Chambers and Penman (1984) ascertain that investors *react less strongly* to interim good news reports than to interim bad news reports. The good news reaction disparity is *predictably decreasing over firm size* as a result of interim bias limitations imposed on large firms by relatively continuous auditor involvement (Kros and Schroeder, (1990)).

To summarise, larger firms' investors react to both good and bad news throughout the year. Smaller firms' investors react only to bad news throughout the year and readjust their perceptions when annual reports are released. This is evidence of a small firm delayed and weak reaction to the 'good news' account's reports at the time when information is scarce, i.e., the first three quarters of the year.

## 7.2. Choosing relevant economy-wide indicators

The choice of relevant economy-wide variables is crucial for achieving high explanatory power of the model. Macroeconomic variables, in general, interact between themselves and therefore are highly correlated. Besides, the cause-effect relationship between them alternates, due to changes in policy, for instance.

Another problem with economy-wide variables is their very low frequency, as well as their more established trends over longer periods. It may appear surprising, but core macroeconomic variables, such as GNP, do not explain stock market variation for horizons shorter than a year - a puzzle resolved by the work of Fama (1981) and Kaul (1987), who find that real activity explains more return variation for longer return horizons. Future production growth rates explain 6% of the variance of monthly returns on the NYSE value-weighted portfolio. The proportion rises to 43% for annual returns. (See Fama 1990a). The highest available frequency GNP series are normally quarterly. In addition, they become publicly accessible only long after the end of the quarter.

It seems that variables with higher frequency are those belonging to the monetary system, such as interest rates and inflation. The existence of a negative significant correlation between inflation and returns on common stocks is a well-established empirical fact in post-war US data, beginning with Jaffe and Mandelker (1976), Bodie (1976) and Nelson (1976). Such an empirical fact is further documented by Fama and Schwert (1977). In his well known article, Fama (1981) outlines the 'proxy hypothesis' as a main explanation for the negative correlation between inflation and stock prices. Firstly, high inflation rates anticipate low growth rates of real aggregate economic activity. As economic growth is expected to slow down, the growth rate of the demand for real cash balances is also expected to decrease, leading to an increase in the future-expected and current inflation. Secondly, high real stock returns anticipate high growth rates of aggregate economic activity. As a result, inflation and stock returns are driven in opposite directions by anticipated business fluctuations and thus correlate negatively. Fama and Schwert (1977) investigated which assets have proved to be a good hedge against inflation surprises and which assets have generated low real returns when inflation is unexpectedly high. Their results suggest that assets whose real returns are sensitive to inflation-in particular those whose real yields fall when prices of consumer goods rise faster than anticipated - should have inflation risk premiums. Corkish and Miles (1994) results for the UK show that most assets are sensitive to inflation shocks, but that the inflation premiums are not very well defined. Most assets appear to generate lower average returns when inflation variability is high, a result which is hard to interpret in terms of an inflation risk premium. Thus, inflation rates, although versatile and generally recognised, may not posit the required characteristics for inclusion.

However, Balduzzi (1995) finds that the rate of interest accounts for a substantial share of the negative correlation between stock returns and inflation and therefore it is more appropriate to relate various interest rates, instead of the inflation rate, with stock returns. Further, yield spreads rather than real interest rates are more useful in forecasting other variables, such as stock returns. In fact, the evidence is that most of the forecasting power of the term structure is for inflation rather than real interest rates[1]. Thus, the final selection of explanatory variables consists of the Term Spread and the Default Spread.

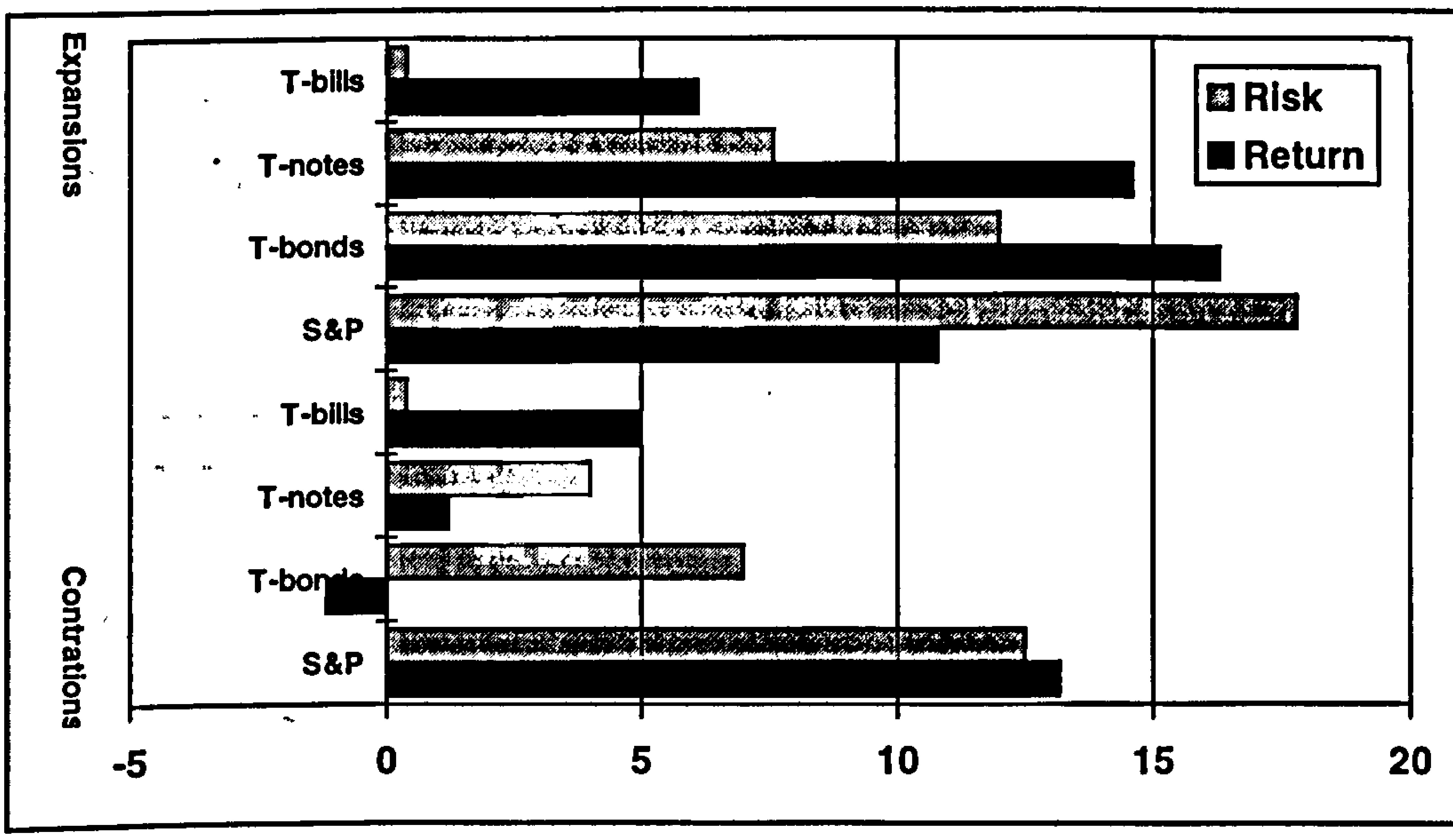
As the economy overheats during a long business boom, interest rates tend to rise, making credit more expensive. The tight money action followed by the Bank's higher interest rate squeezes credit out of the monetary system; and this leads to a slowing of business activity and (ideally) a decline in the rate of price inflation in wholesale and consumer goods. The reverse action is taken to make new housing and cars more affordable to potential buyers. When repressed demand is met with purchases of these big receipt items, inventories of these items and their component parts are expanded, credit is expanded, more jobs are created, the unemployment level generally declines, and the uptrend in growth of GDP is resumed.

Figure 7.1 shows the average return and volatility of different investment instruments in the periods of expansion and contraction of the business cycle.

[1]See Fama (1975, 1990a) and Mishkin (1990a, 1990b).

Figure 7.1.

**Average Returns and Risks of S & P 500, Twenty-Year T-bonds, Ten-Year T-Notes, and Twenty-Day T-Bills for Seven Business Cycles, 1949-1982**




*Source:* Peter I. Berman, "An Asset Allocation Primer for Post-War Business Cycles" *American Business Review,* 10, (January 1992), pp 88-92.

### 7.2.1. Term Spread

Although risk-free short run interest rates affect or correlate negatively with stock market performance, it is prudent to use a complex indicator, which in theory brings about changes in the future spot prices (yields) of short term interest rates. Such an indicator is the so-called term spread. In the popular expectation theory of interest rates, the term spread is the difference in the yields of riskless securities with different times to maturity. Methodological approaches in the empirical literature vary from using the spread as predictor of future movements in spot rates (Campbell and Shiller (1991)) to testing forward rates as unbiased predictors of future spot rates (Fama, 1984, Mishkin, 1988, Dahlquist and Jonsson, 1994).

The empirical evidence differs across countries. The Expectations hypothesis in general is rejected for the United States (Shiller (1979), Campbell and Shiller (1987), (1988), (1991)

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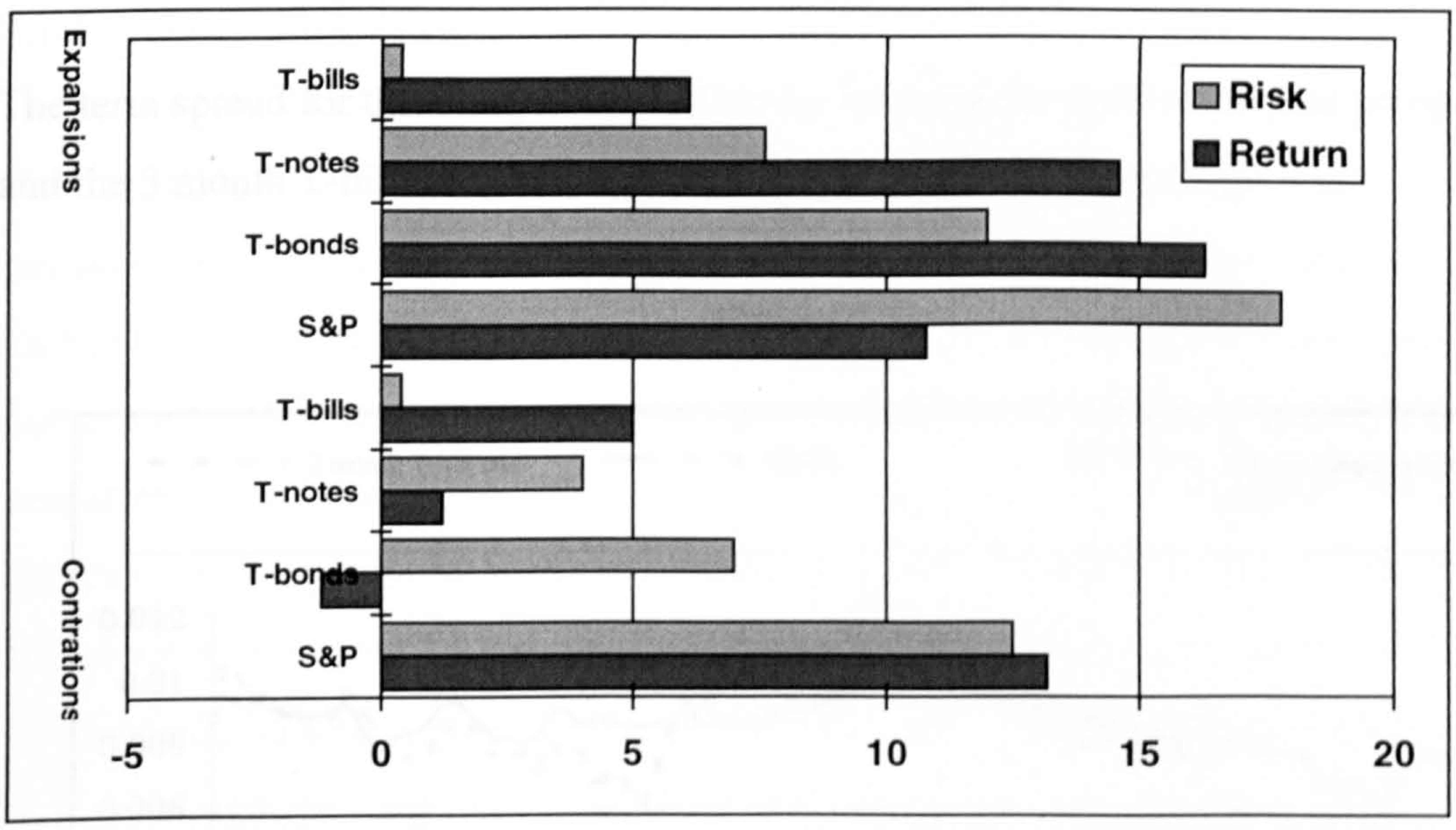
**Average Returns and Risks of S & P 500, Twenty-Year T-bonds, Ten-Year T-Notes, and Twenty-Day T-Bills for Seven Business Cycles, 1949-1982**

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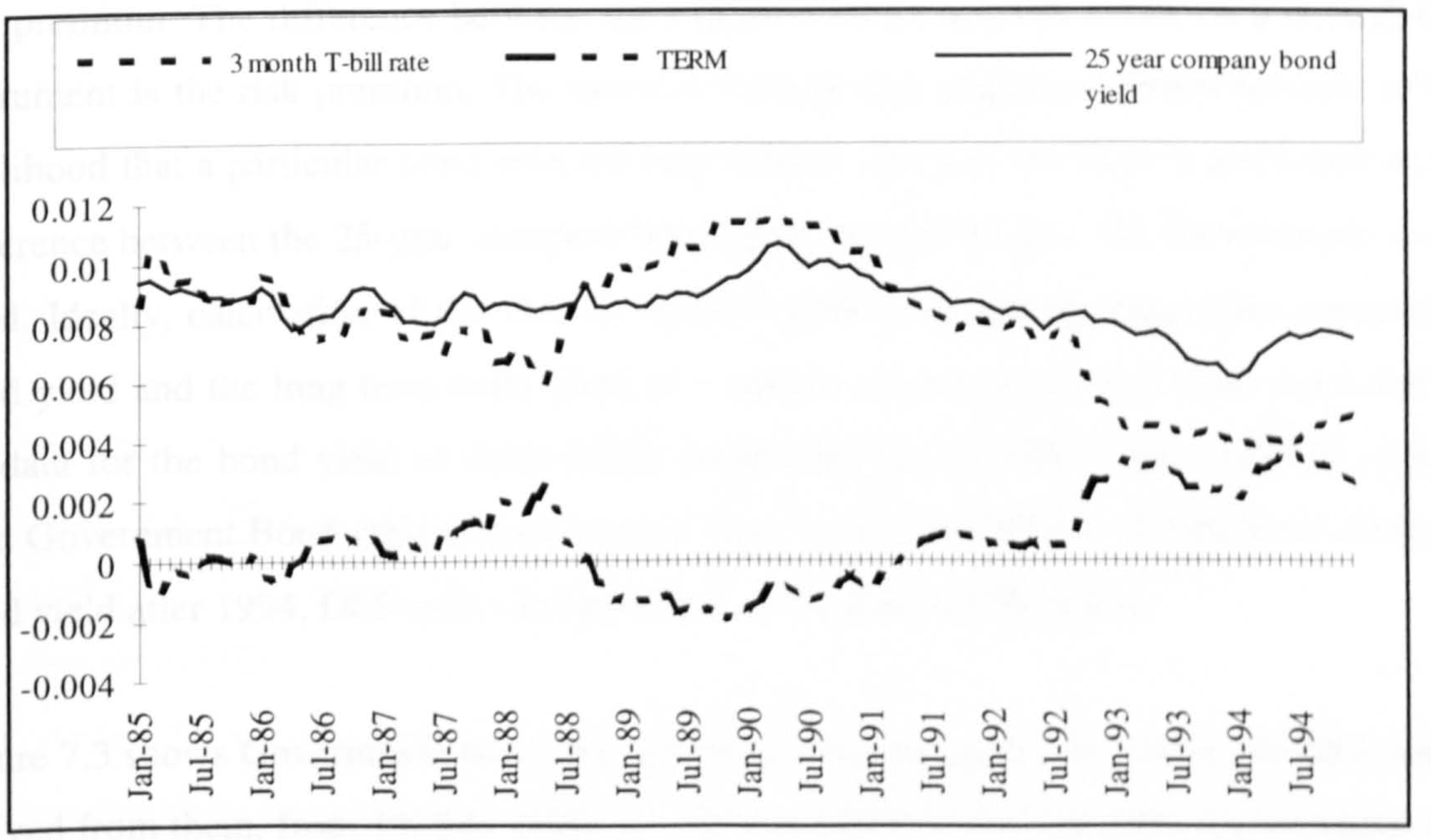
The empirical evidence differs across countries. The Expectations hypothesis in general is rejected for the United States (Shiller (1979), Campbell and Shiller (1987), (1988), (1991) and Shea (1992)). For the UK, however, (Hardouvelis, (1994), Breedon and Brookes, (1994)) the expectation hypothesis is not rejected, although it shows signs of weakness at the short end of the maturity spectrum (Rossi, 1996).

The term spread for this study is the difference between the yield of 25 year company bonds and the 3 month T-bill rate, whose dynamics can be seen in Figure 7.2.

**Figure 7.2.**




The original sample is from 1985 to 1995, but because of unavailable data for the 25-year company bond yield, TERM series are restricted to 1985-1994 period. Data for the 25-year company bond yield was collected from OECD Financial Statistics and HMSO Financial Statistics for relevant years, and after comparing both sources no discrepancies were found.

As Figure 7.2 shows, the two variables from which TERM is derived differ in their patterns. Company bonds seems to have a more stable yield curve, whereas the T-bill rate exhibits a major bounce between 1988 and 1992. This led to a negative TERM spread between July 1988 and June 1991.[2]

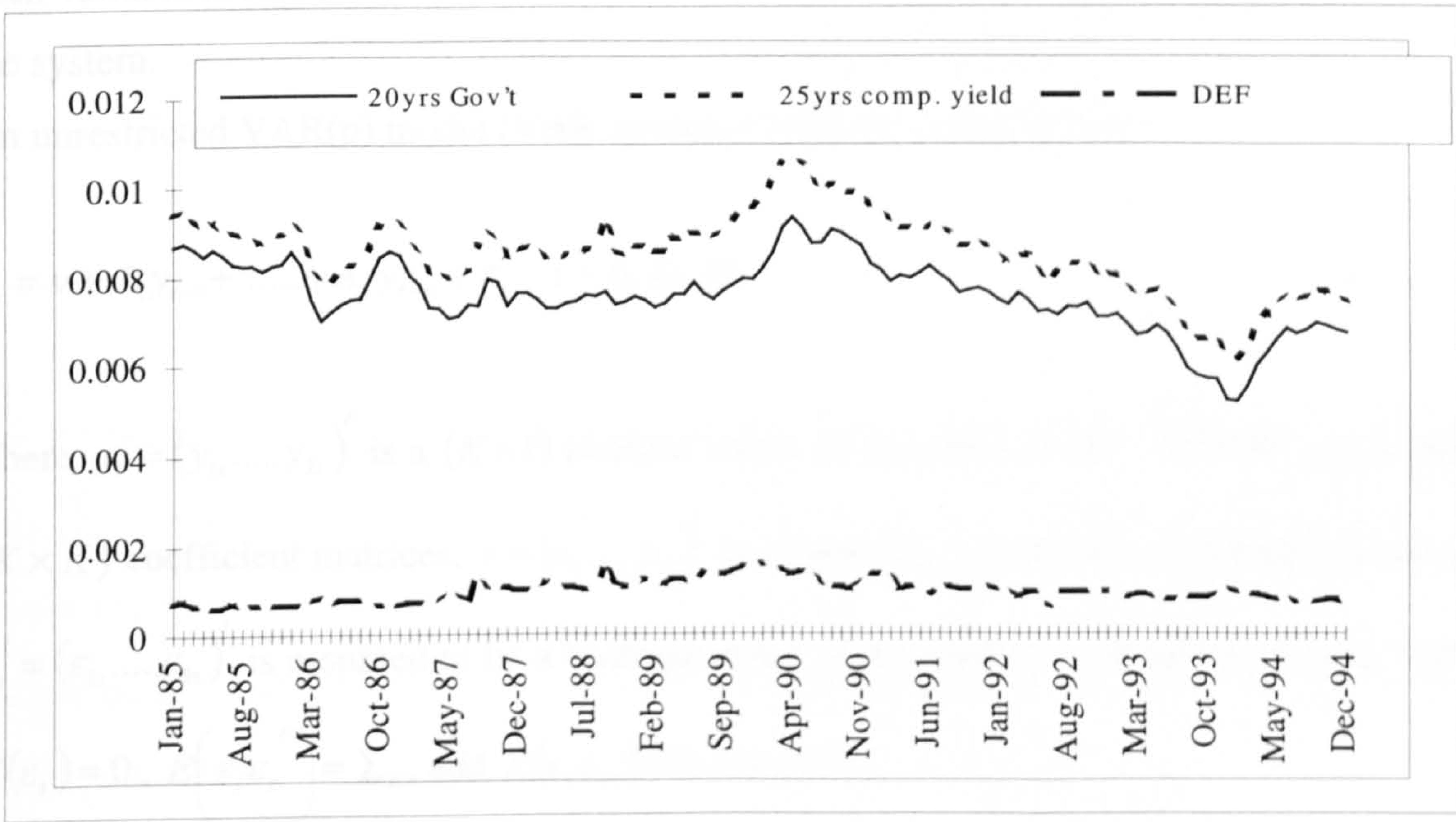
### 7.2.2. Default Risk

Unlike government bonds, there is a risk for corporate bonds that the coupon or principal payments will not be met. Therefore, it is necessary for these bonds that provisions be made for the difference between the promised and expected return, referred to here as the default risk premium. The difference between the expected return and the return on a default-free instrument is the risk premium. The investor requires this additional return because of the likelihood that a particular bond selected may default. The Default Risk is estimated as the difference between the 25-year company bond yield and the 20-year UK Government Bond yield. Ideally, calculation of the Default Spread (DEF) requires the long term companies' bond yield and the long term bond yield of a sample of companies that have AAA rating. As data for the bond yield of AAA-rating companies for the UK is not available, a long term Government Bond yield is used instead. Due to non-availability of long term company bond yield after 1994, DEF series are restricted to the 1985-1994 period.

Figure 7.3 shows Government bond and companies' bonds yields, as well as the DEF series derived from them, from 1985 to 1994. As expected, DEF is not constant. Government and companies' bonds exhibit similar volatility patterns, which is logical considering the incorporation in both series of secular inflation trends. However, both government and companies' long term bond yields seem to be more stable than the 3-month Treasury Bill rate, displayed in Figure 7.2.

[2]The general explanation for the short run interest rate surge and the consequent negative term structure rest in the policy of the Bank of England in this period. The Bank aimed to curb speculation and to foster real investments in the aftermath of the Big Bang 1987. This tendency seems to be further aggravated by Britain joining the ERM on 8/10/1990. Market observers associate the lowering of the long term interest rate after 1993 to present with the market anticipation that Britain will join the EURO-currency after all, and therefore interest rates will fall.

**Figure 7.3.**




The resulting spread (DEF), is more stable than TERM, although still variable on a month-to-month basis. After a significant upsurge just before September 1987, DEF remained high until mid 1992, reaching its maximum at the beginning of 1990. The high level was not the only feature of DEF during this period. The ten biggest positive month-to-month changes in DEF occurred between May 1987 and July 1992. The ten biggest (in absolute value) negative month-to-month changes occurred between July 1987 and January 1993.

## 7.3. The VAR Model

The framework of VAR models has been pioneered by Sims (1980, 1981) and others as an alternative to classical macroeconometric analysis. Sim's main criticism of the latter type of analysis is that macroeconometric models are often not based on sound economic theory and the available theories are not capable of providing a completely specified model. VAR models represent a class of loose models which do not impose *a priori* restrictions on the data generation process.

In principle, Vector Autoregressive (VAR) models are simple multivariate models in which each variable is explained by its own past values and the past values of all other variables in the system.

An unrestricted VAR(p) model (VAR model of order p) can be written

$$y_t = v + A_1 y_{t-1} + \ldots\ldots + A_p y_{t-p} + \varepsilon_t \quad t = 0, \pm 1, \pm 2 \ldots \tag{7.1}$$

where $y_t = (y_{1t} \ldots\ldots y_{kt})'$ is a $(K \times 1)$ random vector of variables in the VAR, the $A_i$ are fixed $(K \times K)$ coefficient matrices, $v = (v_1 \ldots\ldots v_k)'$ is a fixed $(K \times 1)$ vector of intercept terms, and $\varepsilon_t = (\varepsilon_{1t} \ldots\ldots \varepsilon_{kt})'$ is assumed to be a k-dimensional white noise or innovation process, that is $E(\varepsilon_t) = 0$, $E\left(\varepsilon_t \varepsilon_t'\right) = \Sigma_\varepsilon$, and $E(\varepsilon_t \varepsilon_m) = 0$ for $t \neq m$.

Note that even a relatively small VAR process with three variables (k=3) and lag length p=3 requires estimation of 10 (including the intercept) coefficients in each equation. Forecasts made using unrestricted VARs often suffer from overparameterisation, and this leads to large out-of-sample forecast errors. (Doan, 1990, pp 8-16). Hafer and Sheehan (1989) conclude that relatively short lagged models tend to be more accurate. Choosing less than optimal lags will cause information loss, and this leads us to the problem of VAR order selection.

### 7.3.1. VAR Order Selection

The selection of the order of the VAR is one of the most important procedures in establishing the relationships between the variables in the model. The choice of variables in many cases is determined by economic theory, although one's creative intuition may open new horizons to the theory. Economic theory, however, gives an imprecise background on what the appropriate lag structure between a set of variables should be. Luckily, there are criteria which help the selection of an appropriate lag structure. *Microfit 4* reports the results of three selection criteria – the Akaike information criterion (AIC), the Schwarz-Bayesian criterion (SBC) and the log-likelihood ratio test. The log-likelihood ratio statistic for testing the hypothesis that the order of the VAR is p against the alternative P (P>p) is given by

$$\lambda_{LR} = T\left(\ln\left|\tilde{\Sigma}_p\right| - \ln\left|\tilde{\Sigma}_P\right|\right) \tag{7.2}$$

for $p = 0,1,2,\ldots\ldots P-1$, where $P$ is the maximum order for the VAR model selected by the user. $\tilde{\Sigma}_p$ is the error covariance matrix of the VAR system of lag order $p$, respectively $P$. Under the null hypothesis, the LR statistic in (7.2) is asymptotically distributed as a $\chi^2$ variate with $K^2(P-p)$ degrees of freedom. The LR procedure requires a sequence of log-likelihood ratio tests to determine the number of lags in the system.

As VAR models are used for forecasting, it is perhaps wiser to use criteria that minimise the forecast Mean Squared error (MSE), such as AIC or SBC. Here the AIC is preferred to SBC in determining the lag structure, because it is quite usual for the SBC to select a lower order VAR than that selected by the AIC (Pesaran & Pesaran, (1997), p.272). For a VAR(p) process the AIC (Akaike, (1973), (1974)) is defined as

$$\begin{aligned} AIC_{(p)} &= \ln\left|\Sigma_e(p)\right| + \frac{2}{T}(\text{number of freely estimated parameters}) \\ &= \ln\left|\Sigma_e(p)\right| + \frac{2pK^2}{T} \end{aligned} \tag{7.3}$$

The estimate $\hat{p}(\text{AIC})$ for $p$ is chosen in such a way that this criterion is minimised.

Appendix 7.1 presents the tests for the order of the ten VAR systems, each including both the Default Spread, the Term Spread, and the portfolios' returns for size portfolios 1 to 10 respectively, from 1985 to 1995. The maximum order is 12.

The Akaike (AIC) and the Schwarz (SBC) criteria select the orders 3 and 1, respectively, for all VAR systems. The log-likelihood ratio statistics reject orders 0, 1 and 2, but do not reject order 3, except for portfolios 1,2,4 and 6. Thus, the VAR(3) is choosen for all ten VAR systems.

### 7.3.2. VAR Estimation

VARs were constructed to include the Default Spread (DEF) and Term Spread (TERM) and each of the ten size portfolios', 1 through 10 (PF1....PF10), using monthly returns from January 1985 to December 1994. An important pre-condition for the credibility of the above results is the stationarity of series in the VAR system. Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) statistics (with and without trend) for testing the unit root hypothesis reject the null of a unit root (H0:f=1) in the returns of the size portfolios 1 through 10 at the 5 percent significance level. The same test, however, fails to reject the null for TERM and DEF. This does not affect the estimation of the unrestricted VAR, as residuals are stationary. However, Toda and Phillips (1993a,b) by extending the analysis of Sims, Stock and Watson (1990) conclude that, when cointegration is present, standard Wald test of causality constructed from the VAR with an unrestricted estimate of the VAR coefficient matrix, are only distributed asymptotically as chi-square if equal rank condition between the VAR cointegrating matrix and the matrix of causing variables is obeyed. If this rank condition fails, the limit distribution involves a mixture of a chi-square and a non-standard distribution, which includes nuisance parameters. Therefore, results from the causality test should be treated cautiously.

The diagnostic statistics shows that neither of the 30 VAR equations suffer Serial Correlation and Heteroscedasticity problems. This, however, is not the case with Normality. All equations, except one, for portfolio 5, fail their Normality test. The result of each VAR system estimation are shown in Table 7.3.

Table 7.3 shows the estimated coefficients for the ten VARs, when portfolio 1-10 returns are considered as endogenous variables. Each column represents the lagged PF N (-1)...PF N (-3) estimated coefficients, where N stands for the size portfolio number in the corresponding column headings. Thus, each size portfolio (1-10) has its own past values as an explanatory variable, TERM and DEF being common to all 10 size portfolios.

It is apparent that the significance of the lagged returns in explaining the current portfolios' returns diminishes as the size increases. As a result, portfolios' returns with lag 1 are significant in predicting the current returns from size portfolio 1 through 5.

**Table 7.3.**
**Panel I Estimated coefficients of the equations where PF1-PF10 are dependent variables**

| Dep.(N) | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Coef. | | | | | | | | | | |
| PF N(-1) | 0.34 | 0.38 | 0.45 | 0.34 | 0.19 | 0.18 | 0.14 | 0.11 | 0.08 | -0.03 |
| T-ratio | 3.72** | 4.01** | 4.96** | 3.62** | 2.06* | 1.92 | 1.53 | 1.15 | 0.83 | -0.30 |
| PF N(-2) | -0.16 | -0.16 | -0.18 | -0.16 | -0.07 | -0.13 | -0.11 | -0.16 | -0.18 | -0.11 |
| T-ratio | -1.71 | -1.58 | -1.79 | -1.67 | -0.79 | -1.42 | -1.25 | -1.65 | -1.90 | -1.22 |
| PF N(-3) | -0.10 | -0.06 | -0.06 | -0.11 | -0.14 | -0.08 | -0.11 | -0.09 | -0.05 | -0.11 |
| T-ratio | -1.10 | -0.68 | -0.65 | -1.15 | -1.55 | -0.89 | -1.20 | -0.98 | -0.55 | -1.18 |
| TERM(-1) | 41.80 | 21.16 | 22.86 | 25.35 | 31.60 | 23.84 | 28.80 | 21.99 | 16.13 | 15.52 |
| T-ratio | 2.37* | 1.42 | 1.51 | 1.69 | 1.92 | 1.38 | 1.62 | 1.22 | 0.93 | 0.97 |
| TERM(-2) | -67.69 | -35.55 | -44.02 | -47.36 | -58.36 | -40.12 | -47.41 | -37.05 | -26.81 | -31.36 |
| T-ratio | -2.59* | -1.61 | -1.97 | -2.14* | -2.39* | -1.56 | -1.80 | -1.39 | -1.03 | -1.31 |
| TERM(-3) | 30.78 | 17.34 | 20.90 | 22.49 | 26.95 | 16.19 | 16.77 | 14.24 | 9.07 | 10.91 |
| T-ratio | 1.88 | 1.26 | 1.51 | 1.64 | 1.77 | 1.02 | 1.03 | 0.87 | 0.57 | 0.75 |
| DEF(-1) | -6.77 | 15.54 | 27.67 | 33.53 | 42.64 | 60.44 | 63.32 | 67.63 | 90.86 | 74.29 |
| T-ratio | -0.14 | 0.37 | 0.67 | 0.80 | 0.93 | 1.26 | 1.31 | 1.40 | 1.96 | 1.76 |
| DEF(-2) | 109.09 | 102.96 | 95.99 | 95.55 | 78.19 | 84.71 | 98.06 | 67.12 | 24.41 | 31.01 |
| T-ratio | 1.91 | 2.10* | 1.98* | 1.95 | 1.46 | 1.51 | 1.72 | 1.18 | 0.44 | 0.63 |
| DEF(-3) | -153 | -148 | -166 | -160 | -161 | -184 | -204 | -174 | -158 | -141 |
| T-ratio | -3.19** | -3.55** | -4.06** | -3.89** | -3.56** | -3.87** | -4.24** | -3.62** | -3.39** | -3.37** |
| C | 0.08 | 0.04 | 0.05 | 0.04 | 0.05 | 0.05 | 0.06 | 0.05 | 0.05 | 0.05 |
| T-ratio | 2.41* | 1.65 | 2.07* | 1.66 | 1.82 | 1.69 | 1.91 | 1.72 | 1.91 | 1.96 |
| $R^2$ adj. | 0.207 | 0.189 | 0.256 | 0.200 | 0.125 | 0.138 | 0.144 | 0.119 | 0.119 | 0.089 |

** Significant at 1%
* Significant at 5%

TERM with lag 1 and 2, apparently, is significant at 5% in explaining the returns of portfolio 1, and then TERM with lag 2 has a casual relationship with portfolios 4 and 5. In general, TERM does not appear to explain stock returns. DEF with lag 3 is significant across all size portfolios at 1% level, and this relationship is negative. Thus an increase in default risk leads to a reduction in stock returns with a 3 months lag. The regression goodness-of-fit is not very good and diminishes with size. This implies that the ability of the model to forecast portfolios' returns diminishes with size.

The next interesting issue is what the impact is on TERM of the DEF and size portfolios return variability. Panel II reports the results for TERM, where DEF and TERM as lagged independent variables do not change. Only PF1-PF10 are variables which change across the ten regressions, and one matter of interest is how returns of different size portfolios affect the TERM.

**Panel II Estimated coefficients of the equations where TERM is dependent variable**

| term | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
|---|---|---|---|---|---|---|---|---|---|---|
| PF N(-1) | -0.74 | -0.88 | -1.36 | -1.13 | -0.82 | -1.07 | -1.03 | -1.49 | -1.63 | -1.77 |
| T-ratio | -1.50 | -1.46 | -2.37* | -1.93 | -1.54 | -2.07* | -2.11* | -3.09** | -3.21** | -3.26** |
| PF N(-2) | 0.91 | 0.99 | 1.50 | 1.37 | 0.92 | 1.00 | 1.14 | 1.07 | 1.28 | 1.37 |
| T-ratio | 1.78 | 1.57 | 2.41* | 2.27* | 1.71 | 1.92 | 2.32* | 2.17* | 2.51* | 2.46* |
| PF N(-3) | -0.62 | -0.64 | -0.79 | -0.73 | -0.44 | -0.27 | -0.32 | -0.47 | -0.40 | -0.28 |
| T-ratio | -1.23 | -1.05 | -1.35 | -1.24 | -0.83 | -0.52 | -0.65 | -0.96 | -0.76 | -0.50 |
| TERM(-1) | 1243.80 | 1243.10 | 1264.50 | 1264.00 | 1247.60 | 1267.50 | 1272.10 | 1285.90 | 1290.50 | 1301.80 |
| T-ratio | 13.11** | 13.08** | 13.36** | 13.36** | 13.15** | 13.31** | 13.41** | 13.63** | 13.74** | 13.82** |
| TERM(-2) | -338.02 | -339.94 | -355.38 | -360.60 | -339.64 | -369.21 | -367.98 | -381.27 | -387.59 | -407.43 |
| T-ratio | -2.40* | -2.42* | -2.54* | -2.58** | -2.42** | -2.61** | -2.62** | -2.73** | -2.76** | -2.89** |
| TERM(-3) | 57.48 | 59.93 | 52.42 | 59.13 | 54.06 | 64.30 | 58.23 | 58.29 | 59.98 | 67.47 |
| T-ratio | 0.65 | 0.68 | 0.61 | 0.68 | 0.62 | 0.74 | 0.67 | 0.68 | 0.70 | 0.79 |
| DEF(-1) | -312.39 | -312.79 | -334.37 | -329.65 | -272.66 | -320.42 | -301.15 | -303.84 | -299.83 | -212.56 |
| T-ratio | -1.19 | -1.16 | -1.29 | -1.25 | -1.03 | -1.21 | -1.17 | -1.20 | -1.20 | -0.85 |
| DEF(-2) | 613.89 | 643.16 | 671.87 | 703.88 | 641.61 | 719.78 | 709.05 | 717.80 | 794.10 | 689.22 |
| T-ratio | 2.00 | 2.06* | 2.21* | 2.28* | 2.08* | 2.32* | 2.33* | 2.41* | 2.66** | 2.36* |
| DEF(-3) | -477.90 | -498.04 | -513.78 | -535.04 | -527.59 | -552.10 | -556.88 | -579.56 | -661.70 | -629.40 |
| T-ratio | -1.84 | -1.87 | -2.00* | -2.06* | -2.02* | -2.10* | -2.16* | -2.30* | -2.62** | -2.54* |
| C | 0.23 | 0.22 | 0.23 | 0.21 | 0.21 | 0.20 | 0.19 | 0.22 | 0.22 | 0.20 |
| T-ratio | 1.39 | 1.33 | 1.40 | 1.31 | 1.26 | 1.25 | 1.24 | 1.41 | 1.41 | 1.33 |
| $R^2$ adj. | 0.953 | 0.953 | 0.954 | 0.954 | 0.953 | 0.954 | 0.955 | 0.956 | 0.957 | 0.957 |

Note: Coefficient values are premultiplied by 1000.
** Significant at 1%
* Significant at 5%

As expected, small size returns have no explanatory power over TERM. The only exception is portfolio's 3 return, with lag 1 significant at 5 percent. The story alters dramatically from portfolio 6 upwards; portfolios' 6 and 7 lag one returns are significant at 5 percent, whereas portfolios 8, 9 and 10 lag one returns are significant at 1 percent. In addition, the portfolios' returns at lag two become significant at 5 percent from portfolio 7 upwards. Clearly, this suggests increasing predictability of the term spread by the returns of larger stocks. The high significance of TERM lag one and two on the current TERM is justified with the low variability of TERM. DEF with lag two and three are also significant at 5 percent.

Finally, the goodness-of-fit of the Panel 2 regressions, measured by $R^2$, is much better than those of Panel I. For Panel I, fit deteriorates with size, whereas it improves with size in

Panel II. Panel III examines the third equation in the VAR system, i.e., DEF being dependent on the lagged returns of portfolios 1-10, lagged returns of TERM, and on its own lagged values. Again, DEF and TERM past values are identical for all 10 regressions. The difference comes from the lagged returns of portfolios 1 to 10, which are unique for each regression.

**Panel III Estimated coefficients of the equations where DEF is dependent variable**

| Def | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
|---|---|---|---|---|---|---|---|---|---|---|
| PF1(-1) | 0.04 | -0.11 | -0.06 | -0.10 | -0.16 | -0.18 | -0.07 | -0.16 | -0.15 | -0.23 |
| T-ratio | 0.22 | -0.49 | -0.29 | -0.48 | -0.83 | -0.94 | -0.37 | -0.90 | -0.81 | -1.12 |
| PF1(-2) | -0.08 | 0.03 | 0.01 | -0.03 | 0.08 | 0.11 | 0.10 | -0.02 | 0.00 | 0.08 |
| T-ratio | -0.45 | 0.15 | 0.06 | -0.14 | 0.44 | 0.56 | 0.54 | -0.10 | 0.02 | 0.36 |
| PF1(-3) | -0.09 | -0.07 | -0.13 | -0.19 | -0.25 | -0.21 | -0.17 | -0.18 | -0.21 | -0.16 |
| T-ratio | -0.52 | -0.33 | -0.62 | -0.90 | -1.31 | -1.13 | -0.95 | -0.99 | -1.08 | -0.74 |
| TERM(-1) | -37.00 | -36.94 | -35.42 | -35.01 | -32.21 | -29.24 | -29.38 | -34.61 | -32.05 | -28.66 |
| T-ratio | -1.08 | -1.08 | -1.02 | -1.02 | -0.95 | -0.85 | -0.85 | -0.99 | -0.91 | -0.81 |
| TERM(-2) | 8.32 | 10.71 | 6.91 | 6.80 | 2.48 | -1.33 | -1.10 | 5.56 | -1.18 | -2.28 |
| T-ratio | 0.16 | 0.21 | 0.13 | 0.13 | 0.05 | -0.03 | -0.02 | 0.11 | -0.02 | -0.04 |
| TERM(-3) | 17.26 | 14.44 | 16.21 | 15.89 | 17.35 | 18.59 | 18.60 | 16.75 | 20.81 | 18.05 |
| T-ratio | 0.54 | 0.46 | 0.51 | 0.50 | 0.55 | 0.59 | 0.58 | 0.53 | 0.64 | 0.56 |
| DEF(-1) | 595.70 | 580.74 | 587.49 | 580.29 | 583.04 | 580.60 | 594.34 | 579.18 | 582.34 | 591.29 |
| T-ratio | 6.30** | 6.01** | 6.19** | 6.08** | 6.16** | 6.07** | 6.28** | 6.15** | 6.18** | 6.29** |
| DEF(-2) | 41.32 | 50.59 | 46.98 | 47.29 | 56.24 | 66.69 | 57.95 | 51.49 | 56.26 | 56.72 |
| T-ratio | 0.37 | 0.45 | 0.42 | 0.42 | 0.51 | 0.59 | 0.52 | 0.46 | 0.50 | 0.51 |
| DEF(-3) | 239.90 | 247.35 | 240.27 | 243.89 | 229.91 | 226.87 | 228.56 | 243.09 | 233.76 | 231.13 |
| T-ratio | 2.57* | 2.58* | 2.55* | 2.58* | 2.45* | 2.39* | 2.42* | 2.59* | 2.46* | 2.47* |
| C | 0.13 | 0.13 | 0.13 | 0.14 | 0.14 | 0.14 | 0.13 | 0.14 | 0.14 | 0.13 |
| T-ratio | 2.20* | 2.18* | 2.25* | 2.40* | 2.42* | 2.34* | 2.22* | 2.39* | 2.40* | 2.30* |
| $R^2$ adj. | 0.776 | 0.775 | 0.775 | 0.777 | 0.779 | 0.778 | 0.777 | 0.778 | 0.778 | 0.778 |

Note: Coefficient values are premultiplied by 1000.
** Significant at 1%
* Significant at 5%

As Panel III shows, portfolios 1-10 and TERM have no explanatory power over DEF. DEF seems to be affected only by its previous values, oddly enough with lags 1 and 3. Gredenhoff and Karlsson (1997) suggest that inference in VAR models depends crucially on the choice of lag-length, and an unequal lag-length procedure may be more appropriate.

Appendix 7.2 reports the VAR results when the insignificant variables from the standard unrestricted VAR are eliminated.

### 7.3.3. Block Non-Causality test

Another important issue in the investigation into the relationship between the state-variables, TERM and DEF, and the size portfolios' returns is to examine the extent to which shocks in one variable are transmitted to other variables. To do this, the Granger (block) non-causality test is applied to each of the ten trivariate VAR systems, in respect to the term spread (TERM), default spread (DEF) and each of the relevant portfolios 1 to 10 (PF1-PF10). The Granger block non-causality test provides a log-likelihood statistic for the null hypothesis that the coefficients of jointly determined variables in the VAR are equal to zero. The VAR systems presented here consist of three variables; TERM, DEF and one of the ten size portfolios. Thus, for each subset of variables there are ten Granger block non-causality tests. Firstly, portfolios 1 to 10 (PF1-PF10) and TERM to cause DEF, secondly portfolios 1 to 10 (PF1-PF10) and DEF to cause TERM, and finally TERM and DEF to cause portfolios 1 to 10 (PF1-PF10). Table 7.4 provides the relevant Likelihood ratio statistics and the corresponding p-values for the Granger block non-causality test.

**Table 7.4.**

| Panel I | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
|---|---|---|---|---|---|---|---|---|---|---|
| | and TERM to cause DEF | | | | | | | | | |
| LR statistics | 4.78 | 4.32 | 4.52 | 5.29 | 6.30 | 5.95 | 5.15 | 5.68 | 5.62 | 5.76 |
| p-value | (.573) | (.634) | (.606) | (.507) | (.390) | (.429) | (.525) | (.460) | (.467) | (.451) |
| Panel II | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
| | and DEF to cause TERM | | | | | | | | | |
| LR statistics | 9.59 | 8.69 | 13.41 | 11.94 | 9.69 | 11.91 | 13.70 | 17.82 | 20.00 | 21.35 |
| p-value | (.143) | (.192) | (.037) | (.063) | (.138) | (.064) | (.033) | (.007) | (.003) | (.002) |
| Panel III | TERM and DEF to cause | | | | | | | | | |
| | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
| LR statistics | 20.74 | 16.73 | 20.64 | 19.34 | 18.75 | 17.88 | 20.96 | 16.17 | 16.17 | 16.22 |
| p-value | (.002) | (.010) | (.002) | (.004) | (.005) | (.007) | (.002) | (.013) | (.013) | (.013) |

Panel I shows the significance of PF1-PF10 and TERM jointly causing DEF. The log-likelihood statistic for Panel I varies between 4.32 and 6.30, which has moderate statistical significance. In terms of rejection probabilities, shown as p-values, H0 can be rejected with probabilities ranging from (0.39) for portfolio 5 to (0.634) for portfolio 2. There is also a mild tendency for rejection of H0, that PF1-PF10 and TERM do not cause DEF, as the size diminishes, although portfolios 5 and 6 introduce some disharmony. Synchronously with Table 7.4 Panel I, the null for portfolios 7-10 and DEF causing TERM has very low rejection values. Panel III of Table 7.4 reveals the fact that TERM and DEF have high statistical significance in respect to small size portfolios and for the large size portfolios as well. Overall, the panels in which DEF is a cause (II and III) have lowest rejection values. Thus, DEF qualifies as a primary cause. As for TERM and portfolios' returns, the conclusion is somehow split; Large size portfolio returns (8-10) seem to (jointly with DEF) cause TERM (See Panel II, Table 7.4). Small size portfolio returns, however, are being (jointly with DEF) caused by TERM.

### 7.3.4. Separate Causality Test

The Granger block causality test, however, does not show the extent to which shocks in a single variable are transmitted to the other (caused) variables. To investigate these effects, the unrestricted VAR system is run in the *Microfit SURE* estimation menu, where the Wald test of hypotheses on the parameters of the model is available.

The Wald statistics, based on Chi-square distribution, allows us to test for the general linear/non-linear restrictions

$$H_0 : \beta = 0$$

against

$$H_1 : \beta \neq 0$$

where $\beta = (\beta_1, \beta_2, ...., \beta_n)$ is the vector of coefficients of the independent variable(s), which are tested for causing the dependent variable.

Table 7.5 shows the Wald statistics for the significance of the contemporary and lag 1 and 2 coefficients of portfolios 1 to 10 and TERM, and the lag 1 and 2 coefficients of DEF in causing the contemporary level of DEF. Thus, Table 7.5 is similar to Table 7.4, Panel I where the joint significance of portfolios 1 to 10 and TERM in causing DEF is tested. Here, however, is apparent that neither portfolios 1 to 10, nor TERM cause DEF. DEF seems to be explained mainly by its own lagged values.

**Table 7.5.**

| Caused by | Wald Stat. | Caused Variable is DEF | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | pf1 | pf2 | pf3 | pf4 | pf5 | pf6 | pf7 | pf8 | pf9 | pf10 |
| Pf. (N) | Chi-sq. | 0.72 | 0.30 | 0.49 | 1.20 | 2.14 | 1.81 | 1.07 | 1.56 | 1.50 | 1.63 |
| | *p*-ratio | [.868] | [.960] | [.921] | [.753] | [.544] | [.613] | [.785] | [.669] | [.682] | [.652] |
| DEF (lag(-2), (-3)) | Chi-sq. | 11.52 | 12.05 | 11.66 | 12.06 | 11.33 | 11.44 | 11.25 | 12.38 | 11.76 | 11.57 |
| | *p*-ratio | [.003] | [.002] | [.003] | [.002] | [.003] | [.003] | [.004] | [.002] | [.003] | [.003] |
| TERM | Chi-sq. | 3.72 | 3.63 | 3.78 | 3.80 | 3.78 | 3.57 | 3.51 | 3.79 | 3.96 | 3.70 |
| | *p*-ratio | [.293] | [.305] | [.286] | [.284] | [.286] | [.311] | [.319] | [.285] | [.266] | [.296] |

Table 7.6 reports the Wald statistics when TERM is the caused variable. From Table 7.4, Panel II is clear that the joint impact of portfolios 1 to 10 and DEF on TERM gets stronger as the portfolio size gets bigger. Now, it is clear that this impact is mostly driven by the return series of the large firms, rather than DEF. The p-ratio for portfolio 1 is 0.212 and it goes down to 0.006, 0.002 and 0.001 for portfolios 8, 9 and 10 respectively.

Table 7.6 presents also the extent to which TERM is explained by its previous values. Thus, portfolio 10 and TERM lagged values appear equally significant in explaining current TERM.

**Table 7.6.**

| Caused by | Wald Stat. | Caused Variable is TERM | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | pf1 | pf2 | pf3 | pf4 | pf5 | pf6 | pf7 | pf8 | pf9 | pf10 |
| Pf (N) | Chi-sq. | 4.50 | 3.65 | 8.20 | 6.77 | 4.60 | 6.74 | 8.49 | 12.63 | 14.88 | 16.29 |
| | *p*-ratio | [.212] | [.302] | [.042] | [.080] | [.203] | [.081] | [.037] | [.006] | [.002] | [.001] |
| DEF | Chi-sq. | 6.07 | 6.25 | 7.15 | 7.26 | 6.42 | 7.41 | 7.49 | 8.36 | 10.00 | 8.59 |
| | *p*-ratio | [.108] | [.100] | [.067] | [.064] | [.093] | [.060] | [.058] | [.039] | [.019] | [.035] |
| TERM (lag(-2),(-3)) | Chi-sq. | 8.87 | 8.82 | 10.42 | 10.32 | 9.21 | 10.44 | 10.86 | 11.96 | 12.40 | 13.31 |
| | *p*-ratio | [.012] | [.012] | [.005] | [.006] | [.010] | [.005] | [.004] | [.003] | [.002] | [.001] |

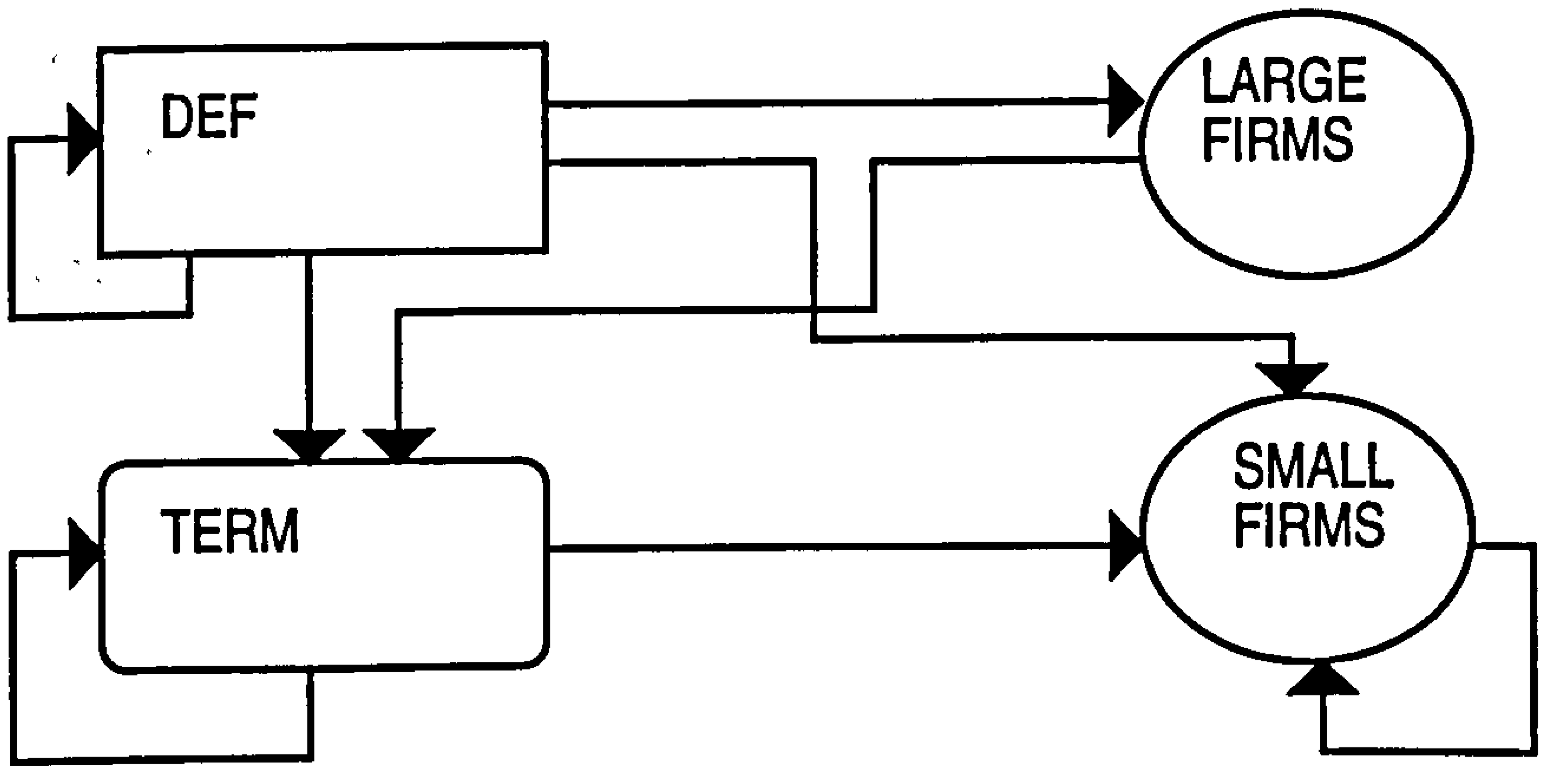
Finally, Table 7.7 is an extended analogue of Table 7.4, Panel III. It is now obvious that the increase of the TERM and DEF combined rejection values with the size is a result of a slight decrease in DEF's rejection values and an increase in TERM's rejection values. DEF appears to cause the whole range of size portfolio returns, while TERM causes only the lowest decile portfolio returns. Furthermore, only the past values of the smallest decile portfolio 1's return seem to affect the current return.

**Table 7.7.**

| Caused by | Wald Stat. | Caused Variable is | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | pf1 | pf2 | pf3 | pf4 | pf5 | pf6 | pf7 | pf8 | pf9 | pf10 |
| Pf.N (lag(-2), (-3)) | Chi-sq. | 5.95 | 4.20 | 5.58 | 6.21 | 3.67 | 3.53 | 3.69 | 4.34 | 4.35 | 3.11 |
| | *p*-ratio | [.051] | [.123] | [.061] | [.045] | [.159] | [.172] | [.158] | [.114] | [.114] | [.212] |
| DEF | Chi-sq. | 11.77 | 13.03 | 17.51 | 15.55 | 13.66 | 16.04 | 19.04 | 14.59 | 15.31 | 14.05 |
| | *p*-ratio | [.008] | [.005] | [.001] | [.001] | [.003] | [.001] | [.000] | [.002] | [.002] | [.003] |
| TERM | Chi-sq. | 7.64 | 3.05 | 3.95 | 4.57 | 5.74 | 2.52 | 3.69 | 2.06 | 1.33 | 3.61 |
| | *p*-ratio | [.054] | [.384] | [.267] | [.206] | [.125] | [.472] | [.297] | [.560] | [.721] | [.307] |

The causal relationship between portfolio returns, DEF and TERM, appears to be a complex one. The bottom line of the established relationship is summarised in Figure 7.4.

**Figure 7.4.**

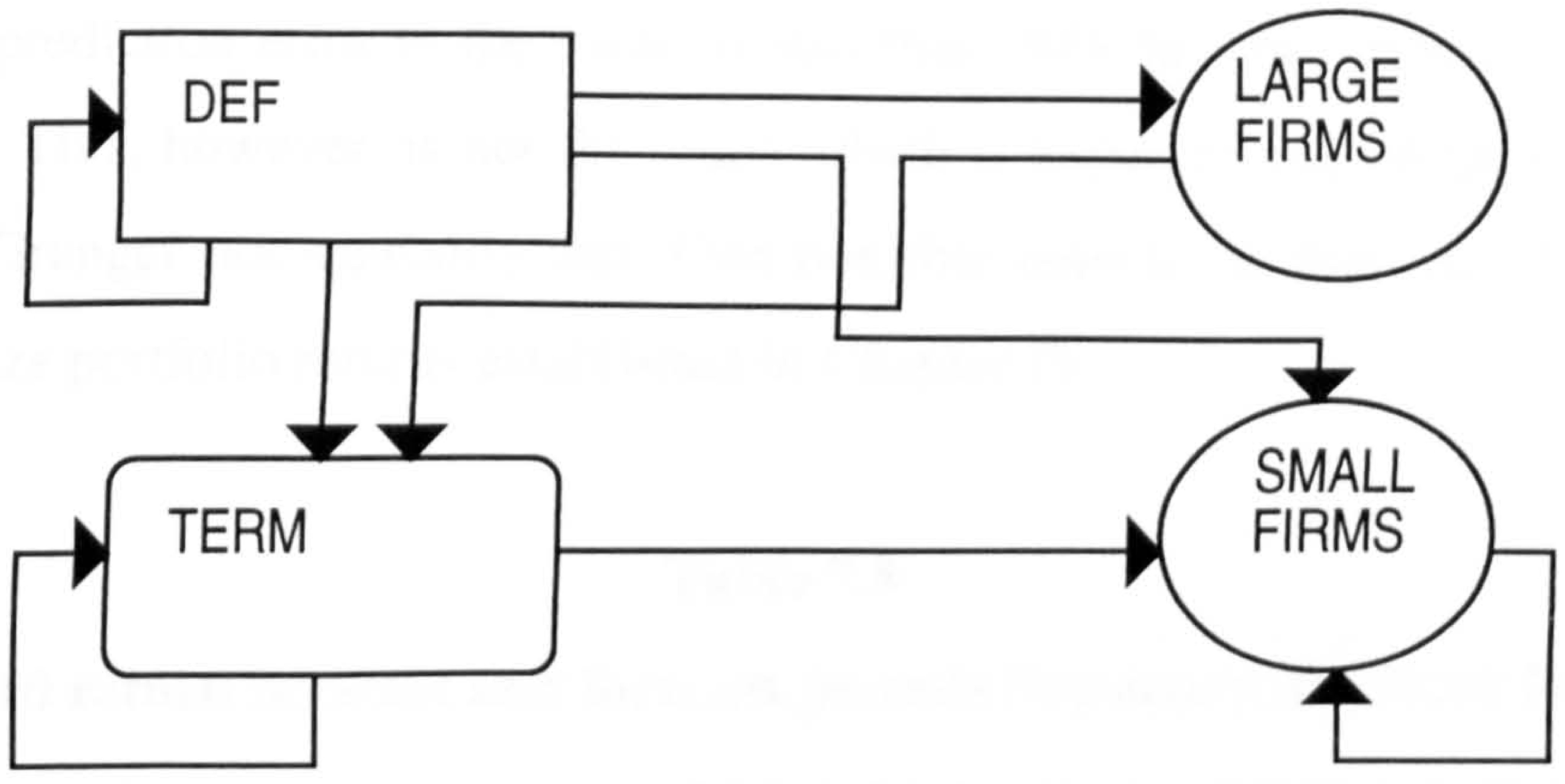



A glance at the Figure 7.4 reveals the following direction of causality - DEF, Large Firms, TERM, and Small Firms.

### 7.3.5. Forecasting portfolios' return, TERM and DEF

Another way of looking at the interaction of the variables in the VAR is to examine the forecasting ability of these variables. As DEF data is available for 1985-1994, the VAR system is re-run for the period January, 1985-July, 1994, allowing for a 6 months' out-of-sample forecast. In addition, a 12-month forecast is made, to test the consistency of the results. The forecasting procedure is carried out for each of the three variables, and results displayed in Table 7.8 for portfolios' return forecasting, Table 7.9 for TERM forecasting, and Table 7.10 for DEF forecasting. As the forecast output contains un-systematised information, which is also difficult to comprehend, the results are abridged into two main indicators - residuals' mean and root mean sum of squares for the estimation and forecast period. Table 7.8 provides a forecast of the 10 size portfolio returns for two periods - six months and twelve months, respectively from July and January 1994 to December 1994. The six month forecast shows diminishing mean forecast error as the size increases, so too the residual mean sum of squares (RMSS). Ideally, a perfect forecast should have a mean of zero and RMSS as low as possible (zero). In our case the forecast mean has a value of -0.051, indicating an overestimation of the average portfolio 1 returns for the second half of 1994 by +0.051. For portfolio 10, on the other hand, we have an underestimation of -0.001,

**Figure 7.4.**




A glance at the Figure 7.4 reveals the following direction of causality - DEF, Large Firms, TERM, and Small Firms.

### 7.3.5. Forecasting portfolios' return, TERM and DEF

Another way of looking at the interaction of the variables in the VAR is to examine the forecasting ability of these variables. As DEF data is available for 1985-1994, the VAR system is re-run for the period January, 1985-July, 1994, allowing for a 6 months' out-of-sample forecast. In addition, a 12-month forecast is made, to test the consistency of the results. The forecasting procedure is carried out for each of the three variables, and results displayed in Table 7.8 for portfolios' return forecasting, Table 7.9 for TERM forecasting, and Table 7.10 for DEF forecasting. As the forecast output contains un-systematised information, which is also difficult to comprehend, the results are abridged into two main indicators - residuals' mean and root mean sum of squares for the estimation and forecast period. Table 7.8 provides a forecast of the 10 size portfolio returns for two periods - six months and twelve months, respectively from July and January 1994 to December 1994. The six month forecast shows diminishing mean forecast error as the size increases, so too the residual mean sum of squares (RMSS). Ideally, a perfect forecast should have a mean of zero and RMSS as low as possible (zero). In our case the forecast mean has a value of -0.051, indicating an overestimation of the average portfolio 1 returns for the second half of 1994 by +0.051. For portfolio 10, on the other hand, we have an underestimation of -0.001, i.e., a mean error forecast of 0.001. Considering an actual portfolio 10 average return of 0.0037, the prediction error in the mean is less than 30% for the second half of 1994 for portfolio 10. This, however, is not the result which is expected regarding VAR estimation results and Granger non-causality test. One possible reason for this may be the seasonal patterns of size portfolio returns established in Chapter IV.

**Table 7.8.**

**Portfolio 1-10 return forecast and forecast periods Summary Statistics for Residuals.**

| | '94.7 -'94.12 - Six months Forecast | | | | '94.1-'94.12-Twelve month Forecast | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | | RMSS | | Mean | | RMSS | |
| | Estimation | Forecast | Estimation | Forecast | Estimation | Forecast | Estimation | Forecast |
| pf1 | 0.000 | -0.051 | 0.058 | 0.063 | 0.000 | -0.015 | 0.057 | 0.055 |
| pf2 | 0.000 | -0.059 | 0.049 | 0.064 | 0.000 | -0.023 | 0.048 | 0.055 |
| pf3 | 0.000 | -0.036 | 0.050 | 0.046 | 0.000 | -0.019 | 0.049 | 0.049 |
| pf4 | 0.000 | -0.036 | 0.049 | 0.047 | 0.000 | -0.015 | 0.049 | 0.046 |
| pf5 | 0.000 | -0.042 | 0.054 | 0.058 | 0.000 | -0.021 | 0.053 | 0.057 |
| pf6 | 0.000 | -0.029 | 0.057 | 0.045 | 0.000 | -0.016 | 0.057 | 0.051 |
| pf7 | 0.000 | -0.039 | 0.058 | 0.056 | 0.000 | -0.021 | 0.057 | 0.056 |
| pf8 | 0.000 | -0.018 | 0.058 | 0.052 | 0.000 | -0.011 | 0.059 | 0.049 |
| pf9 | 0.000 | -0.010 | 0.055 | 0.050 | 0.000 | -0.012 | 0.056 | 0.050 |
| pf10 | 0.000 | 0.001 | 0.051 | 0.041 | 0.000 | -0.009 | 0.051 | 0.046 |

To examine this, a twelve month forecast procedure is carried out in the same manner as for the six-month forecast. Now, the results show a different picture. The residual mean forecast has improved for the small size portfolios, while it has deteriorated for the large size portfolios. Portfolio 1 has a residual mean forecast error of -0.015, i.e., forecast 0.015 higher than the actual average return of 0.03 for the twelve month period, which is within the 50% range. Portfolio 10's residual mean forecast error of -0.009 is four times higher than the actual average return of -0.0023 for the twelve months of 1994. An improvement in the portfolio 1 RMSS, respectively deterioration in the portfolio 10 RMSS is also noticeable. In this instance, the improvement in the forecast results for portfolio 1 supports the conclusion made in respect to VAR estimation results and the Granger non-causality test. It is also an indirect evidence of the seasonal patterns of the size portfolio returns.

Table 7.9 examines the ability of the size portfolio returns, DEF and TERM, to predict TERM at 6 and 12 months horizon.

**Table 7.9.**

**TERM Forecast and Forecast Summary Statistics for Residuals**

| | '94.6 -'94.12 - Six month Forecast | | | | '94.1-'94.12-Twelve month Forecast | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | | RMSS | | Mean | | RMSS | |
| Predictor | Estimation | Forecast | Estimation | Forecast | Estimation | Forecast | Estimation | Forecast |
| pf1&DEF | 0.000 | -0.567 | 0.319 | 0.604 | 0.000 | 1.241 | 0.316 | 1.349 |
| pf2&DEF | 0.000 | -0.586 | 0.320 | 0.623 | 0.000 | 1.225 | 0.318 | 1.334 |
| pf3&DEF | 0.000 | -0.651 | 0.313 | 0.683 | 0.000 | 1.272 | 0.310 | 1.378 |
| pf4&DEF | 0.000 | -0.564 | 0.316 | 0.599 | 0.000 | 1.227 | 0.313 | 1.338 |
| pf5&DEF | 0.000 | -0.566 | 0.319 | 0.599 | 0.000 | 1.241 | 0.318 | 1.350 |
| pf6&DEF | 0.000 | -0.526 | 0.316 | 0.560 | 0.000 | 1.230 | 0.313 | 1.340 |
| pf7&DEF | 0.000 | -0.553 | 0.313 | 0.584 | 0.000 | 1.250 | 0.311 | 1.358 |
| pf8&DEF | 0.000 | -0.588 | 0.307 | 0.619 | 0.000 | 1.237 | 0.305 | 1.346 |
| pf9&DEF | 0.000 | -0.568 | 0.304 | 0.598 | 0.000 | 1.255 | 0.302 | 1.360 |
| pf10&DEF | 0.000 | -0.605 | 0.302 | 0.631 | 0.000 | 1.238 | 0.300 | 1.343 |

Note: Values are premultiplied by 1000.

Previous results, i.e., Panel II VAR regression, imply a significant relationship between lagged returns of the large firms and current TERM. The six-month forecast for TERM fails to recognise large firm superiority in predicting TERM. In fact, the mean residual error of the portfolio 10 forecast is larger than portfolio 1. Portfolio 10 improves its forecast result at the 12 months horizon, suggesting better forecasts as the period increases.

As expected, there is no difference in the predictive power of different size portfolio returns in relation to DEF. Table 7.10 shows that there is no pattern across size portfolios exhibiting either improvement or deterioration in the DEF forecasts for 6 and 12 month horizons.

**Table 7.10.**

**DEF Estimation and Forecast Summary Statistics for Residuals**

| | '94.6 -'94.12 - Six month Forecast | | | | '94.1-'94.12-Twelve month Forecast | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | | RMSS | | Mean | | RMSS | |
| Predictor | Estimation | Forecast | Estimation | Forecast | Estimation | Forecast | Estimation | Forecast |
| pf1&TERM | 0.000 | -0.025 | 0.116 | 0.031 | 0.000 | -0.157 | 0.119 | 0.173 |
| pf2&TERM | 0.000 | -0.024 | 0.116 | 0.030 | 0.000 | -0.154 | 0.119 | 0.170 |
| pf3&TERM | 0.000 | -0.030 | 0.116 | 0.034 | 0.000 | -0.159 | 0.119 | 0.174 |
| pf4&TERM | 0.000 | -0.035 | 0.116 | 0.039 | 0.000 | -0.161 | 0.118 | 0.176 |
| pf5&TERM | 0.000 | -0.045 | 0.115 | 0.049 | 0.000 | -0.160 | 0.118 | 0.174 |
| pf6&TERM | 0.000 | -0.042 | 0.115 | 0.045 | 0.000 | -0.163 | 0.118 | 0.177 |
| pf7&TERM | 0.000 | -0.033 | 0.116 | 0.037 | 0.000 | -0.159 | 0.119 | 0.174 |
| pf8&TERM | 0.000 | -0.037 | 0.115 | 0.041 | 0.000 | -0.157 | 0.118 | 0.172 |
| pf9&TERM | 0.000 | -0.040 | 0.115 | 0.043 | 0.000 | -0.154 | 0.118 | 0.170 |
| pf10&TERM | 0.000 | -0.032 | 0.115 | 0.037 | 0.000 | -0.153 | 0.118 | 0.169 |

Note: Values are premultiplied by 1000.

### 7.3.6. Impulse Responses

Using already estimated parameters of the VAR system, the impulse response analysis aims to work out the effect of a one standard deviation shock in a given variable equation to the variable in question and the remaining variables. The main issues are the extent to which the shocked variable reacts and the length of time necessary for the effect to diminish. The two vertical arrays of charts below, show the impulse response (IR) function for two VAR systems-one with portfolio 1 return and another with portfolio 10 return. The rest of the variables in both systems are identical, i.e., TERM and DEF. The IR function is based on the Generalised IR function. (See Pesaran and Shin (1996, 1997)).

The main idea behind the generalised IR function is to circumvent the problem of the dependence of the orthogonalised IR on the ordering of the variables in the VAR. The problem with the orthogonal IR analysis is that the ordering of the variables cannot be determined with statistical methods, but has to be specified by the analyst.

Sims (1980, 1981) employs the following Cholesky decomposition of $\Sigma$ (i.e. the covariance matrix of the shocks, $u_t$)

$$\Sigma = TT'$$

where $T$ is a lower triangular matrix.

After rewriting the VAR system in a moving average representation, the orthogonalised IR function of a unit shock at time $t$ to the $i$th orthogonalised error, $\varepsilon_{it}$, on the $j$th variable at time $t+N$ is given by

$$OIR_{ij,N} = \varepsilon_j' A_N T \varepsilon_i, \quad i, j, = 1,2,....m$$

where $A_i$ is a $mxm$ coefficient matrix.

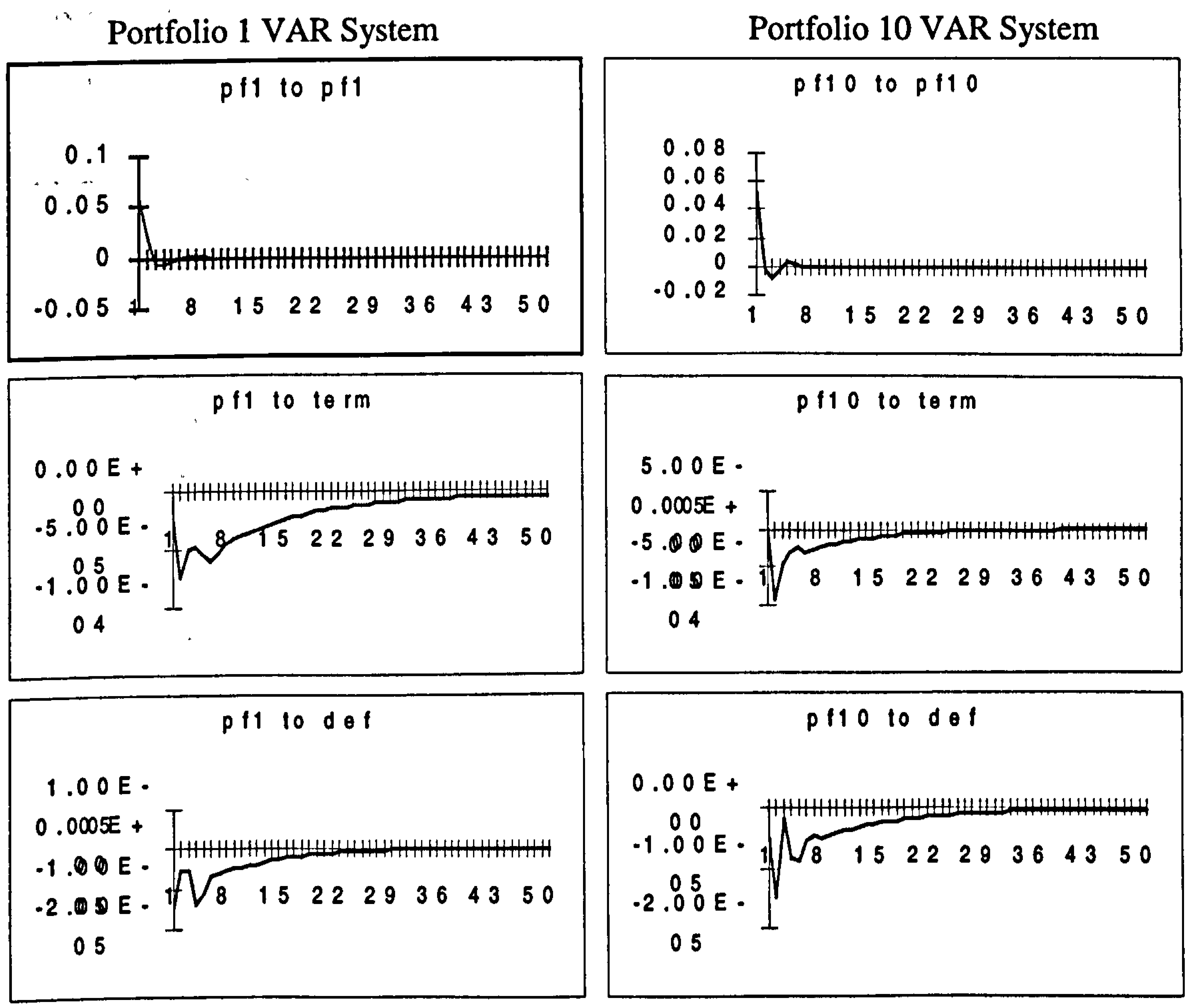
The generalised IR[3] of a unit shock to the $i$th equation in the VAR model on the $j$th variable at horizon N is given by

$$GIR_{ij,N} = \frac{\varepsilon_j' A_N \Sigma \varepsilon_i}{\sqrt{\sigma_{ii}}} \quad i, j, = 1,2,....m$$

where $\sqrt{\sigma_{ii}}$ is the unit shock.

Unlike the orthogonalised impulse responces, the generalised IR are invariant to the ordering of the variables in the VAR.

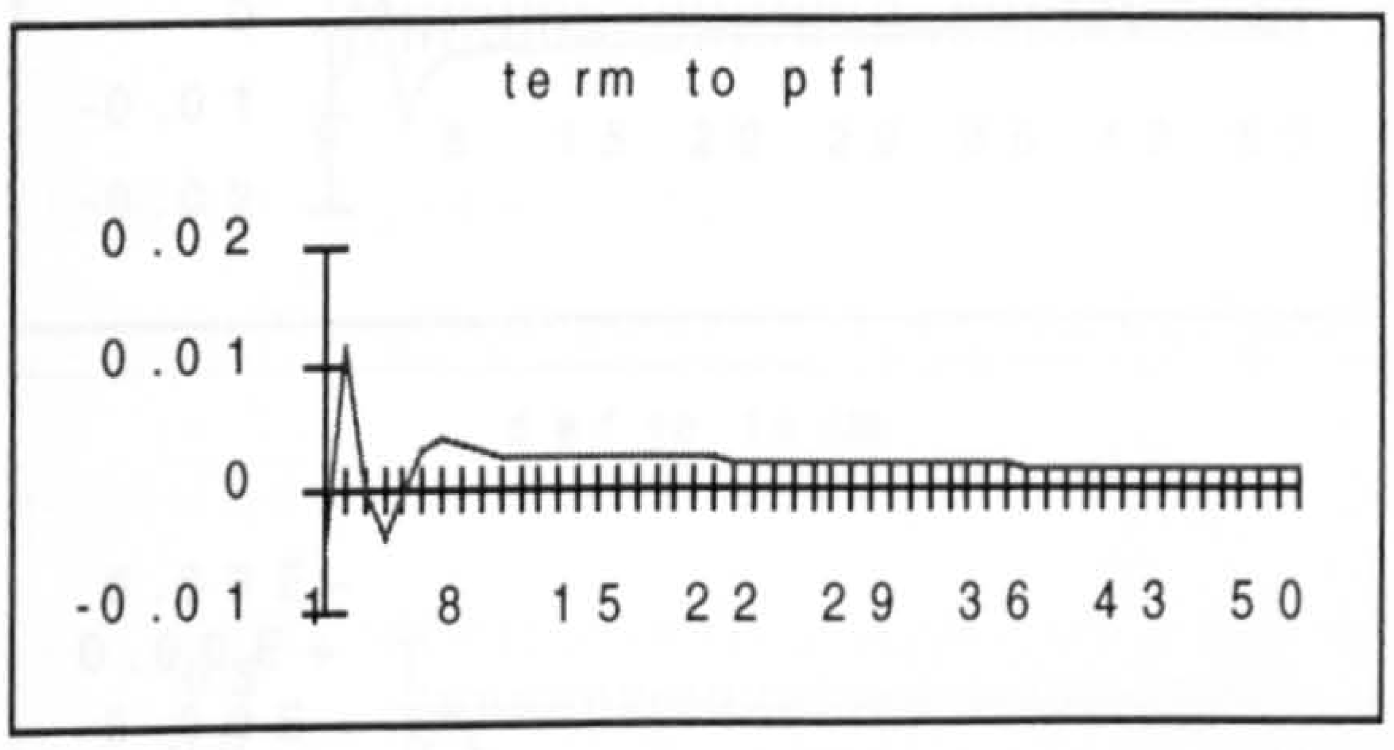
[3] The method of the Generalised IR follows the 'persistence profiles', proposed in Lee and Pesaran (1993), and applied in Pesaran and Shin (1996). Pesaran and Shin (1997) provide a further reference on the Generalised IR method.

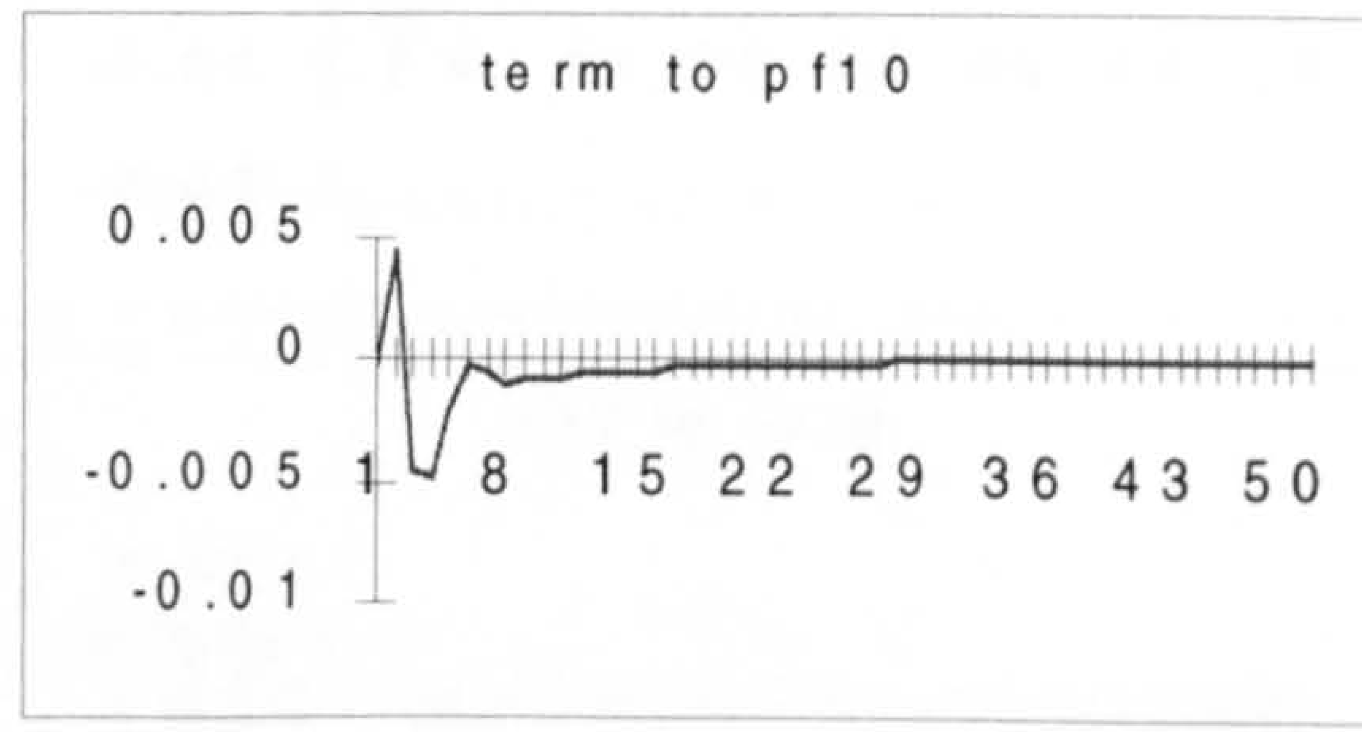


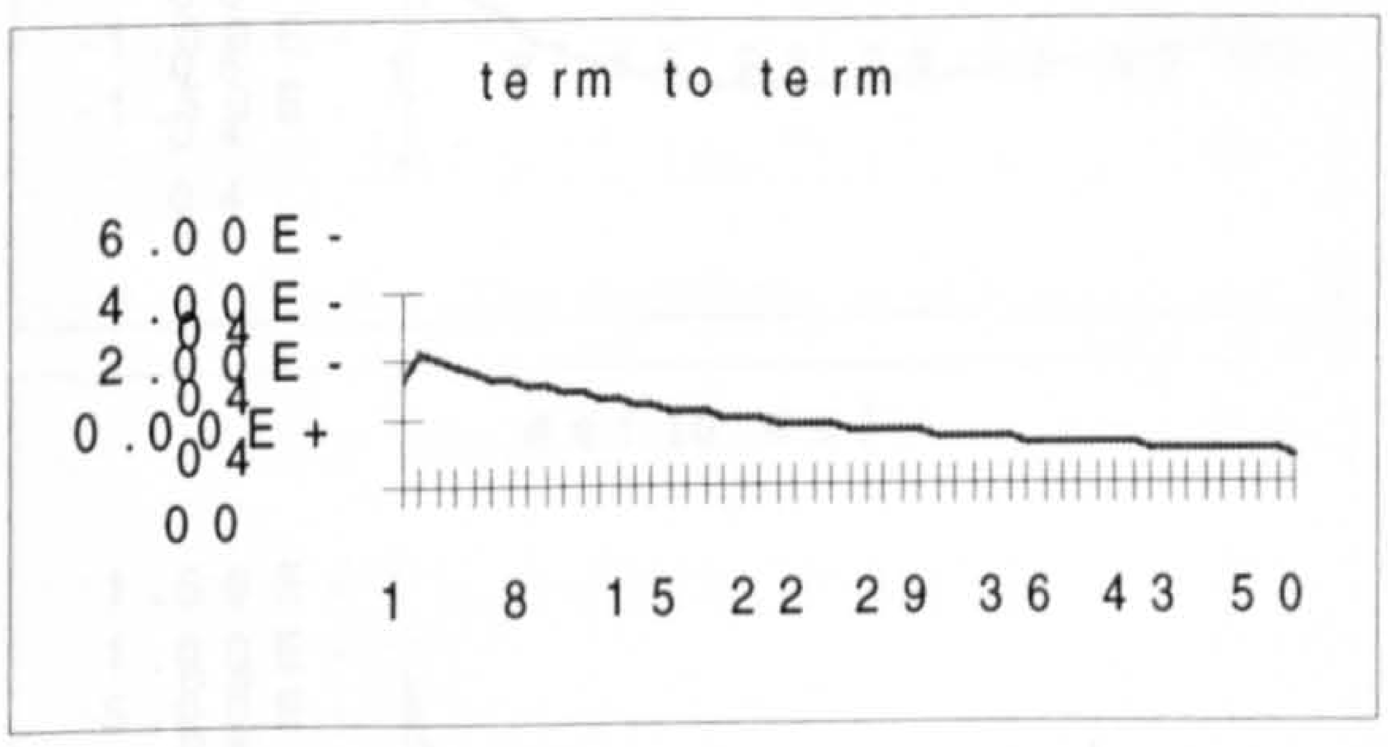

The first three coupled charts show the effect of one portfolio 1 and portfolio 10 SE shock on portfolios 1 and 10 themselves, TERM and DEF. Portfolio 1 and 10 returns have very similar patterns of response and the effect on both portfolios diminishes after 7-9 months. TERM and DEF do not seem to react differently to shocks stemming from portfolios 1 and 10. It also has to be admitted that it is unrealistic to observe a separate impact of portfolios 1 and 10 on TERM and DEF in practice.

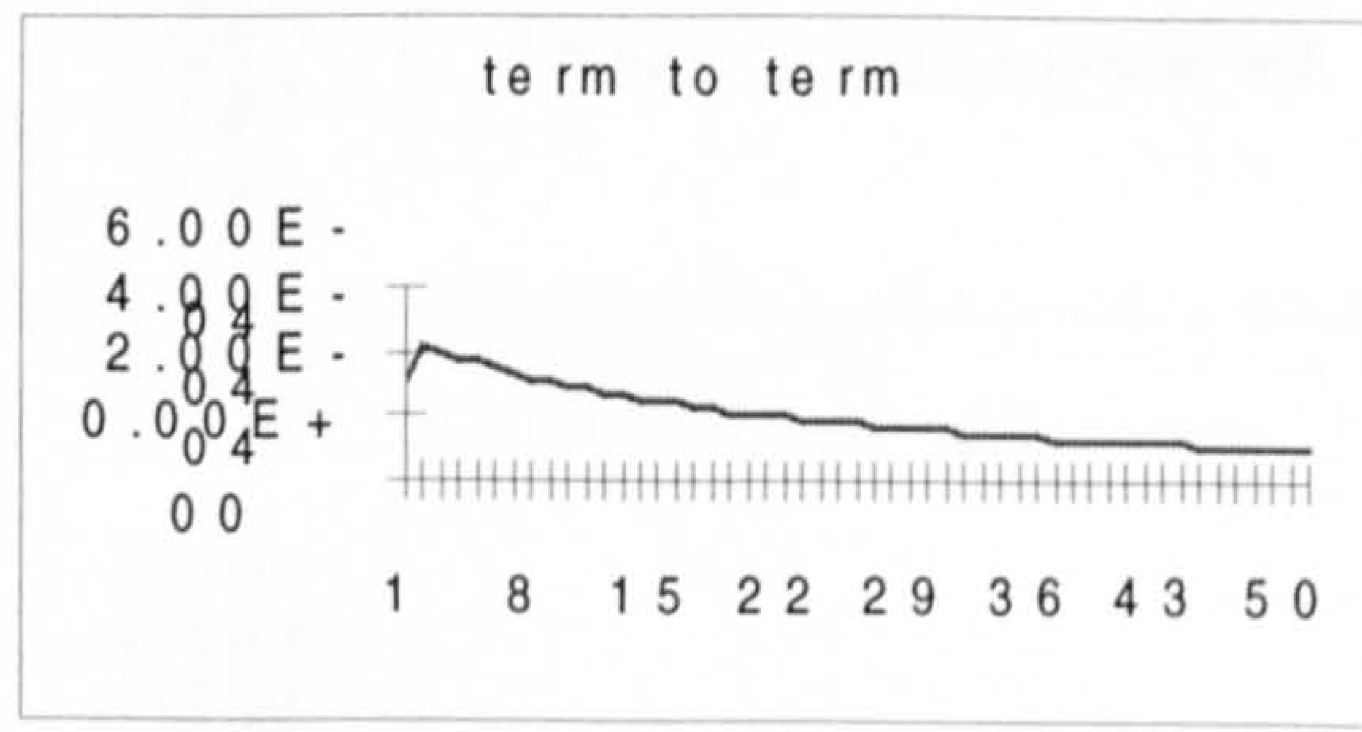
It is however, realistic and interesting to see what is the impact of TERM's one SD shock on portfolios 1 and 10. First of all, portfolio 1 seems to react more vigorously than portfolio 10. Secondly, the impact of portfolio 1 return at zero is 0.5%, whereas it is approximately zero for portfolio 10. Portfolio 10 IR diminishes quickly from below the horizontal axes, and the effect is almost extinguished after 25 months. Portfolio 1 IR to a

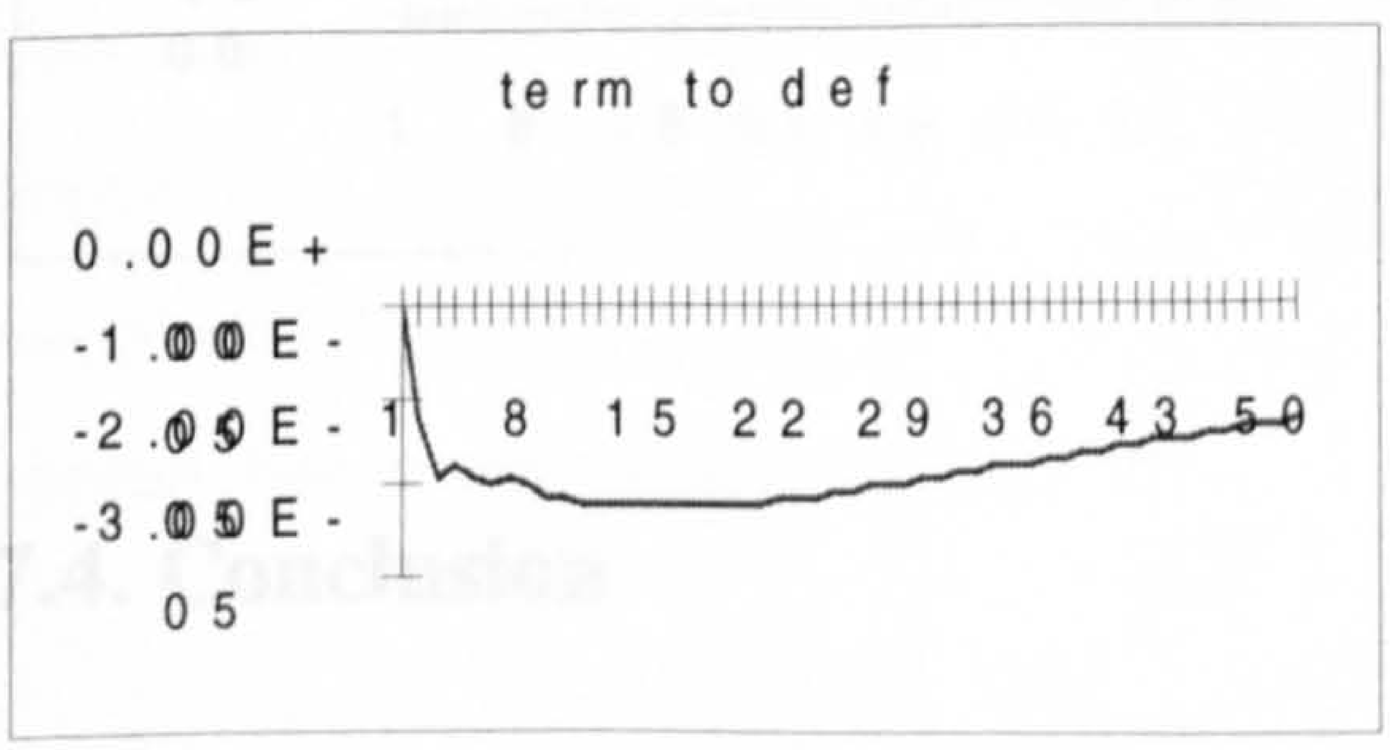
TERM shock diminishes from above the horizontal axes, but never reaches zero even after 50 months.

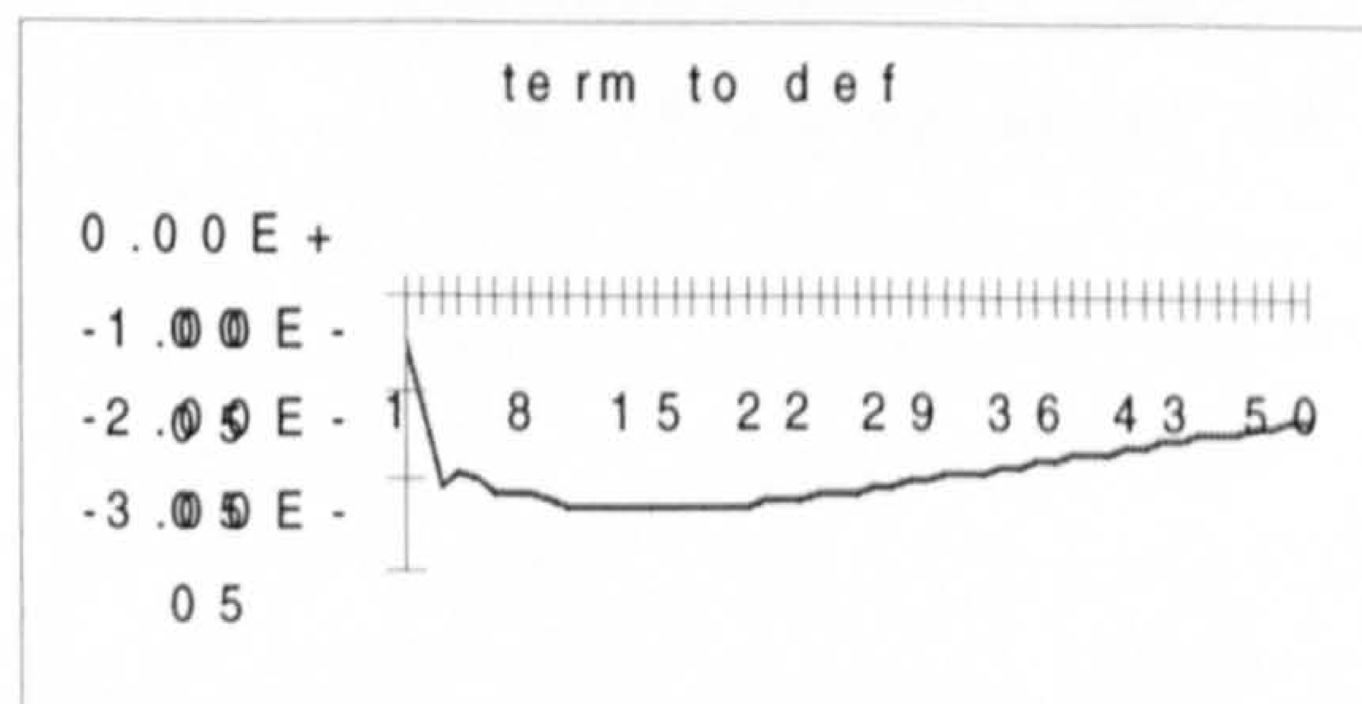


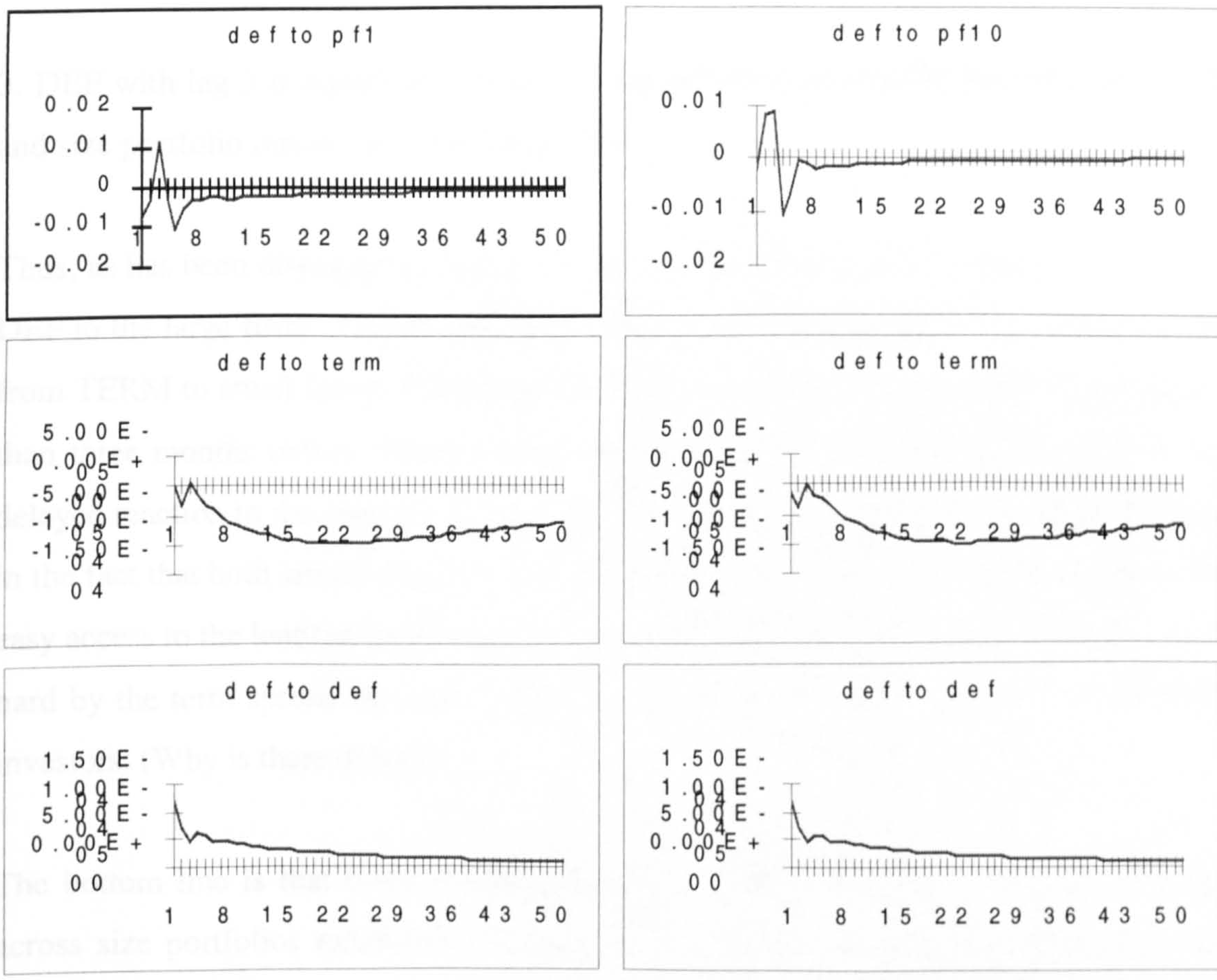




The IRs of TERM and DEF to one TERM SE shock appear to be identical for both VAR systems.

The following group of charts depicts the IR to one SE shock in the DEF equation. Again, DEF and TERM responses have a similar appearance for both VAR systems. As for portfolio 1 and 10 IRs, portfolio 10 appear to be more affected by DEF's shock in relative terms.[4]

[4]Bear in mind that the portfolio 10 return on average is 3 times less than portfolio 1 return, for the period 1985-1995.




## 7.4. Conclusion

On the basis of the analysis carried out so far, the following characteristics of behavioural differences of the small and large size firm returns can be summarised.

1. Large size firm returns are not predictable from their past values. The opposite is the case for the small firms and partly so for medium size firms, portfolios 1 to 5.

2. The TERM spread is significant in explaining the return of the smallest size portfolio 1 with lags 1 and 2, and insignificant in any lag for portfolios 6 to 10. On the other hand, the portfolio 10 return with lag 1 and 2 has a significant relationship with the current TERM, whereas this relationship is flat for small and medium size firm returns.

3. DEF with lag 3 is significant for all 10 size portfolio return. On the other hand, TERM and size portfolio returns do not explain DEF.

Thus, as has been displayed in Figure 7.4, the signal transmission mechanism evolves from DEF to the large firms, TERM and small firms, then from large firms to TERM and finally from TERM to small firms. TERM appears to be incorporated in the large firm prices more than three months before changes occur. Small firms, on the other hand, seem to have a delayed reaction to the changes in the term spread. One possible explanation may be rooted in the fact that both small and large firm ends of the size range exhibit high gearing. Due to easy access to the lending market and lower cost of borrowing, the large firm may not be hit hard by the term spread increase, a fact that causes concern among small size companies' investors. (Why is there delay?)

The bottom line is that macroeconomic factors do affect stock prices. There is a pattern across size portfolios exhibiting changing sensitivity to the variations in macroeconomic variables. Past returns of the large firms are more indicative of the future values of the term spread, hence the expected inflation.

# Appendix 7.1

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF1 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1752.5 | 1641.5 | 1492.7 | ------ | ------ |
| 11 | 1738.7 | 1636.7 | 1499.9 | CHSQ( 9)= 27.5982[.001] | 18.1432[.034] |
| 10 | 1734.8 | 1641.8 | 1517.1 | CHSQ( 18)= 35.4319[.008] | 23.2932[.180] |
| 9 | 1730.2 | 1646.2 | 1533.6 | CHSQ( 27)= 44.6045[.018] | 29.3233[.345] |
| 8 | 1728.3 | 1653.3 | 1552.7 | CHSQ( 36)= 48.4237[.081] | 31.8341[.667] |
| 7 | 1722.2 | 1656.2 | 1567.6 | CHSQ( 45)= 60.7432[.059] | 39.9330[.686] |
| 6 | 1714.1 | 1657.1 | 1580.6 | CHSQ( 54)= 76.9451[.022] | 50.5843[.607] |
| 5 | 1711.6 | 1663.6 | 1599.2 | CHSQ( 63)= 81.8765[.055] | 53.8262[.788] |
| 4 | 1702.3 | 1663.3 | 1611.0 | CHSQ( 72)= 100.4734[.015] | 66.0520[.675] |
| 3 | 1698.2 | 1668.2 | 1628.0 | CHSQ( 81)= 108.6537[.022] | 71.4297[.768] |
| 2 | 1684.4 | 1663.4 | 1635.2 | CHSQ( 90)= 136.2536[.001] | 89.5741[.493] |
| 1 | 1672.9 | 1660.9 | 1644.8 | CHSQ( 99)= 159.3334[.000] | 104.7469[.327] |
| 0 | 1455.3 | 1452.3 | 1448.3 | CHSQ(108)= 594.3598[.000] | 390.7366[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF2 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1774.3 | 1663.3 | 1514.5 | ------ | ------ |
| 11 | 1761.2 | 1659.2 | 1522.4 | CHSQ( 9)= 26.2067[.002] | 17.2284[.045] |
| 10 | 1755.7 | 1662.7 | 1538.0 | CHSQ( 18)= 37.2535[.005] | 24.4907[.140] |
| 9 | 1749.2 | 1665.2 | 1552.6 | CHSQ( 27)= 50.1647[.004] | 32.9786[.198] |
| 8 | 1745.5 | 1670.5 | 1570.0 | CHSQ( 36)= 57.5655[.013] | 37.8440[.385] |
| 7 | 1737.7 | 1671.7 | 1583.2 | CHSQ( 45)= 73.1959[.005] | 48.1195[.348] |
| 6 | 1730.9 | 1673.9 | 1597.4 | CHSQ( 54)= 86.8972[.003] | 57.1269[.360] |
| 5 | 1728.3 | 1680.3 | 1615.9 | CHSQ( 63)= 92.0742[.010] | 60.5302[.565] |
| 4 | 1718.2 | 1679.2 | 1626.9 | CHSQ( 72)= 112.2724[.002] | 73.8087[.419] |
| 3 | 1714.1 | 1684.1 | 1643.8 | CHSQ( 81)= 120.5048[.003] | 79.2208[.535] |
| 2 | 1703.2 | 1682.2 | 1654.1 | CHSQ( 90)= 142.1672[.000] | 93.4618[.380] |
| 1 | 1693.2 | 1681.2 | 1665.1 | CHSQ( 99)= 162.3443[.000] | 106.7264[.280] |
| 0 | 1474.4 | 1471.4 | 1467.4 | CHSQ(108)= 599.8000[.000] | 394.3130[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

# Appendix 7.1 continues

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF3 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1763.9 | 1652.9 | 1504.1 | ------ | ------ |
| 11 | 1752.3 | 1650.3 | 1513.5 | CHSQ( 9)= 23.3399[.005] | 15.3438[.082] |
| 10 | 1749.3 | 1656.3 | 1531.6 | CHSQ( 18)= 29.2140[.046] | 19.2055[.379] |
| 9 | 1747.1 | 1663.1 | 1550.5 | CHSQ( 27)= 33.5900[.178] | 22.0823[.733] |
| 8 | 1744.2 | 1669.2 | 1568.6 | CHSQ( 36)= 39.5754[.313] | 26.0172[.890] |
| 7 | 1738.0 | 1672.0 | 1583.4 | CHSQ( 45)= 51.9792[.221] | 34.1715[.880] |
| 6 | 1732.3 | 1675.3 | 1598.9 | CHSQ( 54)= 63.2046[.183] | 41.5512[.892] |
| 5 | 1726.8 | 1678.8 | 1614.4 | CHSQ( 63)= 74.3352[.155] | 48.8685[.904] |
| 4 | 1718.9 | 1679.9 | 1627.6 | CHSQ( 72)= 90.1549[.073] | 59.2685[.859] |
| 3 | 1715.5 | 1685.5 | 1645.3 | CHSQ( 81)= 96.8864[.110] | 63.6939[.922] |
| 2 | 1701.5 | 1680.5 | 1652.3 | CHSQ( 90)= 124.9206[.009] | 82.1238[.711] |
| 1 | 1689.7 | 1677.7 | 1661.6 | CHSQ( 99)= 148.4638[.001] | 97.6012[.521] |
| 0 | 1468.5 | 1465.5 | 1461.5 | CHSQ(108)= 590.7953[.000] | 388.3932[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF4 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1768.5 | 1657.5 | 1508.7 | ------ | ------ |
| 11 | 1757.2 | 1655.2 | 1518.4 | CHSQ( 9)= 22.6875[.007] | 14.9149[.093] |
| 10 | 1754.3 | 1661.3 | 1536.6 | CHSQ( 18)= 28.4473[.056] | 18.7015[.410] |
| 9 | 1749.9 | 1665.9 | 1553.3 | CHSQ( 27)= 37.2234[.091] | 24.4709[.604] |
| 8 | 1746.9 | 1671.9 | 1571.3 | CHSQ( 36)= 43.2480[.189] | 28.4315[.811] |
| 7 | 1739.9 | 1673.9 | 1585.4 | CHSQ( 45)= 57.2701[.104] | 37.6498[.773] |
| 6 | 1733.2 | 1676.2 | 1599.7 | CHSQ( 54)= 70.6664[.064] | 46.4566[.757] |
| 5 | 1728.6 | 1680.6 | 1616.2 | CHSQ( 63)= 79.8497[.074] | 52.4938[.825] |
| 4 | 1720.0 | 1681.0 | 1628.7 | CHSQ( 72)= 97.0646[.026] | 63.8110[.743] |
| 3 | 1716.3 | 1686.3 | 1646.1 | CHSQ( 81)= 104.3934[.041] | 68.6290[.835] |
| 2 | 1702.5 | 1681.5 | 1653.3 | CHSQ( 90)= 132.0976[.003] | 86.8419[.575] |
| 1 | 1689.9 | 1677.9 | 1661.8 | CHSQ( 99)= 157.3071[.000] | 103.4148[.361] |
| 0 | 1471.5 | 1468.5 | 1464.5 | CHSQ(108)= 594.0002[.000] | 390.5002[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

## Appendix 7.1 continues

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF5 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1755.5 | 1644.5 | 1495.6 | ------ | ------ |
| 11 | 1745.9 | 1643.9 | 1507.1 | CHSQ( 9)= 19.1764[.024] | 12.6067[.181] |
| 10 | 1743.3 | 1650.3 | 1525.6 | CHSQ( 18)= 24.3566[.144] | 16.0122[.592] |
| 9 | 1740.4 | 1656.4 | 1543.8 | CHSQ( 27)= 30.1725[.306] | 19.8357[.838] |
| 8 | 1738.5 | 1663.5 | 1563.0 | CHSQ( 36)= 33.9306[.567] | 22.3062[.964] |
| 7 | 1730.8 | 1664.8 | 1576.3 | CHSQ( 45)= 49.4088[.301] | 32.4817[.918] |
| 6 | 1724.2 | 1667.2 | 1590.8 | CHSQ( 54)= 62.6012[.197] | 41.1545[.901] |
| 5 | 1720.6 | 1672.6 | 1608.2 | CHSQ( 63)= 69.8636[.258] | 45.9288[.948] |
| 4 | 1710.8 | 1671.8 | 1619.5 | CHSQ( 72)= 89.4620[.080] | 58.8130[.868] |
| 3 | 1706.2 | 1676.2 | 1636.0 | CHSQ( 81)= 98.6074[.089] | 64.8252[.905] |
| 2 | 1692.6 | 1671.6 | 1643.5 | CHSQ( 90)= 125.7616[.008] | 82.6766[.695] |
| 1 | 1683.0 | 1671.0 | 1654.9 | CHSQ( 99)= 144.9283[.002] | 95.2769[.587] |
| 0 | 1467.3 | 1464.3 | 1460.3 | CHSQ(108)= 576.3101[.000] | 378.8706[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF6 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1755.8 | 1644.8 | 1496.0 | ------ | ------ |
| 11 | 1746.1 | 1644.1 | 1507.3 | CHSQ( 9)= 19.5067[.021] | 12.8238[.171] |
| 10 | 1741.6 | 1648.6 | 1523.9 | CHSQ( 18)= 28.3647[.057] | 18.6471[.414] |
| 9 | 1738.1 | 1654.1 | 1541.4 | CHSQ( 27)= 35.4601[.128] | 23.3118[.668] |
| 8 | 1735.8 | 1660.8 | 1560.2 | CHSQ( 36)= 40.0122[.297] | 26.3043[.882] |
| 7 | 1727.2 | 1661.2 | 1572.7 | CHSQ( 45)= 57.3001[.103] | 37.6695[.773] |
| 6 | 1720.4 | 1663.4 | 1587.0 | CHSQ( 54)= 70.7593[.063] | 46.5177[.755] |
| 5 | 1715.6 | 1667.6 | 1603.2 | CHSQ( 63)= 80.4727[.068] | 52.9034[.814] |
| 4 | 1706.1 | 1667.1 | 1614.8 | CHSQ( 72)= 99.4243[.018] | 65.3623[.697] |
| 3 | 1703.1 | 1673.1 | 1632.9 | CHSQ( 81)= 105.4775[.035] | 69.3417[.819] |
| 2 | 1690.8 | 1669.8 | 1641.6 | CHSQ( 90)= 130.0756[.004] | 85.5126[.614] |
| 1 | 1678.6 | 1666.6 | 1650.5 | CHSQ( 99)= 154.4815[.000] | 101.5573[.410] |
| 0 | 1461.8 | 1458.8 | 1454.7 | CHSQ(108)= 588.1297[.000] | 386.6409[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

# Appendix 7.1 continues

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF7 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1745.9 | 1634.9 | 1486.0 | ------ | ------ |
| 11 | 1737.7 | 1635.7 | 1498.9 | CHSQ( 9)= 16.2610[.062] | 10.6901[.298] |
| 10 | 1735.5 | 1642.5 | 1517.7 | CHSQ( 18)= 20.7955[.290] | 13.6711[.750] |
| 9 | 1732.6 | 1648.6 | 1536.0 | CHSQ( 27)= 26.4477[.494] | 17.3869[.921] |
| 8 | 1730.6 | 1655.6 | 1555.1 | CHSQ( 36)= 30.4565[.729] | 20.0223[.986] |
| 7 | 1721.4 | 1655.4 | 1566.9 | CHSQ( 45)= 48.8594[.321] | 32.1205[.925] |
| 6 | 1714.4 | 1657.4 | 1580.9 | CHSQ( 54)= 63.0018[.188] | 41.4179[.895] |
| 5 | 1710.1 | 1662.1 | 1597.8 | CHSQ( 63)= 71.4734[.217] | 46.9871[.934] |
| 4 | 1702.0 | 1663.0 | 1610.7 | CHSQ( 72)= 87.6620[.101] | 57.6297[.891] |
| 3 | 1699.0 | 1669.0 | 1628.8 | CHSQ( 81)= 93.7332[.158] | 61.6209[.946] |
| 2 | 1685.1 | 1664.1 | 1636.0 | CHSQ( 90)= 121.4210[.015] | 79.8231[.770] |
| 1 | 1673.5 | 1661.5 | 1645.4 | CHSQ( 99)= 144.7007[.002] | 95.1273[.591] |
| 0 | 1458.1 | 1455.1 | 1451.1 | CHSQ(108)= 575.5365[.000] | 378.3619[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF8 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1751.6 | 1640.6 | 1491.8 | ------ | ------ |
| 11 | 1742.0 | 1640.0 | 1503.2 | CHSQ( 9)= 19.2355[.023] | 12.6455[.179] |
| 10 | 1739.0 | 1646.0 | 1521.3 | CHSQ( 18)= 25.1937[.120] | 16.5625[.553] |
| 9 | 1734.7 | 1650.7 | 1538.0 | CHSQ( 27)= 33.9479[.168] | 22.3176[.721] |
| 8 | 1732.7 | 1657.7 | 1557.1 | CHSQ( 36)= 37.9501[.381] | 24.9487[.917] |
| 7 | 1723.9 | 1657.9 | 1569.3 | CHSQ( 45)= 55.5669[.134] | 36.5301[.812] |
| 6 | 1718.4 | 1661.4 | 1584.9 | CHSQ( 54)= 66.5215[.118] | 43.7317[.840] |
| 5 | 1714.3 | 1666.3 | 1602.0 | CHSQ( 63)= 74.6159[.150] | 49.0531[.901] |
| 4 | 1705.3 | 1666.3 | 1614.0 | CHSQ( 72)= 92.6078[.051] | 60.8811[.822] |
| 3 | 1701.6 | 1671.6 | 1631.4 | CHSQ( 81)= 100.0379[.074] | 65.7657[.890] |
| 2 | 1688.9 | 1667.9 | 1639.8 | CHSQ( 90)= 125.4316[.008] | 82.4597[.701] |
| 1 | 1676.3 | 1664.3 | 1648.2 | CHSQ( 99)= 150.7856[.001] | 99.1276[.477] |
| 0 | 1459.6 | 1456.6 | 1452.5 | CHSQ(108)= 584.1601[.000] | 384.0312[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

# Appendix 7.1 continues

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF9 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1752.7 | 1641.7 | 1492.9 | ------ | ------ |
| 11 | 1743.4 | 1641.4 | 1504.6 | CHSQ( 9)= 18.5830[.029] | 12.2166[.201] |
| 10 | 1741.1 | 1648.1 | 1523.4 | CHSQ( 18)= 23.2124[.183] | 15.2600[.644] |
| 9 | 1736.6 | 1652.6 | 1540.0 | CHSQ( 27)= 32.1595[.226] | 21.1419[.780] |
| 8 | 1734.2 | 1659.2 | 1558.6 | CHSQ( 36)= 37.0514[.420] | 24.3579[.930] |
| 7 | 1725.7 | 1659.7 | 1571.2 | CHSQ( 45)= 53.9478[.169] | 35.4657[.845] |
| 6 | 1720.2 | 1663.2 | 1586.7 | CHSQ( 54)= 65.0715[.144] | 42.7785[.864] |
| 5 | 1716.6 | 1668.6 | 1604.3 | CHSQ( 63)= 72.1834[.200] | 47.4539[.928] |
| 4 | 1709.0 | 1670.0 | 1617.7 | CHSQ( 72)= 87.3615[.105] | 57.4321[.894] |
| 3 | 1706.5 | 1676.5 | 1636.3 | CHSQ( 81)= 92.3304[.183] | 60.6987[.955] |
| 2 | 1694.5 | 1673.5 | 1645.4 | CHSQ( 90)= 116.3678[.032] | 76.5011[.844] |
| 1 | 1680.4 | 1668.4 | 1652.3 | CHSQ( 99)= 144.7254[.002] | 95.1436[.591] |
| 0 | 1463.9 | 1460.9 | 1456.9 | CHSQ(108)= 577.5794[.000] | 379.7050[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

Test Statistics and Choice Criteria for Selecting the Order of the VAR Model

Based on 108 observations from 1986M1 to 1994M12. Order of VAR = 12
List of variables included in the unrestricted VAR:
PF10 TERM DEF
List of deterministic and/or exogenous variables:
C

| Order | LL | AIC | SBC | LR test | Adjusted LR test |
|---|---|---|---|---|---|
| 12 | 1766.6 | 1655.6 | 1506.7 | ------ | ------ |
| 11 | 1758.2 | 1656.2 | 1519.4 | CHSQ( 9)= 16.7736[.052] | 11.0271[.274] |
| 10 | 1754.6 | 1661.6 | 1536.9 | CHSQ( 18)= 23.9190[.158] | 15.7245[.612] |
| 9 | 1749.4 | 1665.4 | 1552.7 | CHSQ( 27)= 34.4362[.154] | 22.6386[.704] |
| 8 | 1748.2 | 1673.2 | 1572.6 | CHSQ( 36)= 36.8105[.431] | 24.1995[.933] |
| 7 | 1737.4 | 1671.4 | 1582.9 | CHSQ( 45)= 58.4399[.086] | 38.4188[.745] |
| 6 | 1731.3 | 1674.3 | 1597.9 | CHSQ( 54)= 70.4779[.065] | 46.3327[.761] |
| 5 | 1727.3 | 1679.3 | 1614.9 | CHSQ( 63)= 78.6356[.088] | 51.6956[.845] |
| 4 | 1718.9 | 1679.9 | 1627.6 | CHSQ( 72)= 95.3876[.034] | 62.7085[.775] |
| 3 | 1716.2 | 1686.2 | 1646.0 | CHSQ( 81)= 100.7297[.068] | 66.2204[.882] |
| 2 | 1703.9 | 1682.9 | 1654.8 | CHSQ( 90)= 125.3150[.008] | 82.3830[.704] |
| 1 | 1691.2 | 1679.2 | 1663.1 | CHSQ( 99)= 150.7737[.001] | 99.1197[.478] |
| 0 | 1474.7 | 1471.7 | 1467.7 | CHSQ(108)= 583.6863[.000] | 383.7197[.000] |

AIC=Akaike Information Criterion SBC=Schwarz Bayesian Criterion

## Appendix 7.2

**Table Appendix 7.2.**

**Panel I Estimated coefficients from unequal lag-length procedure using SURE method where PF1-PF10 are independent variables.**

| Dep.(N) | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
|---|---|---|---|---|---|---|---|---|---|---|
| PF(-1) | 0.37 | 0.37 | 0.45 | 0.34 | 0.17 | 0.16 | 0.13 | | | |
| T-ratio | 4.18 | 4.30 | 5.30 | 4.02 | 1.95 | 1.79 | 1.51 | | | |
| PF(-2) | | | | | | | | -0.16 | -0.20 | |
| T-ratio | | | | | | | | -1.80 | -2.32 | |
| PF(-3) | -0.20 | -0.17 | -0.20 | -0.20 | | | | | | |
| T-ratio | -2.29 | -1.93 | -2.31 | -2.32 | | | | | | |
| TERM(-1) | 37.22 | 12.18 | 18.28 | 18.84 | 27.36 | 19.11 | 23.14 | 15.09 | | |
| T-ratio | 2.15 | 0.87 | 1.25 | 1.29 | 1.70 | 1.18 | 1.38 | 0.88 | | |
| TERM(-2) | -62.47 | -11.58 | -40.06 | -41.24 | -53.12 | -21.07 | -26.42 | -17.37 | | |
| T-ratio | -2.44 | -0.82 | -1.87 | -1.93 | -2.23 | -1.29 | -1.57 | -1.01 | | |
| TERM(-3) | 29.12 | | 20.47 | 21.49 | 24.86 | | | | | |
| T-ratio | 1.82 | | 1.52 | 1.60 | 1.66 | | | | | |
| DEF(-1) | | | | | | 56.55 | 56.77 | 52.79 | 99.09 | 103 |
| T-ratio | | | | | | 1.18 | 1.17 | 1.11 | 2.68 | 3.08 |
| DEF(-2) | 100 | 108 | 111 | 111 | 116 | 105 | 112 | 79.02 | | |
| T-ratio | 2.13 | 2.68 | 2.77 | 2.77 | 2.65 | 1.94 | 2.02 | 1.41 | | |
| DEF(-3) | -147 | -142 | -157 | -146 | -153 | -197 | -210 | -175 | -139 | -123 |
| T-ratio | -3.21 | -3.65 | -4.05 | -3.73 | -3.54 | -4.30 | -4.44 | -3.66 | -3.80 | -3.67 |
| C | 0.07 | 0.05 | 0.06 | 0.05 | 0.05 | 0.04 | 0.05 | 0.06 | 0.05 | 0.03 |
| T-ratio | 2.36 | 2.02 | 2.35 | 1.91 | 1.77 | 1.60 | 1.78 | 1.93 | 2.26 | 1.40 |
| $R^2$ adj. | 0.26 | 0.24 | 0.31 | 0.25 | 0.16 | 0.17 | 0.18 | 0.16 | 0.17 | 0.11 |

**Panel II Estimated coefficients from unequal lag-length procedure using SURE method where TERM is an independent variable.**

| Dep.(N) | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
|---|---|---|---|---|---|---|---|---|---|---|
| PF1(-1) | -0.53 | -0.58 | -1.06 | -0.80 | -0.65 | -0.88 | -0.88 | -1.32 | -1.45 | -1.72 |
| T-ratio | -1.11 | -1.02 | -1.94 | -1.47 | -1.28 | -1.82 | -1.90 | -2.86 | -3.03 | -3.27 |
| PF1(-2) | 0.67 | 0.73 | 1.12 | 1.08 | 0.82 | 0.96 | 1.07 | 1.02 | 1.25 | 1.38 |
| T-ratio | 1.39 | 1.24 | 1.99 | 1.92 | 1.56 | 1.91 | 2.23 | 2.11 | 2.50 | 2.56 |
| TERM(-1) | 1235 | 1226 | 1239 | 1239 | 1231 | 1249 | 1252 | 1266 | 1271 | 1279 |
| T-ratio | 13.10 | 13.37 | 13.65 | 13.65 | 13.52 | 13.73 | 13.89 | 14.05 | 14.26 | 14.45 |
| TERM(-2) | -314 | -263 | -274 | -274 | -267 | -286 | -288 | -302 | -307 | -317 |
| T-ratio | -2.25 | -2.85 | -3.02 | -3.01 | -2.93 | -3.13 | -3.19 | -3.34 | -3.43 | -3.58 |
| TERM(-3) | 43.33 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| T-ratio | 0.50 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| DEF(-2) | 390 | 416 | 424 | 457 | 453 | 500 | 494 | 515 | 588 | 552 |
| T-ratio | 1.52 | 1.59 | 1.67 | 1.78 | 1.75 | 1.93 | 1.95 | 2.06 | 2.36 | 2.27 |
| DEF(-3) | -489 | -517 | -521 | -552 | -558 | -605 | -598 | -628 | -703 | -679 |
| T-ratio | -1.95 | -2.04 | -2.11 | -2.21 | -2.22 | -2.40 | -2.41 | -2.57 | -2.87 | -2.83 |
| C | 0.14 | 0.14 | 0.14 | 0.13 | 0.14 | 0.15 | 0.14 | 0.16 | 0.16 | 0.17 |
| T-ratio | 0.87 | 0.91 | 0.90 | 0.88 | 0.95 | 0.98 | 0.97 | 1.09 | 1.10 | 1.22 |
| $R^2$ adj. | 0.955 | 0.955 | 0.957 | 0.956 | 0.956 | 0.957 | 0.957 | 0.959 | 0.959 | 0.960 |

**Panel III Estimated coefficients from unequal lag-length procedure using SURE method where DEF is an independent variable.**

| Dep.(N) | PF1 | PF2 | PF3 | PF4 | PF5 | PF6 | PF7 | PF8 | PF9 | PF10 |
|---|---|---|---|---|---|---|---|---|---|---|
| DEF(-1) | 0.65 | 0.65 | 0.65 | 0.66 | 0.65 | 0.65 | 0.65 | 0.65 | 0.65 | 0.64 |
| T-ratio | 8.68 | 8.81 | 8.79 | 8.88 | 8.82 | 8.64 | 8.65 | 8.64 | 8.65 | 8.63 |
| DEF(-3) | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.28 |
| T-ratio | 3.69 | 3.68 | 3.63 | 3.60 | 3.62 | 3.68 | 3.68 | 3.68 | 3.68 | 3.69 |
| C | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| T-ratio | 1.72 | 1.71 | 1.70 | 1.69 | 1.69 | 1.72 | 1.72 | 1.72 | 1.72 | 1.73 |
| $R^2$ | 0.78 | 0.78 | 0.78 | 0.78 | 0.78 | 0.78 | 0.78 | 0.78 | 0.78 | 0.78 |

# Chapter 8

# Conclusion

The initial aim of this study was to investigate whether or not the size effect is present in the LSE for the period 1985-1995, and to explain the possible causes of it. The results show that, after applying a standard procedure of allocating firms into size portfolios and rebalancing them annually, the size effect has persisted in the London Stock Exchange over this period. The gross returns of the size portfolios exhibit diminishing returns as size increases. This relationship is discernible for each year of the period 1985-1995 except for 1989 and 1990. It becomes much more apparent when calculated for the overall period.

The market risk (beta) also has a distinct pattern across size portfolios. Small size firms, in general, have high betas; large firms, in contrast, have low betas. The size effect exists even after portfolios' returns are adjusted for market risk (beta), and it is negative. Beta is less significant than size in explaining the cross-sectional differences in portfolio returns, formed on size. This is true even when the whole sample is split into high and low beta sub-samples.

There appear to be some seasonal patterns to size portfolio returns. January is a strong month for large firms, but a weak one for small firms. Small firms perform well in March, April, June, July and October. The concentration of small size returns around March and April possibly related to the tax-year end. The seasonal factors cannot justify the size effects, however, as they appear in different months throughout the year. Nonetheless, there is a mirror image seasonal pattern between the returns of large and small firms – when small firms do well, large firms do badly, and *vice versa*. These patterns are confirmed by the transition probability matrices (Chapter 6) and the cross-autocorrelation patterns in Chapter 7.

The Markov Chain methodology applied here shows that different size firms' returns follow different patterns. Small size firms are prone to bubbles and positive autocorrelation stretching two lags at a minimum. In addition, the test of the Random Walk hypothesis fails to accept randomness of the smallest market capitalisation portfolios.

Bearing in mind that the portfolio returns series are composed of multiple firms, any such dependence as that stated above is evidence of company size dependent factors affecting share prices.

A test of stationarity shows that return series are stationary, implying a stable process during the period 1985-1995.

Tests using the residuals of the Market Model find neither bubbles nor deviation from the Random Walk across all size portfolios. This indicates a proper alteration and adjustment in the Market Model, estimated in Chapter 4. Individual size portfolios' allowances for infrequent trading and autocorrelation error obviously play an important role in achieving the Market Model's good fit.

The fact that the Market Model residual series are random and do not exhibit bubbles should not be taken as an indication that the actual series are white noise. Portfolios' residual series are produced by the relation of portfolios' returns to the market return, and the direction and magnitude of their deviation has nothing to do with the portfolios' gross return deviations. In the Market Model, for instance, a positive residual may be associated with a portfolio's relative outperformance of the market, although the portfolio's absolute gross return may be negative for a particular period. This asks the question of whether the deviations from the average or moving average respectively, or the Market Model residuals should be used for a case study of the "news" impact on market prices. In my opinion the series used for "news" impact on market prices ought to be firms' own, rather that Market Model residuals.

The main question which has to be answered, though, is 'Can an investment strategy based on size beat the market?' The answer, derived from the sample data used in this study, is 'no'. The average return, in excess of the market risk (beta), for the smallest size portfolio is 0.0129 per month, for the period 1985-1995 (Table 4.8). This is the highest excess return amongst portfolios 1, 2 and 3. However, it appears that the gross average return of portfolio 1 reduces from 0.031 to 0.019 net return, allowing for 0.012 average transaction costs after taking into account the number of rebalancing transactions and the Bid-Ask spread per transaction.

The size effect in gross returns, as well as excess of market risk returns before transaction costs, is not subsumed by the book-to-market ratio, nor is a result of dividend differences across size portfolios. Some borrowing ratio effects, though, cannot be ruled out when paired with interest rate movements. Where does the excess return before transaction costs of small firms come from? Are they more efficient in their economic activities?

A comparison between EBIT (Earnings before interest and taxes) and stock market profits is not carried out. An analysis of the composition of portfolio 1 and 10, however, shows that the applied strategy captures previous losers in portfolio 1 and previous winners in portfolio 10, respectively. During the period of their stay in portfolio 1, previous losers regain their value at a high rate, which boosts returns of portfolio 1. The opposite process takes place in the largest portfolio 10.

Even if transaction costs are ignored, that does not make investments in a small size portfolio as attractive as it may look in the first place. We show that the high returns of the smallest portfolio 1 are due to a few outliers, consisting of less than 10 percent of portfolio

1, and less than 1 percent of the total sample. When these outliers are ignored, portfolio 1's gross return drops by a third.

The following characteristics of the behavioural differences between small and large size firm returns can be summarised, based on their relationship with the economy-wide factors Term Spread (TERM) and Default Spread (DEF).

1. Large size firm returns are not predictable from their previous values. The opposite is true for small and partly so for medium size firms, portfolios 1 to 5.

2. The TERM spread is significant in explaining the return of the smallest size portfolio 1 with lags 1 and 2, and insignificant at any lag for portfolios 6 to 10. On the other hand, portfolio 10 return with lag 1 and 2 has a significant relationship to the current TERM, whereas this relationship is flat for small and medium size firm returns.

3. DEF at lag 3 is significant for all 10 size portfolio returns. On the other hand, TERM and size portfolio returns do not explain DEF.

Thus, as has been displayed in Figure 7.1, the signal transmission mechanism evolves from DEF to large firms, TERM and small firms, then from large firms to TERM and finally from TERM to small firms. TERM appears to be incorporated in large firm prices more than three months before changes occur. Small firms, on the other hand, seem to have a delayed reaction to the changes in the term spread. One possible explanation may be rooted in the fact that both the small and large firm extremes of the size range exhibit high gearing. Owing to easy access to the lending market and lower costs of borrowing, the large firm may not be hit so hard by the term spread increase, a fact which causes concern among investors in small size companies.

The bottom line is that macroeconomic factors do affect stock prices. There is a pattern across size portfolios exhibiting changing sensitivity to the variations in macroeconomic variables. Previous returns of large firms are more indicative of the future values of the term spread, hence the expected inflation.

In summary, the excess returns of the small firm portfolios seem to be due to an investment strategy which captures overreaction patterns, rather than a superior profitability. It appears, however, that the small firms' excess return exists more than a year after the portfolio formation. The second year may be equally, if not more, profitable. It appears that some of the firms included in the smallest portfolio earn low, even negligible, returns during the first year. Roughly 60 percent of the firms in portfolio 1 have returns lower than the portfolio mean return, which implies that they improve their performance in the following years. Therefore, fund managers dealing in small size firms may improve their performance by rebalancing less frequently, that is to say, biannually instead of annually.

It is interesting to postulate why small firms have more volatile market value compared to large firms. A couple of hypotheses can be suggested as a basis for further research. The first refers to firm structure. Large firms, because of their size, can diversify into various activities. By doing so, they are less exposed to downturns in a particular industry and their returns are more stable than the returns of small firms. On the other hand, the returns of small firms are not contaminated by diversification.

The second hypothesis relates ownership structure to volatility. Demsetz and Lehn (1985) propose a number of potential determinants of ownership concentration. One is the value-maximising size of the firm: the larger the firm, the greater the cost of obtaining a given fraction of ownership.

A study of the relationship between firm size and ownership concentration was intended as a part of the thesis, but later abandoned, due to the availability of data only for the most recent year of the sample period, i.e., 1995. Even considering that one year, however, the ownership concentrations for portfolio 1 and 10 are quite indicative. The average holdings in excess of 3 percent of the market value of a firm are 52 percent for portfolio 1 and 12 percent for portfolio 10. It is possible that the higher concentration of the ownership of small firms causes the unevenness of the trading volume of portfolio 1. (See Section 5.9).

Further research in these particular areas would help in designing a policy promoting more regular trading in small firms, reducing the overreaction, eventually narrowing the Bid-Ask spread, and finally eradicating the size effect even for those investors who do not bear heavy transaction costs.

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