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Dividend yields and business confidence as predictors of returns on the London Stock Exchange

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Abstract

This thesis examines the relationship between future returns and dividend yields on the London Stock Exchange for the period 1966 to 1993. An additional set of explanatory variables is introduced in the form of the Confederation of British Industries, Industrial Trends Survey data.

A significant relationship was found between dividend yields and future returns when regression statistics were generated by ordinary least squares. The relationship was shown, however, to be attributable only to the period from 1966 to 1980 and in particular to the turbulent era from 1973 to 1975. When allowance was made for the effect of a lagged regressor by use of the Goetzmann and Jorion (1993) simulation model, no significant relationship between dividend yields and future returns for the entire sample period was found.

Ordinary Least Squares estimation of regressions of future returns on the Confederation of British Industries surveys of Business Opinion showed only a modest relationship. This was considerably weakened when the regression coefficients were estimated by randomisation. In common with Dividend Yields the relationship was entirely a feature of the 1966 to 1980 period.

The evidence provided by this study does not enable the refutation of the semi-strong form of market efficiency.

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Notation

Chapter 2 Literature survey

Since material in this chapter covers a period of over 30 years there are frequently variations in usage in notation between authors and over time. The notation in this chapter has been taken directly from the articles cited. In all cases an explanation is given in the text.

Chapter 3, 4 and 5.

Regression

$S_{\hat{\beta}}$	Estimate of standard error
β_0	Hypothesised value of β
$\hat{\beta}$	Estimated regression parameter
$\tilde{\mu}_t$	Random disturbance term
$\tilde{\mathbf{y}}$	Vector of deviations from the mean of the independent variable
α	Coefficient of the constant term
β_1	Coefficient of independent variable 1
$\mathbf{e}$	Vector of residuals
g	Growth rate in dividends
k	Indicates observation number in column vector
K	Number of regressors
P	Price
T	Number of observations
u	Disturbance term
$\boldsymbol{X}$	Matrix of observations of the independent variables
x_1	Independent variable 1
$\mathbf{y}$	Vector of the dependent variable
y	Dependent variable

Notation Applicable to Empirical Work

Stock Market Variables

ADIV	The summation of net dividends paid in the previous 12 months on the Financial Times-Actuaries All Share Index series
AIR	Adjusted income return.
CR	Capital return on the Financial Times-Actuaries All Share Index
D_t	Monthly dividends received on the Financial Times-Actuaries All Share Index
GD	Gross monthly dividend
GDY	The gross dividend yield on the Financial Times-Actuaries All Share Index
IR	Income return on the Financial Times-Actuaries All Share Index
NDY	The net dividend yield on the Financial Times-Actuaries All Share Index
PI	The price index on Financial Times-Actuaries All Share series
TR	Total return on the Financial Times-Actuaries All Share Index
TRI	The total return index on the Financial Times-Actuaries All Share series - extracted from Datastream
tax	The basic rate of income tax

Confederation of British Industries Variables

ΔQ_t	The balance of firms reporting more over those reporting less
Δq_t	The reply to the CBI survey of respondent
CBI	CBI data - an explanatory variable
CBIA	The CBI balance of business optimism series
CBIB	The CBI balance of investment in buildings series
CBIC	The CBI balance of investment in plant series
CBID	The CBI balance of future orders series
w_i	A weighting depending on the relative size of the respondent *i* to the total responding.

CHAPTER 1

INTRODUCTION

Scepticism concerning the validity of the Efficient Market Hypothesis appeared to have reached its zenith by the spring of 1991 when I started this thesis. It was widely believed that long horizon returns were predictable using fundamentals such as dividend yields. Some considered alleged excess volatility of stock market prices to reflect mass investor psychology which was evidenced in fashions and fads. From this standpoint if annual series of dividends are highly autocorrelated, overly low stock prices cause dividend yields to be high. These high dividend yields capture the subsequent increases in stock prices as they revert to their fundamental value[1]. Others disagreed. For example Fama and French (1988b) attribute their findings of a relation between dividend yields and future returns, to time-varying expected returns[2]. Cochrane (1991) argues that apparent dramatic pricing errors can be reinterpreted as small (if persistent) discount rate errors. At the outset I considered replicating studies such as Fama and French (1988b) and (1989), using data from the London Stock Exchange.

Given the state of knowledge in early 1991 it seemed probable that dividend yields would predict future returns. In these circumstances, I considered it more interesting to test whether another variable, Confederation of British Industries Survey data of their members views on Business Optimism might also be a useful predictor of returns. The question then arose as to whether CBI data might add anything to the explanatory power of dividend yields. Since it was possible that other researchers were examining the use of dividends as predictors of returns, the addition of the CBI data provided another interesting, and hopefully unexplored, ingredient in the study. At that time I had little insight into the econometric controversies concerning the use of dividend yields as predictors of returns which subsequently were discussed in the literature.

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1 Similarly, high stock prices cause dividend yields to be low, which in turn predict lower future stock prices.

2 The term time-varying expected returns is used to imply the discount rate at which investors discount future cash flows.

A turning point for my research was the publication of Goetzmann and Jorion' s (1993) article which for the first time modelled specifically the effect of the current stock price which appears as a constituent of both the dependent variable, future return and of the independent variable, dividend yield. The article also forced me to become thoroughly familiar with randomisation as a technique although I had already acquired some knowledge of it though the Noreen's (1989) text which is cited by Kim Nelson and Startz (1991). Given the low cost of computing power it seems likely that this technique will become more widely available through user friendly software packages in the next few years and will provide relatively simple solutions to hitherto intractable statistical problems.

The study of the relationship between future returns and dividend yields presents many interesting econometric challenges. Dividends are a highly autocorrelated series. The current share price therefore determines dividend yield, the explanatory variable, and also forms the datum point for calculating future returns, the dependent variable. A lagged version of the dependent variable therefore enters the regression as an explanatory variable. Furthermore, the limited length of the available data series forces the researcher to use overlapping observations for horizons greater than one year. These induce serial correlation into the residuals. In addition, stock returns are well known to be both heteroscedastic and highly non-normal.

This study adopts the Goetzmann and Jorion (1993) simulation methodology which is robust to the effect of serially correlated residuals, to the presence of a lagged dependent variable used as an explanatory variable, and to non-normality in the return series. Shuffling the return series, however, destroys its temporal pattern of heteroscedasticity and therefore does not allow for its effect. The Goetzmann and Jorion methodology is extended in this study by the use of stratified randomised sampling as in Kim, Nelson and Startz (1991) and by the use of Weighted Least Squares randomisation as in McQueen (1992) to correct for the pattern of heteroscedasticity in the series of returns.

Data on returns and dividend yields from 1965 to 1993 was derived from the daily series of total returns and capital returns extracted on line from Datastream. Survey. Survey data of businessmen's expectations was obtained directly from the Confederation of British Industries.

The first hypothesis tested whether dividend yields were related to future returns for horizons from 3 to 36 months and the second tested whether each of 4 selected series of CBI data were related to future returns. In addition, model selection criteria were use to test whether CBI data might add to the explanatory power of dividend yields.

Using ordinary least squares methodology a strong relation was found between dividend yields and future returns at all time horizons from 3 to 36 months. For the CBI survey data there was a rather weak relationship with future returns, only a relatively few series showing significant results. The model selection criteria[3] suggested that the survey data added little explanatory power to dividend yields.

When the statistical significance of Beta for the dividend yield variable was estimated using the Goetzmann and Jorion (1993) methodology, its coefficients were significant at very few time horizons. Allowance for heteroscedasticity caused a further decrease in the number of series with significant coefficient coefficients.

For the CBI series a very similar pattern was revealed. Allowance for the statistical problems in the data caused the number of series with significant coefficients to fall. The evidence provided by this thesis does not enable the researcher to reject the null hypothesis of no relationship between returns and both the dividend yield variable and the CBI variables.

The data were then split into two sub-samples of equal length. The first ran from 1966 to 1980 and the second from 1981 to 1993. The association between future returns and dividend yields and also the CBI series was shown to be entirely a feature of the first sub-sample when both economic and stock market conditions were unsettled. The "leverage" measure of the regression, (see Belsley, Kuh and Welsch. (1980)) showed the dramatic recovery of the market in 1975 to be highly influential.

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3 $\overline{R}^2$, Akaike Information Criterion and Schwartz Information Criterion were used in this study.

In common with many hundreds of other tests of the semi-strong form of market efficiency, this study is unable to present evidence of a rejection at the conventional 5% level.

The organisation of this thesis is as follows. Chapter 2 reviews the literature on efficient markets and the parallel development of asset pricing models from the early 1950's to the present time. Chapter 3 describes the data used in this study, the hypotheses tested and also the methodology used. Chapter 4 provides the bulk of the empirical results. Chapter 5 deals with some possible objections to the results and also compares the findings of this study with those of similar studies. Finally, chapter 6 reviews the results of the study. It assesses the contribution of this study to knowledge, sets the conclusions in an historical perspective, and provides some suggestions for further research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The task of reviewing the Efficient Market literature has become formidable. Market efficiency is inseparably entwined with asset pricing models and also with rational expectations. In addition to the financial economics literature and its associated statistical material, there is the rapidly developing literature in the area of cognitive psychology. The efficient markets literature has already been thoroughly reviewed by many authors. Fama (1970) covers the early period and for the first time published the distinction between the three forms of market efficiency which are enshrined in the texts used on MBA and undergraduate programmes[1]. Henfrey, Albrecht and Richards (1977) evaluate the early UK empirical evidence. At that time academic thought as expressed in the leading academic journals almost universally supported notions of market efficiency. It was not until the late 1970's and early 1980's that a large number of anomalies became apparent and the leading collection of papers on these is included in Dimson (1988). The paper by Keim (1988) included in that volume provides a thorough review of these anomalies and Levis (1989) provides a useful review focused on UK data. In the early 1980's a substantial body of literature had grown which directly challenged the efficient markets hypothesis and which claimed that share prices were more volatile than could be attributed to a rational expectation of the series of dividends which they were supposed to value. A survey of this work, which is generally sympathetic to notions of excess volatility is West (1988). For an opposite view, see the surveys by Merton (1987) and Cochrane (1991). Gilles and Le Roy (1991) review the econometric aspects of volatility tests. There has been a growing interest in how far asset prices can be attributed to bubbles and fads; see Carmerer (1989) for a review. Probably the most significant and certainly the technically most challenging survey of market efficiency is Le Roy (1989). Fama (1991) provides a most useful sequel to his 1970 review by examining the most recent literature on return forecasting regressions and on possible failures of asset pricing models. Additional recent reviews appear in Ball (1992) and Mills (1992) and (1993).

1 These have been attributed to an unpublished working paper, Roberts (1967).

Thaler (1992), who in contrast to most economists examines the stock market from a behavioural perspective, includes a provocative collection of papers dealing with material from the field of Cognitive Psychology.

The reviewer would not be short of material even if only secondary sources were considered. For the purposes of this thesis I will provide an outline of the major developments over the last 30 years but concentrate mainly on those aspects which are central to my thesis

2.1.1 Organisation of this Section

" Professor, I see a twenty dollar bill on the sidewalk. Should I pick it up?... No of course not, if it were really there, it would have been picked up already" Tobin (1984).

This seemingly trite remark encompasses many of the ideas that have been central to the issue of whether securities markets are efficient. It questions whether gains can be found easily on the stock market; and if they can be found, will not competition among investors rapidly compete them away?

Tobin described four levels of financial market efficiency. These provide a useful starting point for this thesis and a framework from which further analysis can proceed. After that we shall review briefly the development of the early empirical work on stock market behaviour, which suggested that share prices followed a random walk. This was published during the period from 1900 to mid 1965. In 1965, Paul Samuelson showed in his seminal paper "Proof that Properly Anticipated Prices Fluctuate Randomly" that the apparent random fluctuations in stock prices were entirely consistent with a market which instantly assimilated new information. In other words, what appeared quite irrational could be explained by economic theory which was testable by empirical observation. A further milestone in the development of the subject was Fama's publication of his (1970) review article "Efficient Capital Markets: A Review of the Theory and Empirical Evidence." The article describes the metamorphosis of the random walk hypothesis, which was largely considered as an intellectual curiosity, into the efficient market hypothesis, a more soundly formulated and empirically testable proposition which has, apart from some relatively minor modifications arising from criticisms by Le Roy (1976), remained the cornerstone in the edifice of modern financial theory. There has also developed an associated but peripheral literature on market efficiency in conditions of heterogeneous expectations which will be discussed, and finally the section will end with some observations on the current state of Efficient Markets Theory.

2.1.2 Tobin's Categorisations of Efficiency

Tobin (1984) defined four different levels of the efficiency of the financial system. Firstly, a market is said to be information-arbitrage efficient if it is impossible to gain from trading on the basis of generally available public information. "Whatever you and I know, the market has already discounted." In other words competition among investors causes the price of a share to reflect all available information. Since information is widely available among market participants, no one investor has a comparative advantage over another; and therefore, no one can expect to profit.

Secondly, Tobin defines what he described as Fundamental-Valuation Efficiency. "A market in a financial asset is considered to be fundamentally valuation efficient if its valuations reflect accurately the future payments to which the asset gives title". In his following sentence, however, Tobin qualifies this definition, " - to use currently fashionable jargon, if the price of an asset is based on 'rational expectations' of those payments." Clearly no investor can make completely accurate predictions of future dividend streams; all that is necessary is that investors' expectations are rational.

Tobin describes his third form of efficiency of the financial system as Full Insurance Efficiency. A system of financial markets is full insurance efficient if it enables economic agents to ensure themselves of deliveries of goods and services in all future contingencies, either by surrendering some of their own resources now or by contracting to deliver them in specified future contingencies. Contracts for specified goods in specified 'states of nature' are called in economic theory Arrow-Debreu contracts. Arrow and Debreu (1954) imagined a complete system of markets in which commodities are defined not only by their physical characteristics but also by the dates and contingencies. This type of market efficiency refers to the ability of the financial system to provide a wide range of instruments which will cater for all possible financial contingencies.

Tobin's last form of efficiency of the financial system he calls Functional Valuation Efficiency which relates to the economic functions of the financial industries. They include:

1 Pooling of risks and their allocation to those best able to bear them.
2 A generalised insurance function in the Arrow Debreu spirit.
3 The facilitation of transactions by providing mechanisms and networks of payments.
4 The mobilization of savings for investment in physical or human capital.
5 The allocation of savings to their most socially productive uses.

The latter two forms of efficiency are beyond the scope of this thesis. The concern in this thesis will be with information arbitrage efficiency and fundamental-valuation efficiency. For any market to be fundamentally valuation efficient it must also be informationally arbitrage efficient.

We must now trace the development of the early empirical work and the quest for a theory. Since much of the early work was of an exploratory nature, it is inevitable that both theoretical and empirical developments were entwined. Samuelson (1965) provides the watershed between a number of primarily descriptive studies and more rigorous testing which developed in the late 1960's and the early 1970's.

2.1.3 The Early History

In 1900 the French mathematician Louis Bachelier conducted an empirical study of French government bonds and commodities and concluded that their prices followed a random walk, Bachelier (1900). He argued that commodity speculation in France was a 'fair game'. In other words if, after repeated trials the expected future price of a commodity was deducted from the actual (future) price, the sum of the differences would be zero. Therefore the actual price was an unbiased estimate of the future price. The implications Bachelier's pioneering work were largely ignored and it was not until the 1930's when further academic research into the behaviour of stock market prices emerged.

Working (1934) discusses the possibility that stock prices, which when plotted on graphs looked very similar to random walks, might follow a random walk.[2]

Not until the early 1950's when Kendall (1953) examined the behaviour of weekly changes in 19 British industrial share price indices and of spot prices for cotton (New York) and wheat (Chicago), was the proposition that stock prices followed a random walk again seriously examined. After an extensive analysis of serial correlations, he suggests in quite graphic terms:

> *The series looks like a wandering one, almost as if once a week the Demon of chance drew a random number from a symmetrical population of fixed dispersion and added it to the current price to determine the next week's price. (Kendall 1953, p.13).*

Granger and Morgenstern (1963) followed up Kendall's result with an econometric study using spectral analysis which attempted to measure the variation in share prices which could be accounted for by cycles of different lengths. Among the many series they analysed were the monthly changes in the Standard and Poor's index between 1875 and 1952 and the monthly changes of six London ordinary shares between 1959 and 1962. Some of the tests found very faint evidence of a seasonal effect and of a monthly cycle. There were also traces of a 40 month cycle that might be related to a business cycle. In no case, however, was a major departure from the random walk model apparent.

In the meantime Roberts (1959) showed that a series of numbers created by cumulating random numbers had the same visual appearance as a time series of stock prices.

Working independently, Osborne (1959) found a very high degree of conformity between the movements of stock prices and the laws governing Brownian

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2 The term 'random walk' is believed to have first been used in an exchange of correspondence in Nature in 1905, (see Pearson and Rayleigh, (1905)), which concerned the optimal search strategy for finding a drunk who had been left in the middle of a field. The solution is to start exactly where the drunk had been placed, as that point is an unbiased estimate of the drunk's future position since he will presumably stagger along in an unpredictable and random fashion.

motion. He found that the variance of cumulative price changes, appeared to increase proportionately to the length of time. The evidence that the logarithms of price changes are very nearly independent of each other, is consistent with the random walk model.

This model seems at first to contradict the orthodox wisdom of the fundamental analysts. Early practitioner texts such as Benjamin Graham and David Dodd's "The Theory of Investment Value" , Graham and Dodd (1938), put forward the idea that the 'intrinsic' or 'fundamental value' of a security equals the discounted cash flow to which that security represents a claim. Analysts should attempt to compute the intrinsic value of a share by forecasting future cash flows of companies and discounting these to obtain present values. To carry out this calculation they needed to take account of any factors which might influence a firm's cash flow. The question which puzzled academics was how stock prices could be random if they are being determined by brokers' analysts carefully examining all the fundamental factors. Random price changes seemed to imply that the price of securities was exempt from the laws of supply and demand which governed other prices.

An additional paradox was the apparent poor performance of fundamental analysis. Cowles (1933) demonstrated that the recommendations of large brokerage houses which employed many analysts who competed with each other in attempting to predict the intrinsic value of a share, did not perform better than the market. The implication seemed to be that investors who paid for the services of analysts were wasting their money.

By the late 1950's to early 1960's there existed a growing body of evidence that the stock market seemed to follow a random walk and also that brokers' efforts in selecting shares were not successful. Security prices did not appear to be determined by any rational model. The issue which perplexed many economists was what, if any, economic theory could explain these findings.

It was not long before economists suggested a solution. Harry Roberts (1959) argued that in the economist's idealised market of rational individuals one would expect the instantaneous adjustment of prices to new information that the random walk implies. A pattern of systematic slow adjustment to new information, on the other hand, would imply the existence of readily available profitable trading opportunities that were not being exploited. We must now turn to see how Robert's ideas were developed into theory.

2.1.4 Theory of Efficient Markets

It is useful to contrast efficient markets with perfect capital markets. Fama (1970) states

> *" ... it is easy to determine sufficient conditions for capital market efficiency. For example consider a market in which there are (i) no transaction costs in trading securities, (ii) all available information is costlessly available to all market participants, and (iii) all agree on the implications of the current information for the current price and distributions of the future prices of each security. In such a market, the current price of a security obviously reflects all available information."*

Of course in the real world it is unlikely that all these conditions will exist. Fama goes on to argue:

> *"As long as transactions take account of all available information, even large transaction costs ... do not in themselves imply that when transactions do take place, prices will not fully reflect available information."* Similarly *"... the market may be efficient if `sufficient numbers' of investors have access to available information. Disagreements among investors about the implications of given information does not itself imply market inefficiency unless there are investors who can consistently make better evaluations of available information than are implicit in market prices."*

We can therefore see that a market might be informationally efficient despite considerable relaxation of the rigorous requirements of a perfect market.

Parallel with the observation that share prices appeared to follow a random walk was the argument that also they were a 'fair game'. For example, Cootner (1964) p.200, states:

> *If one were to start out with the assumption that a stock or commodity speculation is a 'fair game' with equal expectation of a gain or loss or, more accurately, with an expectation of zero gain, one would be well on the way to picturing the behaviour of speculative prices as a random walk.*

Fama (1970) in his seminal review of the literature discusses three models of efficient markets. Firstly the fair game model, states that $x_{j,t+1} = 0$ in,

$$x_{j,t+1} = p_{j,t+1,} - E(\tilde{p}_{j,t+1}|\Phi_t) \qquad \textbf{(2.01)}$$

where $x_{j,t+1}$ is the excess profits equalling the difference between the actual price of a security j at time $t + 1$ and the expected price at time $t + 1$ given the information set Φ at time t. In an efficient market $x_{j,t+1} = 0$. In a fair game expected excess profits are equal to zero.

Secondly a sub-martingale is a fair game where tomorrow's price is expected to be greater than today's price. Thus

$$E(\tilde{p}_{j,t+1}|\Phi_t) \geq p_{jt} \qquad \textbf{(2.02)}$$

In this form it implies that expected returns are positive.

Finally the martingale model is a fair game in which tomorrow's price is expected to be the same as today's price. Thus

$$E(\tilde{p}_{j,t+1}|\Phi_t) = p_{jt} \qquad \textbf{(2.03)}$$

Since shares are expected to yield a positive return, the sub martingale model is of most interest. Much of the early literature referred to share price changes. We need to modify this, however, to make allowance for dividends. Thus strictly, rather than saying that share price changes follow a sub martingale, we should state that returns follow a sub martingale. Expected returns are defined as:

$$\frac{E\left(\tilde{P}_{j,t+1} + \tilde{D}_{j,t+1} \middle| \Phi\right) - P_{j,t}}{P_{j,t}} \qquad \textbf{(2.04)}$$

Where $P_{j,t}$ and $D_{j,t}$ are the share price and dividend respectively of security j at the end of period t.

Finally the random walk model states that there is no difference between the distribution of returns conditional on a given information structure and the unconditional distribution of returns. Equation 2.05 is a random walk in returns

$$f(r_{j,t+1} \mid \Phi) = f(r_{j,t+1}), \qquad \textbf{(2.05)}$$

Random walks are much stronger conditions than fair games or martingales because they require all the parameters of the distribution to be the same. Furthermore successive drawings must be i.i.d. (independently identically distributed). If returns follow a random walk, then the mean of the underlying distribution does not change over time, and a fair game will result.

Until the publication of Samuelson's (1965) seminal article "Proof that Properly Anticipated Prices Fluctuate Randomly", discussion of the subject had been in terms of the fair game and random walks. After Samuelson's paper, the subject was discussed in terms of martingales. In empirical terms this implied testing market efficiency either in terms of deriving trading rules which could lead to excess profits or alternatively testing whether the market rationally reflected particular pieces of information. Samuelson showed from the rule of iterated expectations that properly anticipated prices would fluctuate randomly. Samuleson's argument was based in terms of futures prices but in a later article, (1973), he restated the argument in terms of share prices. Similar results were presented in Mandelbrot (1966). Some have claimed that Samuelson's article was the single most important contribution to the development of the subject, while others, for example Rubenstein (1975) have dismissed the result as obvious.

Samuelson's result implies that the appearance noted previously of the conflict between the fundamentalist model and the efficient capital markets model of asset prices is entirely illusory. In fact Samuelson's result suggests that if fundamentalists are correct in viewing stock prices as equal to discounted expected cash flows, then it follows that future stock returns are unpredictable, just as postulated in the martingale model.[3]

This result therefore is entirely consistent with a market in which there are a number of traders competing on the basis of available information. In such a market any obvious discrepancy between the actual value of a share and its intrinsic value will immediately disappear. Such a market is a fair game and the martingale model would appear to hold.

The move from the random walk model to the martingale model was a key step in the development of the subject since it provides a model founded in economic theory. Moreover the assumption that a stochastic process, say y_t, follows a random walk is more restrictive than the requirement that it follows a martingale. The martingale rules out any dependence of the conditional expectation of Δy_{t+1} on the information available at t, whereas the random walk rules out not only this but also dependence involving the higher conditional moments of Δy_{t+1}.[4]

Having discussed the metamorphosis from random walks to martingales, we now consider the three levels of market efficiency which were first formally defined in Fama (1970).[5] Fama defines an efficient market as one in which prices "fully reflect available information", and then describes three forms of market efficiency which depend on the information set available.

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3 Le Roy (1973) has shown that the martingale cannot be a correct representation unless investors are risk neutral. Samuelson's result depends on the assumption that investors require an exogenously given expected rate of return. Le Roy argues that conditional expectations will depend on the realisation of the system's past and present random elements, the distribution of which are endogenous and dependent on expectations. In such a context it is no longer possible to take expectations as given if the reasonable assumption that these expectations are unbiased is to be maintained.

4 We shall see later that changes in share prices have been shown not to be independent in their higher moments.

5 These were first presented in an unpublished working paper, Roberts (1967).

First, weak form tests, in which the information set is just historical prices, are discussed. Then semi-strong form tests, in which the concern is whether prices efficiently adjust to other information which is obviously publicly available (e.g. announcement of annual earnings, stock splits etc. are considered). Finally strong form tests, concerned with whether given investors or groups have monopolistic access to any information relevant for price formation, are reviewed.

One of the advantages of this categorisation is that it is hierarchical. Strong form efficiency implies semi-strong and semi-strong efficiency implies, weak form efficiency. The major empirical implication of the efficient market is that since the market instantly reflects available information, it is not possible through analysis of that information to generate superior returns. The next section is devoted to an exposition of the benchmarks against which to assess superior returns.

As already discussed, the sub-martingale model requires that expected returns are both a fair game and that they are positive. Many tests of market efficiency aim to examine whether trading rules can give superior investment performance. It is therefore necessary to test the performance of a portfolio constructed using these rules against a suitable benchmark portfolio. If the market is efficient, there will be no systematic difference between the returns on the two portfolios. The researcher needs to control for any difference in risk between the trial portfolio and the benchmark portfolio. He also needs a model which incorporates risk in the benchmark for assessing whether superior returns have been earned.

2.1.5 The Development of Portfolio Theory and the Capital Asset Pricing Model.

Parallel with the evolution of efficient market theory, a model specifying the return generation process, the capital asset pricing model, CAPM, attributed to Sharpe (1964), Lintner (1965) and Mossin (1966) was being developed. To trace its evolution we must firstly examine Portfolio Theory and the pioneering work of Markowitz (1952).

2.1.5.1 The Development of Portfolio Theory

The foundations of the models that would first explain risk premia were laid by Hicks (1946)), Markowitz (1952) and Tobin (1958). Markowitz developed a rigorous mathematical model of individual behaviour in a 'mean variance world' where investment portfolios were evaluated in terms of their mean returns and the total variance of their returns. He justified focusing on these two distributional characteristics by assuming that either investors had quadratic von Neuman-Morgenstern utility functions or that asset returns were normally distributed. In such a world investors would choose mean variance efficient portfolios. i.e. portfolios with the highest mean for a given level of variance.

The return on a portfolio is simply the weighted average return of its constituents given by:

$$E\left(\tilde{R}_P\right)=\sum_{i=1}^{n} w_i E(\tilde{R}_i) \qquad \textbf{(2.06)}$$

Where $E(\tilde{R}_p)$ is the expected return on the portfolio, w_i is the proportion of the value of the portfolio invested in the security i and $E(\tilde{R}_i)$ is the expected return on the security i.

Markowitz (1952) demonstrated that the risk of a portfolio is a function of the weightings of each of its constituents and the covariance of each of its constituents with each other. This is given by:

$$Var\left(\tilde{R}_P\right)=\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j COV_{ij} \qquad \textbf{(2.07)}$$

where $Var\tilde{R}_p$ is the variance of the portfolio; w_i is the proportion of funds invested in security i; w_j is the proportion invested in security j; and COV_{ji} the covariance between returns for securities i and j. The use of variance as a measure of portfolio risk implicitly assumes that stock returns are normally distributed. As early as 1963 researchers found departures from normality in return data (see Mandelbrot (1963) and Fama (1965)) and since then there have been numerous attempts to satisfactorily model stock returns.

While practitioners had for many years emphasised the importance of holding diversified portfolios, Markowitz's contribution was to define the mathematical formulation which described a portfolio's risk. Markowitz also defined the "efficient frontier" of portfolios in terms of their risk and return. Portfolios offering an optimum combination of risk and return lie along what he described as the efficient frontier. While Markowitz's pioneering work set the framework for the analysis of risk and return in financial markets, it was extremely cumbersome to operate. For example, a portfolio of 100 securities, required the calculation of 100 expected returns, 100 standard deviations and 4,950[6] correlation coefficients.

Tobin (1958) demonstrated that given the possibility of an investment in a risk-free asset as well as in a risky asset or portfolio, an investor can construct a portfolio of two assets and achieve any desired balance of risk and return by shifting the proportions held in each asset.

2.1.5.2 The Capital Asset Pricing Model

The work of Tobin and Markowitz laid the foundations of the capital asset pricing model by Sharpe (1964), Lintner (1965) and Mossin (1966). The contribution of these authors was to demonstrate that, assuming all investors have the same mean variance beliefs, the market portfolio must be mean variance efficient. Thus shareholders could achieve their desired trade-off between risk and return by holding cash and the market in the desired combinations. Furthermore, the additional risk that was added to a portfolio related not to the variance of that security but to the covariance of the securities returns to those of the market. This could be measured by the securities β as is given in equation 2.08 below.

$$E(\tilde{R}_j) = R_f + \beta_j\left[E(\tilde{R}_m) - R_f\right] \qquad \textbf{(2.08)}$$

where, $E(\tilde{R}_j)$ is the expected one period return on the security j, R_f is the one period risk free rate of interest, $E(\tilde{R}_m)$ is the one period expected return on the market and β_j

6 This is calculated from the formula $n(n-1)/2$, where n is the number of securities in the portfolio.

is the estimated systematic risk of the security. β, known as the beta coefficient is given by:

$$\beta_j = \frac{COV(\tilde{R}_j,\tilde{R}_m)}{VAR(\tilde{R}_m)} \qquad \textbf{(2.09)}$$

Where $COV(\tilde{R}_j, \tilde{R}_m)$ is the covariance of returns on the security with returns on the market.

The capital asset pricing model simply states that the risk premium on a share is a function of the risk premium on the market portfolio and of the security's covariance with the returns on the market portfolio reflected by β. Any other risks, known as unsystematic risks, are not material since they can be eliminated by diversification.

The capital asset pricing model relies on the following assumptions:

1 All investors are single-period expected utility maximisers whose utility functions are based only on the mean and variance of return.
2 All investors can borrow and lend an indefinite amount at the risk free interest rate, and there are no restrictions on short sales.
3 All investors have homogeneous expectations of end of the period joint distributions of returns.
4 Securities markets are frictionless and perfectly competitive.

Clearly it is unrealistic to expect that these conditions will be fully met in financial markets. The model may still be valid despite a considerable relaxation of the underlying assumptions. For example Black (1972) has shown that even if an investor cannot borrow and lend at the risk free rate, β is still the appropriate measure of systematic risk for an asset, and the linearity of the model still obtains. The early empirical tests of the Capital Assets Pricing Model were generally supportive[7]. More recent evidence suggests, however, that factors other than β may explain returns on securities.

7 For example see, Friend and Blume (1970), Black Jensen and Scholes (1972), Fama and Macbeth (1973), Miller and Scholes (1972).

2.1.5.3 The CAPM and the EMH: The Joint Hypothesis Problem

If the capital asset pricing model correctly predicts the relationship between systematic risk and expected return, then for a portfolio of a large number of securities the expected error term will be zero. Cumulative errors which are statistically different from zero will represent abnormal returns. Since this model is being used to generate the returns of the benchmark portfolio any use of it to test the Efficient Market Hypothesis will in fact be a joint test of the Efficient Market Hypothesis and also of the Capital Asset Pricing model. If actual returns are not statistically significantly different from the benchmark returns, then the joint null hypothesis cannot be rejected; and the evidence is consistent with both the Capital Asset Pricing Model and the Efficient Markets Hypothesis. If returns are statistically different from zero then it is impossible to say which hypothesis should be rejected, or whether both should.

Roll (1977) takes exception to cross sectional tests of the CAPM which use of abnormal returns. He argues that since the market portfolio should contain all assets both marketable and non-marketable, it is impossible to observe.

2.1.6 Market Efficiency and Heterogeneous Expectations

Following Fama's 1970 article and his 1976 revision, there have been further attempts to redefine market efficiency in situations were market participants have heterogeneous expectations. For example Rubenstein (1975) has argued that a market is efficient if prices would not change given that all private information was revealed. Beaver (1981) has extended this idea to apply to any information set: The market is efficient with respect to an information set given that revealing that information set to all investors would not change equilibrium prices. Latham (1986) has suggested an even more refined form of efficiency. He has argued that a market is efficient with respect to an information set if revealing it to all agents would neither change equilibrium prices nor portfolios. Latham suggests that his definition of efficiency provides opportunities for efficiency tests using trading volume.

The following quotation usefully summarises the position.

"Everyone thinks that they know a duck when they see one, but it is hard to come up with a satisfactory definition. It is rather like that with efficient markets. We have talked about 'well functioning markets' and 'fair markets' without ever saying what that means. Fama defined efficient markets in terms of the difference between the actual price and that which investors expected given a particular set of information. An efficient market is one in which the expect value of this difference is zero"

Brealey and Myers (1996), page 336.

For the purpose of this thesis we will follow the vast majority of the empirical literature which adopts the Fama (1976a) definition. This equates market efficiency with rational expectations and the sub-martingale model.

We now turn our attention to an examination of the empirical work.

2.2 Tests of the Weak Form.

2.2.1 Introduction.

This section surveys the evidence which supports the Efficient Market Hypothesis. Later in the thesis there appear criticisms of this work by Summers (1986) and also descriptions of a number of anomalies in the Efficient Market Hypothesis. Since the number of studies which are claimed to support market efficiency runs into perhaps several hundred, and extensive summaries have been provided elsewhere, (see Fama (1970), Henfrey, Albrecht and Richards (1977), and Keane (1983)), attention will be focused on the US studies which have established the methodology. The evidence of UK studies, is also cited where appropriate since the efficiency of the London Stock Exchange is the focus of this work.

2.2.2 The US Evidence

Section 2.1.3 of this thesis described how early researchers such as Kendall (1953), Granger and Morgenstern (1963), Roberts (1959) and Osborne (1959) found that stock and commodity prices and stock indices appeared to follow a random walk. The mid 1960's saw a developing literature which was concerned firstly with whether stock prices could be predicted using the historic sequence of price changes, and secondly, whether, even if this were not the case, profitable trading rules could be developed. Such trading rules, if successful, would imply rejection of the martingale hypothesis.

In a pioneering study, Fama (1965) examined the successive changes in the natural log[8] of the prices for each of 30 stocks of the Dow Jones Industrial average from 1957 to 1962 for intervals of 1, 4, 9, and 16 days. If price changes are serially correlated, it may be possible to develop profitable trading rules from studying the historic sequence of prices. Fama found that there was no evidence of substantial linear dependence between lagged price changes. For lags of one day he found a slight preponderance of positive autocorrelations and for 4 and 16 day lags a slight preponderance of negative correlations. Even so, the maximum autocorrelation out of his sample of 30 stocks for a one day lag was only 0.118 implying that only a maximum 1.4% of returns could be explained. The likelihood that this minimal forecasting ability could lead to a trading rule which could generate excess profits seems to be very small.

Fama argued.

"It is of course difficult to judge what degree of serial correlation would imply the existence of trading rules with substantial expected profits ... . Moreover, zero covariances are consistent with the fair

8 Fama quoted three main reasons for using changes in natural log price rather than simple price changes. First, the change in log price is the yield, with continuous compounding, from holding the security for that day. Second, Moore (1962) pp 13-15 has shown that the variability of simple price changes for a given stock is an increasing function of the price level of the stock. His work indicates that taking the logarithms seems to neutralise this price level effect. Third, for changes less than ±15 per cent the change in log price is very close to the percentage price change, and for many purposes it is convenient to look at the data in terms of percentage price changes.

game model, but ... there are types of non-linear dependence[9] *that imply the existence of profitable trading systems, and yet do not imply non zero serial covariances. Thus for many reasons, it is desirable to test the profitability of various trading rules. Such tests would provide direct evidence of the fair game or Martingale hypothesis."*

Fama and Blume (1967) conducted such a test. They examined the profitability of filter trading, a method which is widely used by technical analysts. They conclude:

"When commissions are taken into account the largest profits under the filter technique are those of the broker. When commissions are omitted the returns from the filter technique are of course greatly improved but are still not as large as the returns from simply buying and holding."

In a similar study Jensen and Bennington (1970) tested what chartists describe as a relative strength rule on 29 independent samples of 200 securities each over successive 5 year time intervals in the period 1931 to 1965. They found that after transaction costs, the trading rules did not on average earn significantly more than the buy and hold policy. Van Horne and Parker (1967) tested a trading rule using moving averages and obtained similar results.

We therefore see that by 1970 there was substantial evidence consistent with the US stock markets being weak-form efficient. Commenting on the Fama (1970) "Efficient Market Theory: A Review of Theory and Empirical Work", Schwartz (1970), however, sounding a cautious note argued:

"Autoregressive tests, filter analysis, and runs tests do yield quite consistently, evidence of positive dependence in day to day price changes and returns to common stocks. ... Fama concludes, however that this positive dependence does not seem of sufficient importance to warrant the rejection of the martingale efficient markets model ... Yet this methodology can yield a "proof" only if tests are all inclusive.

9 For Fama's allusion to non-linear dependence and comments on his paper, see Schwartz (1972), whose comments pre-empted the considerable interest in modelling volatility which developed in the 1980's.

Unfortunately, an alternative way of examining past data might always be conceived by future analysts. ... "For instance, some characteristic of the distribution of stock prices, such as variance, might yield serial dependence ... The complexity surrounding the distribution of stock prices causes me to have little a priori *conviction that market prices fully reflect the type of information which a volatility analysis might yield. ... The ability to predict future price volatility from past volatility could lead to the development of strategies for trading options."*

It was not until the work of Shiller (1981) and LeRoy and Porter (1981), which is discussed in section 2.9, that an apparent excess of volatility became a major issue in financial economics. Furthermore, it later became apparent that while serial correlations of price changes were low there was some dependence between the volatility of the market in one period and the next. In other words, periods of high volatility tended to persist as did periods of low volatility. There is now a large literature on attempts to model the volatility of the market. These include the ARCH models attributed to Engle (1982) as well as GARCH. (See, Bollerslev (1986)).

We have therefore seen from a number of studies in the US that while some very modest dependence in price series had been detected, direct tests of the martingale hypothesis provide no reason for rejecting the weak form of the efficient market hypothesis. We now turn to the evidence relating to the efficiency of the UK stock market.

2.2.3 The UK Evidence

The number of tests based on data from the London stock exchange is much lower than for the US. The early serial correlation tests of Kendall have already been discussed in section 2.1.3. Dryden (1970) performed both serial correlation coefficients and runs tests for the price changes of 15 shares covering 500 trading days in two periods in the 1960's. Correlation coefficients were low, and he found no evidence to refute the EMH.

Dryden (1969) also replicated the Fama and Blume study on filter rules. Although his findings were inconclusive for large filters due to the short sample period, he found no reason to reject the random walk hypothesis. While Dryden did find some dependence in the series of price changes, he did not find that these were adequate to develop a profitable trading rule.

Brealey (1970) tested the daily movements of the FT-Actuaries Index from 1962-1968 for serial correlations. The first order correlation coefficient was 0.19 and the second order coefficient -0.010. Brealey argued that while these findings did not seriously contradict the random walk hypothesis, they did support the view that there exists a slight positive dependence between successive daily rates of return.

Girmes and Benjamin (1975) carried out tests of randomness on 543 stocks traded on the London Stock Exchange for a period of 600 days from October 1968-1971. They concluded the share prices of large companies appeared to behave as a random walk while the share prices of many smaller companies exhibited non-random behaviour. The authors conclude that the weak form of the efficient market hypothesis applies to large companies on the London Stock Exchange and not to small companies. It has been shown, however, that "non trading effects" can have a significant effect on tests for non-randomness.

A problem arises if a researcher attempts to measure the serial correlations of price changes of infrequently traded shares. Often these shares are listed at the price of the most recent bargain. For some securities this bargain may have taken place a number of days previously and is unlikely to reflect the price at which an actual trade would have taken place. This effect induces spurious autocorrelation into the series of prices. Brealey (1970) when discussing the impact of infrequent trading on stock price indices observed:

> *"A difficulty with all these tests of market behaviour is that the first order coefficient will be biased upward if the prices used to calculate the index do not occur simultaneously. In such circumstances the index measures the average level of the market during the afternoon. It is known that the first differences of averages in a random chain can induce correlations not present in the original data and that the*

coefficient will tend rapidly towards 0.25 as the number of periods is increased. This problem is likely to beset the use of all popular indexes. In the case of American indexes the prices employed are typically the last transaction of the day. In the British case they are usually the prices provided by a jobber when he closes his book in each share."

Non-trading effects can also have a significant impact when the researcher attempts to compute a firm's β.

2.2.4 Normality and Stock Returns

Ever since the early work of Mandelbrot (1963) and Fama (1965), financial economists and statisticians have been concerned with the distribution of stock returns. Their form is a crucial assumption for mean-variance portfolio theory, theoretical models of capital asset prices, the prices of contingent claims and for drawing inferences from the empirical literature. Kendall (1953) and Moore (1964) found that weekly price changes for commodities and stocks, respectively, were approximately normally distributed. Mandelbrot (1963), however, contended that this past research over-emphasised agreements between the empirical distribution of price changes and the normal distribution. In particular Kendall and Moore found that the extreme tails of empirical distributions are fatter than those of a normal distribution i.e. are lepokurtic. Mandelbrot proposed a new approach, which he named the stable paretian hypothesis. This makes two assumptions: firstly, the variances of the empirical distributions behave as if they were infinite, and secondly that they best conform to a family of limiting distributions which he described as stable paretian. Fama (1965) found that stable paretian distributions with a characteristic exponent of less than 2 provided a better description for the returns in his sample than did the standard Gaussian distribution. For example from his sample of 30 stocks, he found that 448 returns were greater than 3 standard deviations from the mean while assumptions of a normal distribution would have only predicted 106 (see Fama (1965) page 50).

There have been numerous further attempts to model the distributional characteristics of short term returns. Most recently, for example, Mantegna and

Stanley (1995) suggest applying a Levy Stable distribution to the centre of the distribution and then adding exponentially declining tails. Sample estimation of the tails of the distribution is complicated by the relatively small number of tail observations. Furthermore, additional research is needed to determine the point at which the central distribution ceases to apply and the tail distribution takes over.

If daily stock returns are non-normal and stable then, by definition, weekly and monthly continuously compounded returns are drawn from stable non-normal distributions. Fama (1976b) p.26, discusses the heavy cost imposed on researchers from any departure from assumptions of normality. He considered, following research by Officer (1972) and Blattberg and Gonedes (1974), that monthly returns were close enough to normal for the normal model to be a good approximation. He emphasises, however, the need to buttress any conclusion with formal tests for normality. The finding that daily stock returns were non-normal, and that monthly returns were nearly normal, implies that stock distributions are not stable. It is incumbent on the researcher therefore, to examine his data carefully for any departures from the assumption of normality. The turbulent stock market periods in the early 1970's and late 1987 are particular episodes which should cause the researcher to examine the robustness of his tests to lack of normality in his data. Early attempts to capture time-varying volatility used informal methods. For example Mandelbrot (1963) used recursive estimates of the variance over time and Klein (1977) took five period moving variance estimates about a ten period moving sample mean. Engle's (1982) ARCH (Autoregressive Conditional Heteroscedasticity) model was the first formal model to capture heteroscedasticity in time series data.

2.2.5 Modelling Volatility

Engle (1982) proposed a model in which the mean of a series y_t was modelled as a function of its past variance. He gives as an example of an ARCH model

$$y_t = \varepsilon_t h_t^{\frac{1}{2}}, \qquad \textbf{(2.10)}$$

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2, \qquad \textbf{(2.11)}$$

with the variance of $(\varepsilon_t) = 1$. Engle extended his model by allowing a number of lags of y_t to enter the equation. Latter Bollerslev (1986) proposed a generalised version of the model which provided a parsimonious parameterisation of the conditional variance and which has become known as GARCH. (Generalised Autoregressive Conditional Heteroscedasticity). Similar models were proposed in Taylor (1986) although his terminology differs slightly from Bollerslev. ARCH and GARCH modelling has become a major branch of financial econometrics. Major reviews of this work appear in Bera and Higgins (1993) and Bollerslev, Chou and Kroner (1992).

2.2.6 Summary

There are fewer tests of the weak form of the efficient market hypothesis in the UK than in the US. In general their quality is lower and this may reflect the less developed computer data bases that were available in UK compared with the US in the late 1960's and early 1970's and also to the smaller number of researchers working in this area. In general, UK price series have shown a slightly greater degree of dependence than have US price series. How much this is due to non-trading effects arising from the lower volume of dealings on London market or how much is due to genuine dependence of the present price changes is difficult to assess. Nevertheless, the dependence of current prices on the past sequence of prices has been low in all studies. Trading rules have shown at best only modest gains. None of these rules have been tested on data independent of that from which they have been derived. Overall, while the data is of lower quality than in the US, it is still strongly consistent with weak form efficiency. Based on the available evidence there is little reason to suppose that excess profits can be made in the UK from analysing short term series of prices.

We now examine the evidence relating to semi-strong efficiency.

2.3 Tests of the Semi-Strong Form

2.3.1 Introduction

Fama (1970) defined semi-strong tests as those "in which the concern is whether prices efficiently adjust to other information that is obviously publicly available (e.g. announcements of annual earnings, stock splits etc.) are considered." The tests therefore seek to examine both the impact of, and speed of reaction to, announcements of information on share prices.

2.3.2 Stock Splits

In their seminal event study Fama Fisher Jensen and Roll (1969), FFJR, examined 940 stock splits on the New York Stock exchange taking place during the period January 1927 to December 1959. In all, 622 securities were represented, some companies splitting their shares more than once. The study sought to examine two related questions.

1 Was there evidence of unusual behaviour in the returns on a stock split in the months surrounding the split?

2 If the splits were associated with unusual behaviour of security returns, to what extent could this be accounted for in other, more fundamental variables?

Since the authors were interested in isolating whatever extraordinary effects of a split and its associated dividend history may have on returns, it was necessary to abstract from these returns the effect of changes in general market movements. The authors used the market model[10] to define cumulative average abnormal returns:

FFJR conclude that,

> *"the evidence indicates that on average the market's judgements concerning the information implications of a split are fully reflected in*

10 See FFJR(1969)

the price of a share at least by the end of the split month but most probably almost immediately after the announcement date. Thus the results of the study lend considerable support to the conclusion that the stock market is "efficient" in the sense that the stock prices adjust very rapidly to new information."

In the UK, Firth (1976) published a similar study to that of FFJR (1969), which examined 227 capitalisation issues made by UK quoted companies in the years 1973 and 1974 using similar methodology to FFJR. Firth found that capitalisation issues themselves have no impact on share prices. The superior price performance usually associated with scripping securities is attributable to concurrent dividends and earnings information.

2.3.3 Earnings Announcements

Ball and Brown (1968) examined the annual earnings announcements for 261 US firms, for the years 1946-1966. The annual earnings announcements for each firm were classified into two categories. In the first were cases where the actual earnings had increased compared with the average earnings of firms in the market index and in the second were those whose earnings decreased compared with the average earnings of firms in the market index. The authors computed abnormal performance indices, that is they extracted general market movements from their figures. The category with increased earnings showed increasing abnormally high returns from as early as 12 months prior to the earnings announcement. For the category where earnings decreased there were abnormal losses in the 12 months prior to the announcement. The authors conclude.

"Most of the information contained in reported income is anticipated by the market before the annual report is released. In fact, anticipation is so accurate that the actual income does not appear to cause any unusual jumps in the Abnormal Performance Index in the announcement month."

The evidence however does not exclusively support market efficiency. Following the Brown and Ball study, a number of authors, including Aharony and Swary (1980), and Watts (1978), have focused on quarterly earnings reports where information revealed to the markets is more timely than from annual reports. Watts (1978) finds statistically significant abnormal returns in two following quarters and from this concludes that the market is inefficient. Aharony and Swary (1980) using daily data, find no evidence of market inefficiency. Patell and Wolfson (1984) found that the market reacts very quickly to unexpected changes to earnings and dividends, the largest portion of the price response occurring within 5-15 minutes of the announcement. In such circumstances it would be very difficult for any investor without access to this information prior to its release, to profit from it.

2.3.4 Macro Economic News

Compared with the numerous studies on the impact of unexpected earnings on stock prices there have been relatively few attempts to assess the impact of items of economic news on stock price indices. Pearce and Rowley (1985), an exception, examined the impact of five items of economic news on the S&P 500 index for the period from September 1987 to October 1992. They were the money stock, inflation, industrial production, unemployment and changes to the Federal reserve discount rate. To be consistent with market efficiency only the unanticipated change in each of these series should have an impact since stock prices should already reflect the anticipated element. The impact should be felt immediately since any slow price adjustment to shocks could lead to profitable trading rules.

The authors found that shocks to both money supply announcements and discount rate changes had an impact on stock prices. There was only limited evidence that inflation or real economic activity surprises had any effect on stock prices. The anticipated component of economic announcements did not affect daily stock prices, a finding which is consistent with market efficiency. Finally there was some evidence which suggested that the response of stock prices to new information may persist beyond the announcement day, although for most economic announcements this was not found. In other words the evidence suggests that stock market prices react rapidly to money supply announcements.

Jain (1988), following the methodology previously adopted by Pearce and Rowley confirmed their findings and reported that most of the reaction to economic news is impounded into stock prices in the first hours of trading.

Goodhart and Smith (1985) examined the impact of the announcement of the money supply, the retail price index, the visible trade balance and the central government borrowing requirement on the FTA 500 index in the UK. Again they used expectations of market participants to isolate shocks to the data. They found an inverse relationship between shocks to the RPI and change in the FTA 500 index. Interestingly, they noted that the response to information on the London Stock Exchange was not as quick as on the New York Stock Exchange, the impact not being felt fully until the working day following the announcement. The authors did not discuss whether this may be due to the effect of thin trading in the shares of small companies inducing a lagged response in the FTA 500 index.

The evidence therefore suggests that most of expected economic news has already been incorporated into stock prices. Where shocks to the series do impact share prices their effect, at least in the US, is felt within hours. All this appears highly consistent with an efficient market.

2.3.5 Mergers and Acquisitions

Numerous studies of the bid premiums in merger and acquisition situations also provide evidence of semi-strong efficiency. One example in the US is Mandelker's (1974) study. His findings were consistent with the hypothesis that the stock market efficiently assimilates information on mergers. The stock prices of the constituent firms at the date when the merger is effective reflect the expected economic gains. The stock prices of merged firms do not undergo post merger adjustments. In addition Mandelker found that stockholders' were not misled either by artificial manipulation of accounting earnings or by increases in earnings per share caused by differential price earnings ratios.

Similar studies providing evidence consistent with semi-strong efficiency include Franks, Broyles and Hecht (1977) and Franks and Harris (1989).

2.3.6 Summary

We have therefore seen from this selection of the very wide evidence available that the market reacts speedily and in the predicted manner to a number of events such as stock splits, merger announcements, and the announcement of annual earnings figures of firms. The evidence has been drawn from both the UK and the US markets. The large volume of such evidence led to the widespread adoption of market efficiency as a core doctrine in corporate finance.

2.4 Tests of the Strong Form

2.4.1 Introduction

Strong form tests concern whether or to what degree share prices reflect privileged information known to only a few. Fama (1970), argued that " ... we would not of course, expect this model to be an exact description of reality", and he draws attention to Niederhoffer and Osborne (1966) who found that specialists on the N.Y.S.E. were able to use their monopolistic access to information concerning unfilled limit orders to generate monopoly profits. Clearly, the strong form model is difficult to test since by definition much of the information which is not publicly available is unavailable to the researcher as well as to the market. Merton (1987) comments somewhat cynically that one could not lose testing market rationality.

> *"If, indeed, significant violations were found, one could earn gold, if not glory by keeping this discovery private and developing portfolio strategies to be sold to professional money managers who would take advantage of the violations. If, instead, one found no significant violations, then this financial failure could be turned to academic success by reporting the results in scientific journals. Thus while each study performed might represent an unbiased test, the collection of such studies* ***published*** *were likely to be biased in favour of not rejecting market rationality ... However, real world professional*

investors with significant resources might well have important information sources and sophisticated models (be they of fundamentals or market psychology) that are used to beat the market systematically. As this version of the story goes, if only the academics could gain access to these proprietary models, they would quickly be able to reject the rational market hypothesis. Unfortunately one assumes that few successful professional investors are likely to reveal their hypothetical profitable models and thereby risk losing their source of income, simply to refute publicly the rationally determined price hypothesis of economists ..."

2.4.2 Theory

Grossman (1976), (1978) developed what he called 'rational expectations equilibrium' arguing that prices were perfect aggregators of information and that all the information in an economy was communicated to a trader through the price system.

He maintain that this implied such an equilibrium could not be dominated by a central planner in a pareto sense since it is not possible to raise the expected utility of one individual without making someone else worse off. This means that there is no advantage in collecting information centrally; an equilibrium in which prices convey all information makes this unnecessary.

Grossman suggested nevertheless that this equilibrium was unrealistic. If the price system conveyed everything to traders there would be no incentive to incur the costs of collecting information. For stock markets to be efficient, however, it is necessary for a number of informed traders to compete amongst themselves.

In a later article Grossman and Stiglitz (1980) offered a resolution to this problem. They argued that informed traders out-perform the uninformed traders in the market but have to pay for the costs of acquiring information. Some of this information is communicated to the uninformed traders but the price signal is noisy and thus informed traders maintain a competitive edge. The price system could never be totally informative since this would destroy the incentive to gather information. Thus, full strong form efficiency is an illusory concept.

2.4.3 Performance of Professionally Managed Funds

Concern over the "secret model" problem led to the next round of empirical tests. The pioneering research by Jensen (1968) served as a model for a number of studies which followed. The rationale for these tests is simple. If security analysts backed by substantial resources have access to private information or secret models, then this should be revealed in superior performance when compared to the rest of the market. Elton and Gruber (1991) p. 425 have argued that a difficulty with these tests is that a failure to earn an excess return could mean either that the analysts could not use the non-public information to earn excess return, or that they did not do so for legal or moral reasons. Acceptance of this argument relegates these tests to tests of the semi-strong form since, clearly, publicly available information falls into the information set which is available to the fund managers.

Jensen examined a sample 115 open end mutual funds for the 10 year period 1955-64. He computed the `excess returns' using the market model shown below.

$$\tilde{R}_{jt} - R_{ft} = \alpha_j + \beta_j\left[\tilde{R}_{mt} - R_{ft}\right] + \tilde{u}_{jt}, \qquad \textbf{(2.12)}$$

where $\tilde{R}_{jt}$ is the return on security j at time t , R_{ft} is the risk free rate and $\tilde{R}_{mt}$ is the return on the market, α_j and β_j are parameters which vary with the security and $\tilde{u}_{jt}$ is the random disturbance term.

Jensen concluded that these 115 mutual funds were on average not able to predict security prices well enough to out-perform a buy and hold policy, but also that there was little evidence that any individual fund was able to do significantly better than that which was expected from random chance. He noted that these conclusions held even when the funds' returns were measured gross of management expenses. Thus, on average the funds apparently were unable to recoup even their brokerage expenses.

A number of other studies in the US such as Friend Blume and Crockett (1970), Treynor (1965), Sharpe (1966) and Williamson (1972) have reached similar conclusions. There is no evidence in these studies to suggest that fund managers as a group out-perform the market. This does not imply that fund managers are not performing a useful service since they enable investors to achieve a degree of diversification which they would not be able to achieve economically with their own resources. More recently, however, Mains (1977) has re-examined the issue of mutual fund performance. He criticised Jensen's work on two counts. Firstly, Mains pointed out that Jensen underestimated rates of return on the funds since by using annual rather than monthly data he understated the value of dividends received. Secondly he claimed that as Jensen assumed that β's were stationary over time, Jensen overestimated β. Using monthly data, Mains' β's were lower than Jensen's. On the basis of gross return Mains estimated that 80% of the funds had performed positively. After taking account of transaction costs and fund management expenses, the net performance was the same as a naive buy and hold strategy.

A number of similar studies have been carried out on the London Stock Exchange. Ward and Saunders (1976) examined the performance of 49 Unit Trusts over the nine year period from 1964-1972. They compared performance of the trusts using the three measures which appear in the literature, Sharpe (1966), Treynor (1965) and Jensen (1968). The ranking given by each measure was virtually identical, the lowest rank correlation being 0.97. Overall they found as a group the sample of Unit Trusts performed relatively poorly compared to the market, rather more so than in the Jensen study, and they considered that higher management expenses in the UK compared with the US might be a possible explanation. They argued that the evidence pointed to the London Stock Exchange being efficient in the sense that high risk (β) portfolios can be expected to earn higher returns than low risk (β) portfolios.

Dimson and Marsh (1984) carried out one of the most extensive tests of strong form efficiency on the London Stock Exchange. With the co-operation of a major fund they examined over 3,300 forecasts of returns over a one year period made by the fund's brokers. The forecasts covered 206 of the largest UK shares and took place during the period 1981-1982. They also examined over 800 forecasts made by the fund's own analysts. Dimson and Marsh found that trades executed by the fund outperformed the market by a modest 2.2% in the year following the trade. They conclude.

> *"Thus while our research may be interpreted as a contradiction of strong form market efficiency, it is not necessarily at variance with the notion of an efficient market in security analysis."*

It is useful to note at this stage that while brokers possessed some forecasting ability, this was very small. The correlation between actual returns and forecast returns amounted to only 0.12 .

Dimson and Fraletti (1986) examined the profitability of following telephone recommendations given daily during 1983 by a leading UK stockbroker. In all, 1,649 recommendations were approved for 90 different companies by the firm's investment committee which met every Friday. The Dimson and Marsh (1984) study had shown that any gains which occur as a result of the brokers' written recommendations arise shortly after their publication, and this provided motivation for testing whether brokers' telephone recommendations, which were given to clients more promptly than written research, led to clients achieving superior returns.

The results were broadly consistent with those in Dimson and Marsh (1984). Between the Friday, on which the stocks recommended as purchases were added to the firm's approved list given to salesmen, and the following Wednesday, there was an abnormal performance of only 0.7%. If the recommended share was purchased on the Wednesday, its longer term out-performance was only 1.2% over the following quarter and 1% over the following year. Thus, the broker's tips only modestly outperformed the market, and by an insufficient margin to cover transaction costs. Dimson and Fraletti conclude that verbal recommendations were of a similar value to their written counterparts.

> *"Neither the freedom given to the brokers to choose their own time to favour a stock, nor the focus on unpublished advice, led to any proof of marked out performance ... The present study reminds us that in a competitive market only a very few investment advisers can consistently be successful. Even those analysts closest to the market*

can rarely expect to do a great deal better than picking stocks with a pin."

This research has shown that even institutions which are well placed to receive the best brokerage advice were unable, after transaction costs, to make abnormal returns. Nevertheless, these tests inevitably are limited to the performance of large publicly listed funds. It is not always clear what information may be in the public domain. Furthermore, it may be possible for individuals who are in a position to receive market sensitive information consistently, to make abnormal profits. See for example the anecdotal evidence in Boesky and Madrick (1986). How far these gains are economically significant, or how far market prices are imperfect because private information has not reached the market, is less clear. Some argue that only a few insiders, can profit. Others contend that insiders have an overall beneficial effect because their dealings are likely to help correct any mispricing earlier than would otherwise be the case. Institutional consensus, however, does not favour insider dealing, which is illegal in both the UK and the US.

2.4.4 Summary

The evidence which has been presented supports the proposition that capital markets absorb new information rapidly and even those closest to the market place cannot consistently achieve superior returns. The next section of this thesis will examine an increasing number of anomalies to the efficient market hypothesis which have been revealed in recent years. It will then consider alternative hypotheses to market rationality and it will examine studies which argue that stock markets are more volatile than can be explained by any rational assessment of underlying fundamentals. Finally, a relatively recent research interest, that is of the ability to forecast long horizon returns will be considered.

2.5 Stock Market Anomalies

2.5.1 Introduction

We have already seen how the efficient market hypothesis became widely accepted in the academic community following the publication of the Fama (1970) review article. By the mid-1970's it formed, together with the capital asset pricing model, the intellectual foundation of many finance courses in Universities and Business Schools. However, by the late 1970's a number of studies were published which cast doubts on the earlier findings. These studies have been described in the literature as anomalies to the efficient market hypothesis rather than as evidence in refutation of the hypothesis.

The main anomalies which have been recorded in the literature include:

1. a size effect, that is investments in the equity of small companies have provided higher returns than investments in large companies,

2. a price earnings ratio effect, investments in the equity of companies with low price earnings ratios, have given higher returns than those with high price earnings ratios,

3. a price to book value effect, where shares in companies with a low price to book value ratio have shown excess returns,

4. a range of seasonal and calendar effects of which the most important is what has come to be known as the January effect,

and finally,

5. a number of other studies which do not fall neatly into any of the above categories.

A major problem in discussing these anomalies is that many of them are closely related, and it is therefore often difficult to distinguish the effect of one anomaly from that of another.

2.5.2 Size Effect

Banz (1981) was the first to show a positive relationship between firm's size, measured by its market capitalisation, and its return. His sample included all common stocks which had been traded on the NYSE for at least 5 years between 1926 and 1975. He found that on average small NYSE firms had significantly larger risk-adjusted returns than large NYSE firms over a forty year period from 1936-75. Banz calculated that the average excess return from holding very small firms long, and very large firms short, was 19.8% on an annualised basis. This strategy, which suggests large profit opportunities, however, leaves the investor with a poorly diversified portfolio. He found that the size effect was not linear but was most pronounced for the smallest firms in his sample. An analysis of his four, 10-year sub-periods shows substantial differences in the magnitude of the coefficient of the size factor so the effect was not uniform throughout the period. Banz offered no conclusions as to why small firms should have given a much larger return than large firms but rather suggested that his results may be due to a mis-specification of the capital asset pricing model.

Reinganum (1981, 1982) using daily data for NYSE and AMEX firms over the period 1963 to 1977 confirmed Banz's finding that portfolios of small firms had substantially higher returns on average, than larger firms. The difference in returns between the smallest and the largest firms was about 30% annually. The portfolio strategy implicit in his paper however requires daily re-balancing his portfolio. Blume and Stambaugh (1983) showed that if adequate allowance was made for the bid-asked spread being inversely related to size, the size premium reported by Reinganum, was halved.

The small firm effect does not seem to be confined to US stock markets. Similar effects have been shown in Australia by Brown, Kleidon and Marsh (1983), in Canada by, Berges McConnel and Schlarbaum (1984), in Japan by, Nakamura and Terada (1984) and in the UK by, Reinganum and Shapiro (1983). In a more recent study, Levis (1989), found for the period from April 1961 to March 1985 a size effect on the London Stock Exchange. The observed size premium of 5.1% per annum was considerably lower than that recorded for other markets. Whether this is due to the time periods being dissimilar between the studies, problems in measuring risk for small shares on the LSE, or resulting from some small capitalisation companies being excluded from the London Share Price Database prior to January 1975 is not clear. Levis reports also that the size effect was related closely to a share price effect, a dividend yield effect and a P.E. effect.

A number of reservations must be made to these conclusions. Firstly, the smaller the firm, the less liquid the market for its securities. Recall that the highest returns were recorded for the smallest companies so there is no guarantee that large deals could be made at the prices quoted. Also the securities of small firms may not meet the minimum capitalisation requirements for many institutional investors. Klein and Bawa (1977) have argued that if insufficient information is available on a subset of securities, investors will not hold these securities because of the estimation risk, i.e. uncertainty about the true parameters of the return distribution. Christie and Hertzel (1981) argue that the size effect could be due to the non-stationarity of β. A firm whose stock price has become low, and therefore appears as a small firm, may have fallen on hard times and increased its borrowings with a resulting increase to the risk of its equity. Historical estimates of β fail to allow for such an increase in risk and therefore the excess return earned by small companies is overstated. Roll (1981) suggests that large abnormal returns of small firms could be due to systematic biases in β estimates caused by the low volume of trading typical for shares of small companies. Stoll and Whaley (1983) have shown that round-trip transaction costs average 6.8% for the smallest decile of the New York Stock Exchange while they average only 2.7% for the largest decile. They found that the costs of a round-trip transaction undertaken every 3 months was enough to eliminate the small firm effect. This, however, provides only a partial explanation for the size effect. Whether the size effect is an inefficiency in capital markets or whether the equilibrium model for assessing risk and returns in capital markets is mis-specified is unclear. Reinganum (1981) has argued that the size effect seems closely related to another anomaly in capital markets, the P.E. effect to which we now turn our attention.

2.5.3 Price Earnings Ratios

Long standing market folklore suggests that low P.E. companies may be undervalued. Nicholson (1960) and (1968) provided the first comprehensive evidence of this phenomenon by showing a strong negative relationship between P.E. and return for 5, 10 and 20 year periods between 1937 and 1957. His studies were relatively unsophisticated, no allowance being made for risk or even for the impact of dividends.

Later Basu (1977) carried out a more rigorous study which allowed for risk, the differing tax treatment of dividends and capital gains, and also avoided any survivorship bias. Again he found that companies with low P.E.'s tended to produce higher returns than predicted.

Similar results, but using more recent data from both NYSE and AMEX firms, appear in Reinganum (1981). He also presented evidence which suggests that the P.E. effect is a proxy for the size effect. In other words the companies with low P.E. ratios tend to be small companies, whereas Basu (1977) presented evidence that suggested that size effect was an imperfect proxy for the P.E. effect.

Some researchers have argued that since companies within the same industry are likely to have similar P.E.'s, the tests based on P.E. ratios act as a proxy for industry effects. Peavy and Goodman (1983), addressed this bias and examined the P.E. ratio of a stock, relative to the industry P.E. They again found a negative relation between P.E. and abnormal returns over the 1970-80 period.

2.5.4 Price to Book Value

Rosenberg, Reid and Lanstein (1985) examined a sample of 1,400 companies over the period 1980-1984 and found that excess returns could be earned by investing in companies which had a low share-price to book-value ratio (book value is the value of the equity in the company's accounts divided by the number of shares outstanding). In many ways this conclusion is not surprising given the results published above. All three groups of anomalies, the small firm effect, the P.E. effect and the book value effect, are linked by the common factor, a low market capitalisation.

2.5.5 Seasonal and other Calendar Effects

Wachtel (1942), first recorded that share prices in the US tended to be depressed in December and rise in early January. He attributed this to investors selling shares in December both to establish a tax loss and to realise cash for seasonal needs.

The first rigorous study which confirmed the existence of the January effect was by Rozeff and Kinney (1975). They examined the monthly returns on all the stocks on the New York Stock Exchange from 1904-1974 and established that the average return in January amounted to 3.5%. If these returns could be repeated throughout the year the annual return would be above 50%. Their research showed, however, that average monthly returns for the remaining 11 months in the year were less than 1%. When they divided their results into 3 sub-periods of 1904-28, 1929-40 and 1941-74 they found that the January effect appeared in each period. At the time, the Rozeff and Kinney research attracted relatively modest interest. It was the identification of the small firm effect by Banz and the P.E. effect by Basu which provided motivation for further investigation into anomalies. Keim (1983), in studying the small firm effect identified that, of the extra return earned by the smallest firms, one quarter was earned during the first 5 trading days of the year. Nearly 50% of the size effect occurs in January.

There have been numerous other studies which have documented the January effect. Examples are Roll (1983), Tinic and West (1984), Chan (1985), DeBondt and Thaler (1985), Corhay et al. (1988), Guletkin and Guletkin (1987), and Lakonishok and Smidt (1988).

Attempts to explain the January effect have largely concentrated on the tax loss hypothesis. For example Brown, Keim, Kleidon and Marsh (1983) have argued that investors sell shares which have recently seen large falls, so that they might establish a tax loss. Small firms are likely to be candidates for tax loss selling since the variance of their stock price movements is typically larger than that for large firms. The evidence for the tax loss selling hypothesis is less than conclusive, however, Reinganum (1983) and Roll (1983) found that part, but not all of the abnormal returns in January were related to tax loss selling. Some light can be shed on the tax loss selling hypothesis by examination of the January effect in international markets since some countries have tax years which do not end on 31 December, while other countries do not tax capital gains.

Guletkin and Guletkin (1983) applied the Rozeff and Kinney methodology to the stock markets in 15 different countries using monthly data between January 1959 and 1979. In all the markets they studied they found that returns were higher in January than in the rest of the year. For most of the countries studied the January effect was larger than in the United States. In ten of the fifteen countries they found that January contributes more than 50% of the total return for the year. Not all countries, however, have the same tax year end as the calendar year end. Some countries do not tax capital gains tax. For example the U. K. has a tax year end of 5 April, and Japan has no capital gains tax. Arguments in support of the tax loss selling hypothesis are at best inconclusive.

A number of authors have argued that the January effect may not only be an anomaly in its own right but also that its existence fails to support the capital asset model. Tinic and West (1984, 1986) have shown that since the majority of stock returns occur in January, investors are not rewarded for the risk that they bear throughout the rest of the year.

A number of other studies have identified calendar anomalies. These include regularities related to time of the day, Harris (1986); the day of the week, Ball and Bowers (1986), Cross (1973), French (1980), Gibbons and Hess (1981), Jaffe and Westerfield (1985), Keim and Stambaugh (1984), and Lakonishok and Levi (1982); the time of the month Ariel (1987); and the January effect, Haugen and Lakonishok (1988), Lakonishok and Smidt (1984) and Shultz (1985). In a major study using 90 years of daily data, Lakonishok and Smidt (1988) have confirmed the existence of pricing anomalies around turn of the week, turn of the month, January, and around holidays.

2.5.6 Other Anomalies

There is a growing body of evidence in the cognitive psychology literature, see section 2.6.3, which suggests that individuals, far from being rational tend, to over-react to recent events and news. DeBondt and Thaler (1985) have argued that shares which had performed poorly in recent years were under-priced and those which performed well were over-priced. Using monthly data from the NYSE from January 1926 to December 1982 they formed portfolios of winners and losers. They found that over their sample period loser portfolios of 35 stocks out-performed the market by on average, 19.6% per annum. Winner portfolios earned about 5% less than the market. Similar results were found in the UK by Power, Lonie and Lonie (1991). DeBondt and Thaler also found that most of the gains made by losers occurred in one month, January. In a sense this last finding is not entirely surprising since, as we have already discussed, the January effect was apparent in the NYSE throughout this period; and this is evidently reflected in DeBondt and Thaler's particular subset of the market. DeBondt and Thaler (1990), in a later study, found that security analysts tend to over-react to recent evidence. Zarowin (1989), however, argues that DeBondt and Thaler's conclusions have been over-stated and that part of the effect may be attributable to losers being small companies. Clare and Thomas (1995) found only very slight superior performance by losers in the UK. Ball and Kothari (1989) argue that the over performance identified by De Bondt and Thaler is in fact due to an underestimation of β. Poorly performing firms have usually increased their borrowings recently and become extremely risky. Therefore their β's, which are measured from historical data, are understated. Chopra, Lakonishok and Ritter (1992) and Lakonishok, Shleifer, Vishny (1994) find, even after adjusting for size and β, an economically important over-reaction effect. Researchers however disagree over the interpretation of these findings. For an alternative view see Jegadeesh and Titman (1993). A further challenge to the over-reaction hypothesis appears in Conrad and Kaul (1993). They argue that after adjusting for a number of measurement errors for example due to an incorrect treatment of the bid-asked spread, all non-January returns due to long term contrarian strategies are eliminated.

French and Roll (1986) examined the volatility of the NYSE on Wednesdays for a period in 1968 when the market was closed in order to allow brokerage houses to catch up with paper work. If the same amount of information was generated about fundamentals on Wednesday as other days in the week, volatility ought to be no different. Their study revealed that volatility was in fact lower on the Wednesdays, suggesting that volatility might be attributable to trading rather than to fundamentals. This is an aspect to which we shall return later in the thesis on the section on excess volatility.

The shares of investment trusts in both the UK and the US have traded at prices substantially different from the value of their net assets per share. This represents an apparent anomaly since it is irrational for a bundle of stocks representing a given dividend stream to be traded at a different price from that of the same dividend stream flowing from individual stocks. The amount of the premium above, or the discount below, net asset value varies from trust to trust and over time. There have been examples of trusts whose shares have traded at over double their net asset value for short periods, while more commonly in the UK, investment trust shares have traded at prices some 20% to 30% below net asset value. This apparent anomaly represents an active research area with recent contributions from Lee, Shleifer and Thaler (1991), Ammer (1990), Levis and Thomas (1992), Chen (1993), Chopra (1993).

In an interesting attempt to test directly the efficient market hypothesis Roll (1984) has examined the impact of the weather on the price of orange juice futures. Roll argued that information on the probability of a freeze, which would adversely affect the orange crop in Florida, should be the dominant influence on orange juice futures prices. His results showed that weather information could explain only a small fraction of these prices and he could not identify any variable that explained the remainder of the variation.

Le Roy (1989), in his major review of the efficient market literature, draws attention to the high volume of trading on organised securities markets. Le Roy argues:

> *" ... no minor tinkering with efficient market models seems likely to provide an intelligible reason why rational agents would exchange securities as much as real world participants do. The willingness for investors to pay for information is equally problematic: ... if the purchased information makes profitable trades possible, securities*

markets cannot be informationally efficient, while if it does not, agents are irrationally wasting their money. Neither is consistent with efficiency. These considerations suggest that a large number of market participants act as if they do not believe the market is efficient."

We have already seen how Grossman and Stiglitz (1980) have argued that strong form efficiency is an illusory concept since unless some profit is expected to be earned to recoup the costs of acquiring information, then there would be no motivation to trade. It is only the active intervention of a sufficient number of informed traders that makes the market efficient.

2.5.7 Summary

Overall, the reaction of researchers to these anomalies has been mixed, depending largely on the author's position on efficient markets. Merton (1987) has observed that academic journals are more likely to publish studies showing anomalies than rather repetitive studies confirming the EMH. Therefore, the literature may now be skewed in favour of rejecting EMH.

In a similar vein, Keane (1991) has argued that while from a purely academic viewpoint these anomalies may reflect inefficient pricing of securities, from an investor's perspective the anomalies have to be sufficiently large to make a departure from a purely passive policy of buy and hold, profitable. In other words, they have to be sufficiently large to pay for transaction costs as well of the costs of detecting and acting on the anomalies. The critical tests of market efficiency are therefore to be found in the performance evaluation literature. For most investors the round-trip costs will greatly exceed the excess returns. For example Lakonishok and Smidt (1988) showed negative returns for the Weekend effect (Monday) effect averaging only 0.14%.

The only calendar anomaly that appears to offer the potential for exploitation is the January/small firm phenomena, and this is dominated by the size effect as much as by the seasonal dimension. Moreover, recent evidence has shown that the volatility of security prices in January is significantly greater than in other months. Rogalski and Tinic, (1986) argue that the higher returns in January, may be explained partly as compensation of higher seasonal risk. In addition, other recent tests have suggested that the residual size effect may simply be a measurement error, and attributable to inadequacies in standard β and variance risk errors. See, Friend and Lang (1988).

How far these anomalies are likely to persist in markets in which professionals compete amongst themselves is a matter for conjecture. The most significant anomaly seems to be the size effect. An increase in institutional interest in the shares of small companies would of course tend to eliminate such an anomaly. Additional costs of monitoring small companies may act as a barrier to the exploitation of these anomalies. Keane (1991), argues that an anomaly is only worth exploiting when:

1 the investor has confidence in his model,
2 his profits will exceed transaction costs,
3 he has the skill required to implement his strategy, and
4 he is confident that the other investors will not have identified the anomaly and competed it away.

In short, while a number of anomalies have been shown to have existed, no consensus has been reached as to whether these reflect a mis-specification of the CAPM, or provide evidence against the EMH. Furthermore, it is not clear how far anomalies which may have existed in the past are likely to continue in the future. The anomaly literature suggests that the EMH, or the CAPM may, at least, be misspecified. Alternative models which seek to explain stock market activity in forms of less than rational human behaviour are now be examined.

2.6 The Stock Market and Human Behaviour

2.6.1 Introduction

Economics is probably unique among social sciences in attributing rational behaviour to individuals. Human beings are assumed to be rational expected utility maximisers and to have stable, well defined, preferences in markets which clear. In this section, literature from the discipline of cognitive psychology, which challenges assumptions that people act in this way, is described.

2.6.2 Rationality and utility

Tversky and Kahneman (1986) list 4 substantive assumptions of expected utility theory in order of their normative appeal. These are based on the original work of Von Neumann and Morgenstern (1944).

> Cancellation. Any state which gives the same outcome as another state regardless of one's choice must be eliminated. The choice between options should therefore only depend on states which yield different outcomes.
>
> Transitivity (sometimes called consistency). If A is preferred to B and B is preferred to C, then A is preferred to C, the preference being based on the greater utility. Transitivity is satisfied if it is possible to assign to each option a value which does not depend on other available options.
>
> Dominance. If one option dominates in that it is better than another in one state and at least as good as the other in all other states, the dominant option should be chosen.
>
> Invariance. Invariance requires that different representations of the same choice problem should yield the same preference. Therefore preference between options should be independent of the way in which they are described.

Tversky and Kahneman (1986) have argued that invariance and dominance seem essential axioms for cardinal utility, while transitivity can be questioned, and they stated that cancellation has been rejected by many authors, see for example Allias (1953) and Ellsberg (1961).

2.6.3 The Evidence

The cognitive psychology literature contains numerous examples which illustrate that decisions frequently are made involving failures of transitivity, dominance and invariance.

In an early study, Slovic and Lichenstein (1968) found that both buying and selling prices of gambles were primarily determined by payoffs, whereas choices between gambles were in the first place influenced by the probability of winning and losing. Thus, given the following choices:

H bet: 28/36 chance to win \$10
L bet: 3/36 chance to win \$100

most subjects chose the H bet with an expected pay-off of \$7.78 in preference to the L bet with an expected pay-off of \$8.33. When asked however to state their lowest selling price, the majority state a higher price for the L bet than the H bet. In other words when the same problem is reformulated the subjects reversed their preference. This phenomenon is called preference reversal, and this example demonstrates a failure of both the transitivity and invariance axioms.

Later, Lichenstein and Slovic (1971, 1973) replicated these experiments with similar results. In one, the subjects were experienced gamblers playing for real money on the floor of the Four Queens Casino in Las Vegas.

These findings created considerable controversy and motivated Grether and Plott (1979) to conduct a series of experiments aimed at discrediting psychologists' work when applied to economics. By carefully designing their tests to allow for a number of objections raised to early research, for example that the researchers were psychologists (thereby creating suspicions and causing the subjects to behave in an unusual way), or that lack of incentives affected the response pattern, they hoped to show that preference reversal was irrelevant to modern economic theory. Their results, however, confirmed those of previous studies. Furthermore, the existence of preference reversal was somewhat more common among subjects responding to financial incentives. This result is inconsistent with the argument that agents would act in a different way in the real world when given the opportunity to make real gains or suffer real losses from their activities.

In a further study by McNeil, Pauker, Sox and Tversky (1981), respondents were given statistical information about the outcomes for two treatments of lung cancer, surgery and radiation therapy. The same statistics were presented to some respondents in terms of mortality rates and to others in terms of survival rates. The respondents then indicated their preferred treatment.

The reader will have noticed that the two problems are essentially the same. In the first, the problem has been formulated by simply expressing the number of subjects who survive rather than die, and in the second the number who die rather than survive. This minor change in formulation produced a marked effect. The overall percentage of respondents who favoured radiation therapy rose from 18% in the survival frame to 44% in the mortality frame. Perhaps somewhat surprisingly, similar results were found when the experiment was repeated with experienced physicians and statistically sophisticated business students. This demonstrates that the framing of the question has an important impact on the decisions which the subject made and provides an example of the failure of invariance.

In a separate strand of research Tversky and Kahneman (1983) investigated individuals' ability to make rational forecasts when faced with information of varying predictive ability. Where the predictive ability of information is considered to be low subjects should give mean regressive forecasts. Subjects were asked to predict the future grade point average (GPA) for each of ten students on the basis of a percentile score of a predictor. Three predictors were used, percentile scores for GPA, for a test of mental concentration and for a sense of humour. Obviously percentile scores for GPA are a much better predictor of actual GPA than is a measure of mental concentration which in turn is much more reliable than information on a sense of humour. Subjects therefore should give mean regressive forecasts in the last two conditions. The results indicated that people were insufficiently sensitive to this consideration. Subjects that were given a nearly useless predictor, sense of humour, made predictions that were almost as extreme in variation as those given a nearly perfect predictor. This pattern leads to systematic biases: forecasts that diverge the most from the mean will tend to be too extreme, implying that forecast errors are predictable.

This evidence motivated a series of research studies on the overreaction hypothesis. The findings of De Bondt and Thaler (1985), who claimed that portfolios which had in previous periods performed poorly, outperformed the market by 19.6% per annum, were examined in the previous section. In a later study, De Bondt and Thaler (1990) examined the forecasting behaviour of security analysts. They found that forecast changes were simply too extreme to be considered rational and claim that the fact that the same pattern is observed in economists' forecasts of changes in exchange rates, and macro economic variables adds force to the conclusion that generalised over-reaction can pervade even the most professional of predictions.

So far in this chapter we have examined psychological literature which casts doubt on the rationality by which many individuals reach decisions, and also an example of how stock market professionals seem not to be immune from a tendency to overreact to recent information. We shall now turn our attention to examine other models which may explain stock market behaviour in the absence of total rationality.

2.6.4 Fashions and Fads

Claims that the stock market is rational and that share prices represent the present values of expected future dividends seemed to differ widely from many investors' personal experiences. The high volatility of the market appears to many observers to bear little relation to underlying economic events. For example, Keynes (1936) commented on the stock market.

> *"Professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick, not those faces which he himself finds the prettiest, but those which he thinks likeliest to catch the fancy of other competitors, all of*

whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best judgement, are really the prettiest, nor even which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligences to anticipating what average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees. [page 156]

More recently the October 1987, crash which did not seem to be associated with the announcement any news event of sufficient significance to cause such a dramatic fall in share prices, provides an example that some would use to illustrate such an argument.

Keynes's "beauty contest analogy" seems to be quite alien to that of an efficient market in which prices are formed from an unbiased forecast of future dividends. In the early efficient market literature, Cootner (1964) argued that prices may depart from their fundamental value until they become so obviously cheap or expensive that speculative trading would drive the prices back towards their intrinsic value. Cootner described such upper and lower bounds of price as reflecting barriers.

Shiller (1984, 1988) has argued that if fashions and fads are present in a wide variety of human activities, why should they not be present in the stock market. He gives a number of anecdotal examples of significant activities which seem to be influenced by fashions. For example, he cites the fashion for jogging which has only in the 1980's become popular despite the benefits of regular exercise for health being widely known many years previously. Clearly, rather more is at work than the publication of a number of papers in medical journals. Shiller argues that social movements may spread relatively rapidly, or they may take years to permeate through society. He refers to the mathematical theory of epidemics, Bailey (1957), which sociologists use to model the diffusion process of news or rumour. The spread of an infection is determined by the number of carriers, the infection rate and the number of susceptibles as well as by the number of carriers that cease to be carriers. The rate of spread of the infection and its abatement may therefore vary from one outbreak to another. Shiller suggests that a fad or a fashion may spread in a similar way through the investment community. Good news about one stock may bring it to the attention of investors causing a rise in its price. This may make some investors wealthy. Other investors may observe this and wish to participate in the game causing a further increase in the price. The contagion would then spread further as more investors are attracted to the stock. One is reminded of the Keynes beauty contest analogy, the art of investment being not to estimate the fundamental value of a security but to estimate what other investors consider it to be worth. Price rises caused by speculators guessing how other speculators will act are known as bubbles.

The possibility of bubbles existing in the stock market is an active research area but one which is not central to this thesis. Contributions to the discussion of this topic include those by Blanchard (1979), Blanchard and Watson (1983), Diba and Grossman 1988, and West (1987 and 1988b). These are reviewed in Carmerer (1989).

Shiller then examines gambling, which reveals some aspects of human behaviour that are likely to be important for the understanding of financial markets. Gambling has been described as a form of adult play yielding a psychological high. See, Kusyszyn (1977). In a similar manner it has been shown that private investors derive considerable enjoyment from playing the market, (Lease et al. (1974)). Shiller argues that institutional investors are those who have chosen investing as an occupation and it is reasonable to assume that they enjoy it at least as much, and are as 'ego' involved, as private investors. He argues,

> *" It is plausible that investors whose interest is piqued by some speculative asset may go ahead and invest in that asset even after analysis indicates that initial reasons to invest in it are not really good. Not playing would be a psychological let down." p 60.*

The fads model implies that share prices depart substantially from their fundamental values but that such departures may, after some period, be self correcting. The amount of the departure and the length of time taken for the share price to return to its fundamental value will depend on the parameters of the model. The movement of share prices in such a model can be considered as autoregressive as they will eventually return to their mean.

2.6.5 Noise

Fisher Black (1986) has added another dimension by arguing that there are two types of traders at work in financial markets. Firstly there are information traders who trade on information and secondly there are noise traders who trade on noise. Black does not define noise but a dictionary definition is 'irrelevant or meaningless information occurring within desired information', (Longman (1984)). Rubenstein (1975), Milgrom and Stokey (1982) and Hakansson, Kunkel and Ohlson (1982) have shown that in a state preference world, differences in information may affect prices without causing people to trade. But if there is little or no trading in individual shares, there can be no trading in unit trusts or derivatives. The whole structure of financial markets depends on relatively liquid markets in shares of individual firms, and this in turns depends on the level of trading. Therefore, the more noise trading there is the more liquid markets will be. Noise trading, however, puts noise into market prices. Black argues that a degree of inefficiency is necessary for any market to be liquid.

Traders with information can never be sure whether they are trading on information or noise. The noise that noise traders put into stock prices will be cumulative as in a random walk. The further a share price moves from its intrinsic value the more the information traders will be tempted to enter the market. Thus the price of the share may move towards its intrinsic value over time. Since, however, all prices are noisy we can never be sure how far a price departs from intrinsic value. While noise creates the opportunity to trade profitably, at the same time it makes it more difficult for sophisticated dealers to trade profitably. Black argues that a market may be efficient even though the price differs from fundamental value by a factor of as much as 2. Noise will cause prices to behave like a geometric random walk process with non-zero means.

This possibility and also the likelihood that there may be other models of stock market behaviour than those implied by rationality, have motivated researchers to examine the power of the statistical tests that were used in the early studies of market efficiency.

2.7 The Power of Weak and Semi-Strong Form Tests

The limitations of statistical testing in rejecting a scientific theory are well understood. Failure to reject a null hypothesis is not equivalent to its acceptance. Repeated failure to reject a plausible hypothesis, however, may lead the scientific community to accept the hypothesis as the best explanation for the phenomenon being investigated. The acceptance is likely to remain until either further testing reveals evidence which is inconsistent with the hypothesis or until an alternative hypothesis is presented which has more support from the available evidence[11]. Shiller's fads model provides such an alternative hypothesis. A number of authors have examined the power of the early tests of serial correlation (see section 2.2.2) to discriminate between an uncorrelated series and a number of interesting and plausible alternatives to market efficiency. An early example is Taylor (1982), later examples being Shiller and Perron (1985) and Summers (1986). Since Summers explicitly considered an autoregressive model of the type proposed by Shiller, we turn our attention to his work. Summers argued that a natural alternative hypothesis to market efficiency is,

$$p_t = p_t^* + u_t \qquad \textbf{(2.13)}$$

where

$$u_t = \alpha u_{t-1} + v_t \qquad \textbf{(2.14)}$$

The lower case letters indicate logarithms and u_t and v_t represent random shocks. This hypothesis implies that market valuations differ from rational expectations of the present values of future cash flows by a multiplicative factor approximately equal to $(1 + u_t)$. The deviations are assumed to follow a first order autoregressive process. It seems reasonable to suppose that deviations persist so that $0 \leq \alpha \leq 1$. The assumption that u_t follows an autoregressive process was made for ease of exposition and does not affect any of the substantive points at issue.

Summers showed, by simulating a number of cases typical of market data, that the conventional autocorrelation tests used by early researchers lacked the power to reject his alternative 'fads' model. Using these tests it would be necessary to have, under Summers assumptions, data for just over 5,000 years to reject the null hypothesis of no mispricing.

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11 See Hemple (1965) for a full explanation of the issues involved.

Summers extended his analysis to tests of the semi-strong form of efficiency. Equation (2.14) implies that expected excess returns should be negative when $p_t > p_t^*$ and positive when $p_t < p_t^*$. This reflects the tendency for market prices to return towards their intrinsic value. The key question is whether these expected excess returns are large enough to be detectable. Summers concludes that tests of semi-strong efficiency do not have much more power against the type of inefficiency considered here, than do tests of the serial correlation properties of excess returns.

Summers argued,

> *"This means that the evidence found in many studies that the hypothesis of efficiency cannot be rejected should not lead us to conclude that market prices represent rational valuations ... The standard theoretical argument is that unless securities are priced efficiently, there will be opportunities to earn excess returns. Speculators will take advantage of the opportunities by arbitraging away any inefficiencies in the pricing of securities. The argument does not explain how speculators became aware of profit opportunities. The same problems of identification described here which confront financial economists also plague speculators." See Summers page 598-599.*

Conclusions such as these could conceivably have a profound influence for the future development of financial economics. At this point, however, it is perhaps useful to consider the reflections of two leading authorities. Firstly, Le Roy (1989) commented,

> *" ... there remains the fads model proposed by Shiller (1981 and 1984). Most economists are extremely reluctant to resort to fads models because doing so would involve relaxing the stable preferences assumption that many economists regard as an indispensable part of their outlook. (George Stigler and Gary Becker (1977)). In any case, pending a theory of what causes fads to come and go, or a specification of potential phenomena that would be inconsistent with a*

fads model, it is not clear that anything is to be gained by characterising an unexplained variation in asset prices as a fad. ... Advocacy of a fads model is perhaps best interpreted as a statement of belief that the most fruitful avenues of future research will involve social or cognitive psychology, rather than referring to any well formed model that is now available." [page 1,604]

And commenting on the psychological evidence, Robert Merton (1987) states.

"As discussed in Arrow (1982), the empirical findings of such systematic misperceptions in repeated laboratory experiments appear sound, and there would appear to be many test cases within economics. In terms of the current state of empirical evidence in both cognitive psychology and financial economics, it would seem somewhat premature, however to conclude that cognitive misperceptions are an important determinant of aggregate stock market behaviour. Specifically the same sharp empirical findings of cognitive misperceptions have not (at least to my knowledge) been shown to apply to individual decision making when the individual is permitted to interact with others (as a group) in analysing an important decision and when the group is repeatedly called upon to make similar types of important decisions. But, this is, of course exactly the environment in which professional investors make their stock market decisions.

"If professional investors are not materially affected by these cognitive misperceptions, then it would seem that either competition among professional investors would lead to stock prices that do not reflect cognitive errors of other types of investors, or professional investors should earn substantial excess returns from exploiting the deviations in price from fundamental value."[page 95].

Financial economists were far from convinced that the research on the efficient markets hypothesis has been wasted. An attack on the foundations of one hypothesis is, of itself, not a great help in establishing the credentials of another hypothesis.

2.8 Summary

The discovery of a number of possible anomalies and the articulation of an alternative model of price formulation in the 1980's, divided academic opinion. Probably the majority of the profession still holds that the EMH to be the best available model of price formation in the market place. A recent 'polemic' text, Haugen (1995) categorises those who maintain the hypothesis as zealots and those who dispute it as heretics. The detection of anomalies was only the beginning of the sceptics' attack on market efficiency. In the early 1980's a number of researchers began to investigate the volatility of the market. They questioned why stock prices could be so volatile while the fundamentals, dividends and earnings, were all relatively stable series. This led to renewed academic controversy concerning the appropriate use of econometric techniques.

2.9 Excess Volatility

Many observers have commented on the apparent implausibility of the Efficient Market Hypothesis, since stock prices seem to be more volatile than warranted by fundamental factors. (See Keynes (1936)). In the mid-1970's researchers began to investigate how the stock market could be so volatile when it was claimed by some to represent an optimal forecast of future dividends discounted at shareholders' required rates of return. Apparent excess volatility, presumably attributed to fads, motivated other researchers, to test whether long horizon returns were mean-reverting. If a market is more volatile than fundamentals imply, and if it does show a mean reversion tendency, then it should be predictable. This leads to direct test of the martingale hypothesis. Tests of excess volatility, mean reversion and the predictability of medium to long horizon returns represent a second generation of statistical testing of the Efficient Markets Hypothesis. Early second generation tests seemed to show strong evidence against market efficiency. Later tests have considerably weakened the case against market efficiency. This research has been characterised by the use of increasingly sophisticated econometric techniques. Much of the controversy has concerned the capability of these techniques to deal with the statistical peculiarities which are a feature of stock market returns. This section will be concluded with a review of the recent Pesaran and Timmermann (1995) study where the authors claim to have developed a model which earns excess returns. This provides a direct test of the martingale hypothesis and seems to reject market efficiency as defined by Jensen (1978).

2.9.1 The Early Variance Bounds Tests

Shiller (1981) and Le Roy and Porter (1981) carried out the early studies on the alleged excess volatility of stock market prices. Since Shiller's paper represents the seminal work in the area, his methodology and results, as well as a number of objections to his study will be discussed in some detail.

Shiller constructed two data series. The first was the Standard and Poors Composite Stock Price Index from 1871-1979 and the second was the Dow Jones

Industrial Average from 1928-1979. Both series were deflated to real values and then detrended by dividing by a long run exponential growth factor.

Shiller also computed what he termed the `ex post rational' or `perfect foresight price'[12] P^* by discounting actual aggregate dividend on the indices. The terminal value at the end of 1979 was the actual value of the index at that time. This series was also deflated to real values and then detrended by a long run growth factor.

In the efficient markets model, the real price P_t of a share is given by,

$$P_t = \sum_{k=0}^{\infty} \gamma^{k+1} E_t D_{t+k} \qquad 0<\gamma<1, \tag{2.15}$$

Where, P_t is the stock price index before detrending, D_t is the real dividend at the end of time t, E_t denotes the mathematical expectation conditional on information available at the time t, and γ is the constant real discount factor. The Efficient Market Model does not say that the actual price P should equal the perfect foresight price P^*. It does however assert, according to Shiller, that P_t is an optimal forecast of P_t^*. The forecast error is given as $u_t = P_t^* - P_t$. A fundamental principle of optimal forecasts is that the error u_t must be uncorrelated with the forecast. The variance of two uncorrelated variables is the sum of their variances. One then has:

$$\mathrm{var}(P^*) = \mathrm{var}(\mu) + \mathrm{var}(P) \tag{2.16}$$

Since variances cannot be negative,

$$\mathrm{var}(P) \leq \mathrm{var}(P^*) \tag{2.17}$$

or in terms of standard deviations

$$\sigma(P) \leq \sigma(P^*) \tag{2.18}$$

In other words, if the actual price is an optimal forecast of the perfect foresight price, the standard deviation of the actual price movements should be less than the standard deviation of the perfect foresight price changes. Shiller calculated that for his Standard and Poor's data set which ran from 1871-1979 the standard deviation of the

12 'Perfect foresight price' is a misnomer since, if investors did have perfect foresight dividends would represent certain cash flows which ought to be discounted at a risk free interest rate. Nevertheless, at the expense of some accuracy the term usefully captures the idea and graphically explains what should be properly described as the ex-post rational price.

actual price series was 5.6 times as high as that for the ex-post price series. For his second data set, the Dow Jones Industrial Share Index, the comparable figure was 13.3 times as high.

Shiller anticipated a number of criticisms of his work. The first was the choice of his discount rate. Shiller used a single rate calculated by taking the average real dividends divided by the average real prices. Sceptics argued that time-varying discount rates might possibly explain the apparent excess volatility.

To counter these criticisms, Shiller assessed the level of discount rate necessary to account for the discrepancy between the fluctuations of the actual price series and the ex-post price series. He computed, under what he considered to be conservative assumptions, that real interest rates would have to range from -3.9% to 13.5% for data set 1 and -8.6% to 17.2% for data set 2. These movements were much larger than the movements in the nominal interest rates over the sample period and would seem to imply large swings in the equity risk premium.

Another potential source of criticism was that Shiller's use of ex-post actual dividends to compute the perfect foresight prices understated the true uncertainty which investors attached to future dividends. To quote Shiller,

> *"Perhaps the market was rightfully fearful of much larger movements than actually materialised. One is led to doubt this after a century of observations in which nothing happened that could remotely justify the stock price movements."*

At the same time as, and independently of, Shiller's work, Le Roy and Porter (1981) carried out similar tests, but adopting slightly different econometric techniques and using an earnings series in preference to a dividend series. Le Roy and Porter's work was based on a considerably shorter data series, the Standard and Poor's Composite index, quarterly observations of price and earnings data from 1955-1973. They calculated the coefficient of dispersion (the ratio of the standard deviation to the mean) for the price series to be 0.452 and for the earnings to be 0.172 and so again the authors found that the price series was more volatile than implied by the earnings series. To justify the inequality the authors use the following intuitive argument.

"However, the result that if markets are efficient the coefficient of dispersion of stock prices should be less than that of earnings makes sense if it is observed that the present value equation defines stock prices as a kind of weighted average of earnings, and an average is generally less volatile than its components."

2.9.2 Objections to the Early Studies

The work of these researchers led to considerable controversy. Flavin (1983), criticised Shiller's methodology on a number of grounds. Her main objection was that the variances of the perfect foresight prices were understated. Mankiw et al. (1985) usefully summarise her argument.

"Flavin's criticism concerns the small sample properties of the test. Sample variances are downwards-biased estimators of population variances because sample means are used instead of population means. The smoother and therefore the more autocorrelated the series is, the greater the downward bias. Suppose, to consider Flavin's example, that the fundamental series follows a first order auto-regressive process. Then the market price is proportional to dividends. Since P_t^* is the weighted sum of future dividends, it is the weighted sum of future prices. This effect tends to smooth P^* relative to P, and thus make the bias in estimating the variance of P^* greater than the bias in estimating the variance of P. Flavin finds considerable biases."

In her conclusion Flavin refers to Shiller's 1979 study on the volatility of long term interest rates and shows that her argument considerably weakens Shiller's position.

Kleidon (1986), raised three objections to Shiller's results. Firstly, he argued that since investors did not have perfect foresight, Shiller's perfect foresight price series effectively eliminated much of the volatility that could be expected to arise from investors changing expectations of dividends. He prepared a chart very similar to that presented by Shiller but generated by using a geometric random walk traditionally regarded in finance as an excellent empirical description of the price process in actual data. He carried out a number of simulations which demonstrated that, using what he argued were reasonable assumptions, variance bounds would be breached. Secondly, following Lintner (1956), he argued that directors smoothed dividends and therefore these did not represent economic fundamentals as well as earnings. Lastly, he argued that it is not possible to reject the hypothesis, even with the detrending used by Shiller[13], that the price series were non-stationary and that the gross violations of the bounds that have been reported in the literature are consistent with the incorrect application of estimation techniques that assume stationarity to a non-stationary series.

Marsh and Merton (1986) also raised the issue of the smoothing of dividends. To quote the authors,

> *" Our own analysis turns this perspective `on its head' by asking `if stock prices are rational why do dividends show so little volatility (relative to stock prices)'. Our answer is simply that managers choose dividend policies so as to smooth the effect of changes in intrinsic values (and hence on rational stock prices) on the changes in dividends."*

In reply to these criticisms Shiller (1989), page 85, has pointed out that while some of the claims made by these authors may be correct, none of their papers provided examples where the violation of the original variance bounds would have been as dramatic as he reported in his (1981) study. For example in his reply to Kleidon, Shiller (1988) showed, that after correcting for some errors in his analysis, Kleidon's own Monte Carlo methods imply the probability of a gross violation of the variance inequality is less than 1% even under the random walk model. Shiller also claims that the models used by many of his critics to simulate future dividends were unrealistic.

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13 De Jong and Whitman (1991) commenting on Kleidon (1986) argue that Shiller's detrending of the data is justified.

"They assume a dividend process such that any change in dividends from year to year tends to cause a major change in all expected future dividends ... Therefore these models build in a lot of price volatility. ... Dividends seem to show short run oscillations contrary to the random walk assumption. What this amounts to, is that the log random walk model for real dividends does not appear to be a good one. Real dividends appear to show a tendency to revert to trend or to a long run moving average of their own lagged values."
Shiller (1989b) page 86.

Shiller also challenged the Marsh and Merton (1986) model of the dividend setting process claiming that their model seemed circular and also that they may have misinterpreted John Lintner's (1956) paper on dividend setting behaviour.

Thus we can see that by the mid-1980's two papers, those of Shiller (1981) and LeRoy and Porter (1981), had been published which claimed to show that stock prices were more volatile than could be attributed to streams of dividends or earnings. The conclusions, particularly of Shiller's paper, had been challenged on a number of econometric grounds. What remained in dispute between the protagonists was the extent to which the econometric criticisms of Shiller's 1981 study, which were largely accepted by both sides in the argument, invalidated Shiller's conclusion that actual prices showed excess volatility compared with perfect foresight prices.

By the mid-1980's however researchers had developed tests which overcame some of these objections. Mankiw, Romer and Shapiro (1986) presented an ingenious solution to many of the statistical problems mentioned above and their methodology avoids many of the econometric problems associated with the Shiller (1981) study. The authors found that their inequalities were uniformly violated. They summarise their study by saying

"... while our unbiased volatility tests do not find evidence as striking as that Shiller reports, we do find evidence contradicting the model. In particular, the naive prediction that dividends will never change outperforms the market as a forecast of the present value of ex-post dividends."

2.9.3 More Sophisticated Tests

During the 1980's there were a number of advances to statistical methods which enabled researchers to overcome some of the econometric difficulties which had led Flavin (1983) and Kleidon (1986) to challenge the early work of Shiller and Le Roy and Porter.

The development of the theory of cointegrated processes, see (Phillips and Durlaf (1986), Engle and Granger (1987) and Stock (1987)), provided the base from which a further series of tests of market volatility could proceed. In particular, it was no longer necessary to make the assumption that dividends were stationary around a fixed time trend or that they followed a linear process with a unit root. Campbell and Shiller presented a number of papers in the late 1980's which used cointegrated processes and vector autoregressions. These studies represent a new level of econometric sophistication.

In the first study Campbell and Shiller (1987) showed how the present value model of stock prices may be tested when dividends and stock prices are stationary in first differences rather than in levels. If the present value model is true, a linear combination of the two variables, the co-integrating vector - which they called the spread - is stationary. Campbell and Shiller evaluated the fit of the cointegrating model by using a vector auto-regression to construct an optimal unrestricted forecast of the present value of future dividend changes and compared this with the spread. If the model is true, the unrestricted forecast or 'theoretical spread' should equal the actual spread. They found that the spread between stock prices and dividends moves too much and that deviations from the present value model are persistent, although the strength depends on the discount rate used for the test.

The second study by Campbell and Shiller (1988a) examined the reasons why the dividend price ratio fluctuated over time. In particular Campbell and Shiller wished to investigate how much of the fluctuation was due to the changing outlook for dividends, changes in discount rates, and an unexplained variation.

They tested four versions of a linearised model by using vector autoregressive methods. They overcome the problems of stationarity in the data, which caused Kleidon (1986) to criticise the work of Shiller (1981), by working with the log of the dividend price ratio and the log of differences of dividends and prices. Their model accommodates the geometric random walk of Kleidon and the dividend smoothing model of Marsh and Merton (1987). They conclude that the long-term real return on stock is highly variable and that it does not move in parallel with short term interest rates.

Also, in a separate paper, Campbell and Shiller (1988b) dealt with the criticism made by Flavin (1983) that their results may falsely show excess volatility because of the small sample properties of their tests. In a series of Monte Carlo simulations they showed that any small sample bias was unlikely to affect their conclusions. Campbell and Shiller found that actual prices had about twice the standard deviation of the prices implied by their model. By using econometric methods which accommodated the criticisms of the early volatility studies their results still revealed excess volatility, although at a considerably lower level.

In the last study Campbell and Shiller (1988b) showed that accounting earnings when averaged over a number of years help to predict the present value of future real dividends. The ratio of this earnings variable to current prices is a powerful predictor for long horizon returns.

West (1988a), carried out a further variance bound test using Shiller's data. Again West modified his test procedures to allow for the econometric shortcomings of Shiller's early work. West's results show that his variance bound is violated by between 4 and 20 times. In other words assuming a constant discount rate, stock prices appear to be too volatile to equal the expected present value of future dividends. West estimated that in order to explain this volatility, real expected returns would have to vary from -17% to + 31% (page 58), a range which he considered implausibly large.

We have thus seen evidence from a number of studies based on data from the United States which suggests that stock prices are more volatile than can be attributed to movements of underlying series of dividends and earnings.

There have been relatively few studies of excess volatility on markets outside the US. In one, Bulkley and Tonks (1989) examined the volatility of the UK stock market using data from 1918 - 1985 by replicating the Shiller (1981) test. They found that the standard deviation of actual prices was 5 times that of ex-post rational prices. Since Shiller's original results had been criticised for assuming that stock prices followed a stationary process, they tested their data for non-stationarity using the Fuller (1976) and the Dickey Fuller (1979) procedures. In contrast with Nelson and Plossner (1982) and Kleidon (1986) who used the US data, Bulkley and Tonks were able to reject the null hypothesis of non-stationarity in their data. They also provided a direct test of market efficiency by devising a trading rule which they tested on out of sample data. The trading rule stated:

> *"If actual prices are more than K% above the expectation of the perfect foresight price, the investor sells the index and buys bonds. The investor holds the bonds until actual prices are more than K% below expectation and the investor buys back into the index."*

The optimal value for K is determined at any date t, by taking the value of K_t which would have maximised profits over the period $(0,_{t-1})$. This value of K_t is then incorporated into the decision rule where the expected value of the perfect foresight price is calculated at each date. Decisions whether to switch in or out of shares are made on 31 December each year. The model shows a pre-tax excess return of 1.6% per annum and a post-tax excess return of 1.5% per annum.

Bulkley and Tonks (1992) develop a similar trading rule for the US which they claim earned excess returns of 1.18% per annum. Since the rule relies only on the historic sequences of prices, its existence seems to confirm that stock market prices are sufficiently volatile to reject Jensen's relatively weak definition of an efficient market.

More recently Ackert and Smith (1993) have challenged the findings of West (1988a) and Cochrane (1991) that stock prices are too volatile to be determined by the expected discounted value of cash dividends. In empirically testing the present value relation, the earlier studies had relied on a narrow definition of cash dividends. However as Ackert and Smith observe, dividends include all cash distributions to shareholders. For example in the seminal work of Modigliani and Miller (1961), cash distributed through share repurchases has the same economic role as ordinary cash dividends. Ackert and Smith use the methodology in West (1988b) to test that stock prices are not too volatile. Their data is taken from the Toronto Stock Exchange for the period from 1950 to 1991. Their first tests which narrowly define dividends, confirm the West (1988b) results. When the definition of dividends is widened to include cash received by investors from share repurchases and mergers and acquisitions, excess volatility disappears.

2.9.4 Volatility Tests Summary

In this section we have seen that a number of studies both in the US and the UK have shown that markets seem to be more volatile than can be attributed to any movement in the series of actual dividends and earnings. Many authorities however dispute that this apparent excess volatility represents a departure from rational behaviour. Cochrane (1991) argues that many economists and lay readers of academic economics have misinterpreted volatility tests to provide scientific evidence that the driving price behind stock prices is a model in which fads, fashions and the psychology of crowds provides the driving force. He states that this view is wrong since volatility tests are in fact tests of only specific discount rate models and they are equivalent to conventional return-forecasting (Euler equations) tests. Thus they are joint tests of both the discount rate model and of market efficiency. Cochrane goes on to argue that a relatively small adjustment to real discount rates makes an enormous difference to stock prices.

> *"For example with constant dividend growth g and a discount rate r, the price dividend ratio is P/D = 1/(r-g). If the price dividend ratio is 20, r-g = 5%. A two percentage point discount rate error to r-g = 3% implies a 66% increase in price. Therefore, the argument can be reversed: dramatic pricing errors can be rewritten as small, (if persistent), discount-rate errors to make the same rejection suggest refinement of discount rate models rather than inefficiency."*

This argument is also emphasised by Fama (1991) who in his review, Efficient Capital Markets II, deals with volatility tests in three short paragraphs. He argues that by the end of the 1970's evidence that expected stock and bond returns vary with expected inflation rates was becoming common place, ((Bodie(1976), Jaffe and Mandelker (1976), Nelson (1976), Fama (1976a,b), Fama and Schwert (1977)) and that when considered with all the more recent evidence on return predictability, which is reviewed later in this thesis, it now seems that volatility tests are another useful way to show that expected returns vary through time.

The claim by some researchers that the market was more volatile than could be attributed to fundamentals leads to a number of tests of mean reversion.

2.10 Mean Reversion

2.10.1 Return autocorrelation and variance ratios

If the stock market exhibits excess volatility, then returns are likely to be autocorrelated as in Summers (1986) fads model. Poterba and Summers (1988) used variance ratios to test whether autocorrelations of stock returns were in fact zero. The variance-ratio test exploits the fact that if the logarithm of the stock price, including cumulated dividends, follows a random walk, the return variance should be proportional to the return horizon. For monthly returns, the variance ratio is therefore,

$$R(k) = \frac{\dfrac{\operatorname{var}(R_t^k)}{k}}{\dfrac{\operatorname{var}(R_t^{12})}{12}} \qquad \textbf{(2.19)}$$

where $R_t^k = \sum_{i=0}^{k-1} R_{t-1}$

R_t denotes the total log return in the month t. This statistic converges to unity if returns are uncorrelated over time. If part of the price variation is due to transitory factors, autocorrelations at some lags will be negative and the variance ratio will fall below one.

Poterba and Summers found the variance ratios increased for periods from 1 month to 2 years, but when measured over periods of 2,3,4,5,6,7 and 8 years for both value and equal weighted indices on the NYSE from 1926-1985, they declined. This suggests some positive autocorrelations for periods under 2 years but thereafter suggests negative autocorrelations.

The authors also examined mean reversion in stock prices indices in 17 countries. Canadian data were taken from the period since 1919, in Britain since 1939 and in 15 other countries for a shorter post-war period. The stock indices in most countries displayed negative serial correlation for long horizon returns, except for South Africa, Spain and Finland where the variance ratio for 8 year intervals was above one. The authors summarise:

> *" ... there is some tendency for more mean reversion in less broadly based and less sophisticated equity markets. The US data before 1925 shows greater evidence of mean reversion than the post 1926 data ... In recent years mean reversion is more pronounced in small foreign equity markets than in the US."*

It will be recalled, however, that any test of market efficiency is a joint test of efficiency and of the model specifying equilibrium required returns. Thus mean reversion may be as much the result of time varying discount rates as of market inefficiencies. To investigate the changes in discount rates necessary to explain their results, Poterba and Summers calculated, for a wide range of assumptions, the standard deviation in the required rates of return. They found that, under what they considered as reasonable assumptions, the standard deviation of ex-ante returns must be 5.8% per annum and they conclude that it is difficult to think of risk factors which could account for such a large variation in required returns.

Thus West (1988a) and Poterba and Summers (1988) take opposing views from Cochrane (1991) and Fama (1991) on the plausibility of changes in discount rates accounting for excess volatility.

Poterba and Summers conclude that their tests of a number of data sets strengthen the case against the random walk hypothesis. They argue that the presence of transitory price components suggests the desirability of investment strategies, such as those considered by De Bondt and Thaler (1986) involving the purchase of securities that have recently declined in value.

The finding of transitory components in stock prices led to a more direct test of return autocorrelation by Fama and French (1988a). It will be recalled that the early researchers, for example Kendall (1952), Fama (1965), found virtually zero correlation in share and commodity returns when measured over short horizons. However Summers (1986) demonstrated that these early tests were not powerful enough to discriminate between the random walk hypothesis and a fads model which could be represented by an autoregressive (AR1) process. Fama and French examined return correlations for much longer periods of 1,2,3,4,5,6,8 and 10 years for a portfolio of all N.Y.S.E. stocks between 1926 and 1985. They argued that any predictable component in stock prices was consistent with models of an irrational market in which stock prices take temporary swings away from fundamental values. But they also recognised that predictability might result from time varying equilibrium expected returns generated by rational pricing generated in an efficient market.

Fama and French showed that $\beta(T)$, being the slope in a regression of the return $r(t,t+T)$ on $r(t-T,t)$ approaches -0.5 for large values of T, where the price does not have a random walk component. Fama and French argue:

> *"If however the stock price has a random walk and stationary component the mean reversion of the stationary component tends to push the β slopes towards -0.5 for long term horizons while the variance of the white noise component pushes the slope towards 0.0. Since the variance of $z(t+T) - z(t)$ approaches $2\sigma^2(z)$ as the return horizon increases and the white noise grows like T, the white noise element eventually dominates. Thus if stock prices have both a random walk and slowly decaying stationary components the slopes of β in regressions might form a U shaped pattern, starting around 0.0 for short term horizons, becoming more negative as T increases and then moving back towards 0.0 as the white noise variance begins to dominate long horizons."*

This is exactly what Fama and French found. The slopes of the regressions were as shown in Table 2.1 below:

Table 2-1
Fama and French (1988a)
Beta Coefficients

Return horizon years	1	2	3	4	5	6	8	10
Bias-adjusted slopes	-0.03	-0.20	-0.30	-0.34	-0.32	-0.14	0.02	0.08

This strongly suggests that stock prices have a slowly decaying transitory component. The authors, however, found strong evidence of autocorrelation in the first 15 years from 1926-1940. The autocorrelations for the period after 1941 were close to zero suggesting that they occurred only in the early period which included the stock market crash of 1929. The observation that the time series properties of stock market returns seem to be subject to changes in regime is of considerable importance and will reappear again in this thesis.

Cutler Poterba and Summers (1991) studied mean reversion in equity and bond markets for 13 countries for the period 1960-1988. While they found significant positive serial correlation in monthly excess returns for equities for other time horizons, their results were mixed.

In contrast to Fama and French (1988a) and Poterba and Summers (1988) who found negative correlations in longer term returns, Lo and Mackinlay (1988) found positive correlations when studying weekly returns on the CRSP NYSE-AMEX market return index. Using 1,216 weekly observations from September 1962 to December 1985, they discovered a weekly first order autocorrelation coefficient as high as 0.3. They comment that the finding of positive autocorrelations for short periods are not necessarily inconsistent with negative autocorrelation over longer term horizons. They suggest that their results indicate that the sum of a random walk and a mean reverting process cannot be a complete description of stock price behaviour. Fama (1991), page 1578, speculates that the positive autocorrelations might be due to the non-synchronous trading effect since autocorrelations were stronger for smaller stocks. We now consider a number of studies which have attempted to examine these issues.

2.10.2 Objections to Studies on Mean Reversion

The empirical evidence of excess volatility and mean reversion both seemed to support Shiller's fads model. Shortly after the publication of Poterba and Summers (1988) and Fama and French's (1988a) research, Kim Nelson and Startz (1991) (KNS), challenge the findings of Fama and French and Poterba and Summers. Their findings are interesting for a number of reasons. Firstly, they use a novel and pioneering methodology designed to overcome some of the technical shortcomings of earlier papers and secondly they find that mean reversion is only a feature of the pre-war period.

Stock returns are well known to be non-normal and heteroscedastic. It may therefore be dangerous to rely on inferences which are based on assumptions of normality. Furthermore to secure sufficient degrees of freedom when computing the autocorrelation statistics for long horizon returns Fama and French used the method in Hansen and Hodrick (1980) to adjust the standard errors for the positive autocorrelation in residuals that is induced by overlapping observations. This method is only asymptotically valid, however, and its small sample properties are not well understood.

To overcome these difficulties KNS used randomisation, a form of Monte Carlo simulation. Randomisation focuses on the null hypothesis that one variable is distributed independently of another. In this case the null hypothesis is that returns are distributed independently of their ordering in time. Randomisation shuffles the data to destroy any time dependence and then recalculates the test statistic for each reshuffling to estimate its distribution under the null. The experiment was repeated 1,000 times, and the number of times the calculated variance ratio after randomisation exceeded the actual conventional statistic was computed to estimate the significance factor. The variance of stock prices was much higher in the 1929 to 1939 period than in the last part of the sample. Since randomisation shuffles the data, it destroys the time series characteristics of any heteroscedasticity which may be present. To overcome this difficulty KNS stratified their data into two regimes. The first is the turbulent period which includes the effect of the great depression in the 1930's and the second the more stable period reflecting post World War II prosperity.

KNS have two main findings. Firstly, the results using the randomisation methodology are significantly weaker than reported by Fama and French (1988a) and Poterba and Summers (1988) and, secondly, that mean reversion is a feature only of the turbulent pre-war period which saw a fall in the Standard and Poor's Composite Stock price index from 24.86 in January 1929 to 7.09 in January 1933. From then it rose to 17.59 in 1937 but fell back to 8.93 in January 1942 following the Japanese attack on Pearl Harbour.

The Fama and French autocorrelation method lends itself to out of sample testing. KNS use the 1926-1946 period sample estimates, the whole sample 1926-1986 estimates and a recursive method using all historic return data to up date their forecast to develop predictive models of returns. Correlation coefficients between forecasts and actuals range from -0.08 to -0.4 implying that only between 0.64% and 16% of returns could be explained.[14]

Cecchetti, Lam and Mark (1991) challenged the economic interpretation of Poterba and Summers' findings. In particular they argued that their results might equally well be consistent with an asset pricing model in which economic agents care about smoothing their consumption. They also observed that 116 annual observations used in the studies do not provide much information when computing statistics based on 5 or 10 year horizons. In order to discriminate between the random walk model and a model of mean reverting fads, the authors, perhaps somewhat light heartedly, comment that dividend and price data as far back as 1066 is necessary. This is the very issue of the power of the statistics to discriminate between two competing hypotheses raised by Summers (1986).

McQueen (1992) provides a further challenge to Poterba and Summer's (1988) finding of mean reversion in stock indices and to Fama and French's (1988a) finding of long term autocorrelation in stock returns. He draws attention to a number of

14 It would be premature to assume that returns in the post war period are unpredictable. We shall see later that Pesaran and Timmermann (1995) claim to have developed a trading rule which appears to generate excess returns.

econometric difficulties arising in the data. Firstly, the use of overlapping observations for long horizon returns as a device to increase the number of degrees of freedom, results in a moving average error in the residuals. While the method of Hansen and Holdrick (1980) provides a valid asymptotic adjustment, McQueen notes that in samples of 10 year returns over the period 1926 to 1987 there are only 6 truly independent observations. Secondly, he draws attention to the observations which include the stock market collapse of the late 1920's and the depression of the early thirties. These observations are multiplied by the number of overlapping periods. McQueen also notes that OLS β's where a lagged variable is used as the explanatory variable are biased towards 1. The third complication which is noted by McQueen is that returns are highly heteroscedastic. Fama and French (1988a) attempt to adjust for heteroscedasticity by the method of both White (1980) and Hansen (1982). However while these adjustments are asymptotically valid their properties in small samples are poorly understood.

To overcome these problems McQueen performed generalised least squares randomisation tests. In these he first estimated the monthly variance of stock market returns from the daily values of the Standard and Poor's index These variances were then accumulated to the appropriate time horizons and used to weight the returns for the same time horizon. Since my thesis will use McQueen's weighted least squares randomisation technique, it will be described in much greater detail in section 3.4.6.

McQueen found that for his entire sample period from 1926 to 1987 it was not possible to reject the random walk hypothesis at the 5% level. McQueen did find, however, statistically significant mean reversion at three and four year horizons for the turbulent 1926 to 1946 period which includes the depression of the early 1930's, a recession in 1937 and early 1938 and a decline in stock prices prior to the beginning of World War II. Following Pearl Harbour the U.S. economy boomed as the economy engaged in war time production. McQueen argues that since there was no statistically significant mean reversion in the whole sample, the existence of mean reversion in just one sub-sample hardly provides convincing evidence against the random walk hypothesis.

In a more recent study Cochran and De Fina (1995), using data spanning the period from 1969 to 1990 for 18 countries, found only weak evidence of statistically significant mean reversion.

2.11 Return Forecasting Regressions[15].

2.11.1 The Early Tests

The variance ratios tests of Poterba and Summers (1988), the return correlations of Fama and French (1988a), and the excess volatility tests indicated a possibility that returns on the stock market could be forecast. For practitioners this idea was certainly not new. Early texts such as Dow (1920), Rose (1960) and Morgan and Thomas (1962) suggested that a number of variables connected with the business cycle predict returns. Variables discussed by these studies include interest rates, dividend yields, industrial production and company earnings.

The early academic evidence found that daily returns were unpredictable[16]. More recent tests suggested very modest predictability of under 3% for monthly returns. See for example, Fama and Schwert (1977), Fama (1981) and Keim and Stambaugh (1986). By the mid 1980's a substantial body of evidence in the academic literature suggested that dividend yields forecast annual returns. (See the studies by Rozeff (1984), Shiller (1984), Flood, Hodrick and Kaplan (1986) and Campbell and Shiller (1987).)

Fama and French (1988b) (F&F hereafter) tested the proposition that dividend yields forecast returns on both value and equal weighted portfolios on the New York Stock Exchange for return horizons from one month to four years. In a 'fads' model dividend yields are low when stock prices are artificially high. In the efficient markets version low dividend yields signify investor confidence and low risk premia on equities. Consider a discrete-time perfect-certainty model in which $D(t)$, the dividend per share for the time period from t-1 to t, grows at a constant rate g, and the market interest

15 The term forecast is taken from the literature. Strictly it should only be used only where a model derived from in sample data predicts out of sample. The rest of this chapter follows the extensive literature in using term forecast to describe the relationship between the explanatory variable and future returns.

16 See the studies mentioned in section 2.2 .

rate that relates the stream of future dividends to the stock price $P(t\text{-}1)$ at time t-1 is the constant r. In this model, the price $P(t\text{-}1)$ is

$$P(t-1)=\frac{D(t)}{1+r}\left(1+\frac{1+g}{1+r}+\frac{(1+g)^2}{(1+r)^2}+...\right)=\frac{D(t)}{r-g} \tag{2.20}$$

The dividend yield is equal to the interest rate less the dividend growth rate,

$$\frac{D(t)}{P(t-1)}=r-g \tag{2.21}$$

In the certainty model, the interest rate r is the discount rate for dividends and the period-by-period return on the stock. The direct relation between the dividend yield and the interest rate in the certainty model (2.20) illustrates that dividend yields may reflect changes in expected returns.

Fama and French's test centres on the regression of future returns $r(t,t+T)$ on the dividend yield, $Y(t)$

$$r(t,t+T) = \alpha(T) + \beta(T)Y(t) + \varepsilon(t,t+T) \tag{2.22}$$

The authors obtained significant R^2 from equation 2.22 and provide a range of statistics for various sub-periods and versions of the model. The R^2 of dividend yields was much higher for nominal returns than for real returns and for longer periods than for shorter periods. Tables 2.2 and 2.3 summarise respectively, F&F's R^2s' and slope coefficients for value weighted nominal returns.

Table 2-2

Fama and French (1988b)

R^2

	Monthly	Quarterly	1 year	2 years	3 years	4 years
1927-1986	0.00	0.01	0.01	0.09	0.13	0.19
1927-1956	0.00	0.01	0.03	0.07	0.18	0.30
1957-1986	0.02	0.05	0.22	0.45	0.51	0.57
1941-1986	0.01	0.03	0.14	0.35	0.51	0.64

Table 2-3

Fama and French (1988b)

Beta Coefficients

	Monthly	Quarterly	1 year	2 years	3 years	4 years
1927-1986	0.21	1.07*	2.47	7.38*	9.94*	12.86*
1927-1956	0.17	1.16	1.50	8.92	15.27*	20.86
1957-1986	0.68*	2.33*	9.32*	16.40*	17.12*	19.69*
1941-1986	0.36*	1.20*	5.09*	10.34*	12.94*	15.35*

* indicates significant at 5% level.

F & F draw attention to a number of statistical difficulties which they encountered in their research. To increase the degrees of freedom they used overlapping observations of return for time horizons of two years and above. As is well known, this results in a moving average error in the residuals. They then used the method in Hansen and Hodrick (1980) to adjust the standard error of their β coefficients for the moving average error in the residuals induced by this procedure. They also refer to biases arising from the use of dividend yield as an explanatory variable, which is determined endogenously rather than exogenously as in the standard statistical models. Shocks to price affect both return on the left hand side of the equation and dividend yield on the right hand side. Since dividends are a relatively smooth series any shocks to price are directly imparted to dividend yield. It is well known that the inclusion of a lagged dependant variable as an explanatory variable may causes bias in the regression coefficient and consequent overstatement of the *'t'* statistic. Fama attempts to overcome this problem by defining dividend yield as *D(t)/P(t-1)* and produces tables of separate statistics on this basis. These indicated substantially less power. In F&F's words:

> *Confident conclusions that D(t)/P(t) or D(t)/P(t-1) produce regressions that overstate or understate the variation in expected returns cannot be made on* a priori *grounds. D(t)/P(t-1) is more conservative. ... Moreover, because P(t-1) can only reflect information about expected returns available at t-1, D(t)/P(t-1) is about a year out of date with respect to expected returns forward from t. If the current shocks have a decaying effect on expected returns, using an 'old' yield to track expected returns is likely to understate the variation of expected returns. We present results for the more timely measure D(t)/P(t) as well as D(t)/P(t-1).*

Fama and French (1988b) page 7 & 8.

F&F support their conclusions with out of sample forecasts for the period 1967 to 1986 based on the coefficients derived from the previous 30 year returns and yields. The in sample figures are those for the period 1957-1986 which appear in Table 2.2.

Table 2-4
Fama and French (1988b)
Out of Sample R^2

	Monthly	Quarterly	1 year	2 years	3 years	4 years
In sample	0.02	0.05	0.22	0.45	0.51	0.57
Out of sample	0.02	0.06	0.23	0.43	0.48	0.50

They argue that the explanatory power of their model improves at longer horizons since short horizon expected returns are autocorrelated but slowly mean reverting. The persistence of short horizon expected returns implied by mean reversion causes the variances of multi-period expected returns to grow more slowly than in proportion to the return horizon.

Fama and French interpret their results with caution. They agree that they are consistent with common models of an inefficient market, for example Shiller (1984) and Summers (1986), in which stock prices take long temporary swings away from fundamental values. A high dividend yield may signal that future returns will be high because stock prices are temporarily irrationally low and vice versa. They also argue, however, that their results are consistent with mean reverting equilibrium expected returns. In short, they interpret return predictability as attributable to expected changes in the discount rate rather than to market inefficiency.

The question which now faced researchers was whether this mean reversion in discount rates might be due to changes in business conditions and whether similar economic factors affected the returns on stocks and bonds. Fama and French (1989), investigated these questions. In particular they tested the hypotheses that the same variables which forecast bond returns, forecast excess stock returns. They found that the expected excess returns on corporate bonds and stocks move together. Dividend yields, which had previously been shown to forecast stock returns, (Fama and French (1988b)), also forecast bond returns. In addition, the default spread, which is the difference between the yield on Aaa bonds and the yield on the market portfolio of corporate bonds, captures a similar variation in expected bond and stock returns. The dividend yield and the default spread both predict high returns when business conditions are persistently weak and low returns when conditions are strong.

Fama and French also examined the relationship between term spread and expected returns on stocks and bonds. The term spread is the difference between the yield on Aaa bonds and the one month bill rate. The slopes in the regressions using term spread were positive and similar in magnitude for all stock portfolios and long term bond portfolios. Fama and French argue that this suggests that the term spread tracks a term maturity premium in expected returns that is similar for all long term assets and that a reasonable and old hypothesis is that the premium compensates for exposure to discount rate shocks that affect all long term securities including stocks and bonds.

Their regressions showed very considerable success in forecasting returns of stocks and low grade bonds. The table below extracted from Fama and French (page

34 and 35) shows the R^2 for two of the models which they tested. Results for the period 1941 to 1987 appear below.

Table 2-5
Fama and French 1989
R^2

		Monthly	Quarterly	Yearly	2 years	3 years	4 years
Model 1	**Lg**	0.05	0.10	0.35	0.44	0.46	0.51
	Vw	0.03	0.06	0.16	0.36	0.53	0.60
Model 2	**Lg**	0.06	0.11	0.45	0.59	0.70	0.71
	Vw	0.02	0.04	0.09	0.21	0.39	0.43

Lg is the excess return on low grade bonds
Vw is the excess return on the value weighted index of the NYSE.

Model 1 was $r(t,t+T) = a + bD(t)/P(t) + cTERM(t) + e(t,t+T)$

and model 2 $r(t,t+T) = a + bDEF(t) + cTERM(t) + e(t,t+T)$

where, (*TERM*) is the term spread, (*D/P*) is the value weighted dividend yield, (*DEF*) is the default spread.[17]

Fama and French's success in forecasting returns might suggest market inefficiencies and potential for profitable trading rules. The authors argue, however, that the evidence provided by their study suggests that the three forecasting variables, dividend yield, the default premium and the term premium, all related to business conditions, track common variation in the returns on stocks and bonds. They also argue that it is comforting that the variation in dividend yield which might otherwise be interpreted as the result of bubbles in stock prices, forecasts bond returns as well as

[17] The variables *D/P* and (*DEF*) were highly correlated so it was necessary to construct two models to test their relationship with excess returns.

stock returns.[18] In short, they lean towards the explanation that rational variations in the risk premium attributable to changing business conditions account for the predictability of returns.

A number of studies have provided evidence which has suggested that other variables may predict stock returns. For example, Balvers, Cosimano and McDonald, (1990) have shown that future returns are negatively related to industrial production. They find that for the period from 1947 to 1952 $\overline{R}^2$ for US data ranges from 0.028 for monthly returns to 0.30 for 3 years returns. The authors explain their results in the framework of market efficiency, and they argue that their findings are consistent with a world in which investors attempt to maximise their utility by smoothing their consumption and by adjusting their required rate of return for financial assets.

2.11.2 Objections to the Return Forecasting Regressions.

Two important articles appeared in the June 1993 edition of the Journal of Finance , Nelson and Kim (1993) and Goetzmann and Jorion (1993), which showed the findings of previous studies of return predictability to be much weaker than previously supposed. Both articles argue, from slightly different perspectives, that the significance of the standard statistical tests, i.e. R^2 and the t coefficients are overstated since:

1 The standard adjustments for serial correlation induced by overlapping observations, Hansen (1982) and Newey West (1987), have poor small sample qualities.

2 Dividend yields are largely determined by prices since dividends are a highly autocorrelated and stable series. As returns are determined in the main part by the first differences of prices, regressions of dividend yield on returns involve the classical problem that the right hand variable is a lagged dependent variable. Dickey Fuller (1979) tabulate by simulation, values for the OLS t statistic under the null hypothesis.

18 A possible explanation might however be that the same over-reaction by investors to improving (worsening) business conditions causes both dividend yields and default premiums to rise (fall).

The downward bias is shown to be substantial in small samples, and is of the order of (4/n), where n is the sample size.

A number of authors had previously raised the problem of the small sample properties of the standard adjustment for overlapping observations. These include, Hodrick (1992), Kim Nelson and Startz (1991), Richardson and Smith (1991), Richardson and Stock (1989) and Boudoukh and Richardson (1994). Nelson and Kim (1993) following the arguments in Stambaugh (1986) also attempt to show that in addition to biases in the standard errors, the β coefficients are biased.

Both Goetzmann and Jorion (1993) and Nelson and Kim (1993) carry out a number of simulations to determine the true distribution-free value of the test statistics for the data in the sample. Each article takes a slightly different perspective.

Goetzmann and Jorion replicate Fama's and French's work and find very similar R^2 for the sub-period 1927-1958 and 1959-1990, 0.49 and 0.53 respectively. However, for the whole period, R^2 at 0.39 is considerably lower than for each of the individual sub-periods, and they argue that this demonstrates clear evidence of small sample bias.

They simulate the empirical distributions of the test statistics using bootstrapping techniques. These involve sampling with replacement. Goetzmann and Jorion comment:

> *For sufficiently large sample sizes, an important advantage of the bootstrap is that it allows the researcher to control for the presence of potentially biasing factors such as the use of overlapping return intervals, the lagged correlation between independent and dependent variables, and other idiosyncrasies in the distribution of the returns or in the error structure.*

Goetzman and Jorion derive the empirical distribution of a number of the test statistics using Monte Carlo sampling. In particular, they allow for the first time specifically for the biases caused by use of a lagged independent variable as an explanatory variable. They conclude that there is little statistical evidence that the slope coefficients are different from what could be expected under the null hypothesis of no forecasting ability.

They also examine the sensitivity of their results to the distribution assumptions. They replicated their results using returns drawn from a normal distribution with the same mean and variance as their sample data. They conclude that in spite of slight differences their general conclusions are not affected by the distributional assumptions behind the return simulations.

The authors offer the following explanation of why the bootstrap results are so different from traditional regression.

> *The results of the dividend yield regressions, for which the price process is endogenous, bear a close resemblance to the well-known simulations performed by Granger and Newbould (1974) and further analysed by Phillips (1986). Granger and Newbold regressed two independent random walks, and found rejection of the null the rule rather than the exception. Indeed, their paper has been frequently cited as justification for the need to use differenced price series in econometric studies. These results help understand the spuriously high R^2 in the preceding tests. The greater the overlap in the return series, the more closely the return series resembles a price level series rather than a return series. The series comprised of a rolling sum of returns is not therefore independent. Likewise also dividends also resemble random walks. It would not be surprising that the combination of these two series in a regression could result in spurious conclusions regarding both significance and explanatory power.*

The authors finally regress historic returns on the stock price and a time trend and obtain similar R^2's to the Fama and French study. They therefore show that the time trend can proxy for dividends as an explanatory variable. In short Goetzmann and Jorion found that when adequate allowance had been made for the statistical difficulties, β coefficients were non-significant and that the previously forecast power was in fact spurious.

In the other study also published in the June 1993 edition of the Journal of Finance, Nelson and Kim (1993) also find that return predictability is considerably lower than previously believed. In contrast to Goetzmann and Jorion, however, they find significant test statistics.

They use the Stambaugh (1986) approximation to show that the regression coefficient will also be biased if the predictor is jointly endogenous with the return, even if it is predetermined. They argue that a lagged value of the independent variable may appear as a predictor of the dependent variable even though it has no predictive power. This effect will be stronger the more autocorrelated it is, the stronger the contemporaneous relation between the innovations, and the smaller the sample size.

Nelson and Kim (1993) simulated the artificial histories of returns and dividend yield using a vector autoregressive approximation to this present value model. The resulting artificial return and yield data are consistent with this model under the restriction that returns are not predictable, but will also have serial correlation and dispersion similar to the historical series. They draw residual pairs without replacement, which is called randomisation. They find that the empirical t values are much larger than they would be if the data were normally distributed.

To account for the effect of heteroscedasticity their data were stratified according to whether an observation falls within the high variance period 1929 to 1939 or not. The authors found that taking into account the effect of heteroscedasticity on the sampling distributions clearly weakens the evidence for predictability.

They also examined the predictability of monthly New York Stock Exchange returns. The use of monthly returns greatly increases the number of observations and so may be expected to reduce the bias due to the small size of the sample. Nelson and Kim found, however, that gains from increasing the sample size are offset by losses from the series of monthly dividend yields being more autocorrelated than the series of annual dividend yields.

Some literature has suggested that macroeconomic variables could help forecast stock returns. For example in section 2.11.1 reference was made to Balvers, Cosimano and McDonald (1990) who reported that the log of industrial production along with a time trend explain about 20% of the variation in one year real returns during the period 1947 to 1987. Nelson and Kim argue that macroeconomic variables are determined jointly with stock returns since shocks such as innovations in monetary policy or oil prices will affect both. They simulated the appropriate distributions and argued that their results showed that predictive power falls. Regressions predicting monthly returns remained highly significant, although they found no strong evidence of predictability at longer horizons. Nelson and Kim (1993) conclude:

> *The conclusion which we draw from these experiments is that valid inferences cannot be drawn from predictive regressions using conventional tables that are appropriate in the case of classical regression. The investigator would seem to be obliged to develop the empirical distribution of the statistics under the null hypothesis using simulation methods before drawing inferences.*

The results of the two studies described above would seem considerably to weaken the argument that returns are predictable. Much will depend on the data subjected to testing. Returns are known to be non-normal and heteroscedastic. Lagged stochastic regressors are also known to cause biases in regressions. Finally, the use of overlapping observations results in serial correlation in the residuals. The standard methods for correcting for these characteristics perform poorly in small samples. The present state of knowledge demands that the researcher allow for these biases by using numerical methods to simulate the empirical distribution of the test statistics.

Recently, and after the bulk of the empirical work on this thesis had been completed, Goetzmann and Jorion (1995) have published their results of long horizon 'return forecasting' regressions using data taken from the US and the UK markets for a sample period from 1872 to 1992. They find, for both US and UK data, little evidence of predictability over the whole sample period. When considering the period prior to 1926 in the US, they detect negligible and insignificant correlations. In the post 1926 period, they find modest correlations with R^2 of nearly 0.18 for 4 year returns. However regression coefficients are not significant at conventional levels when estimated by bootstrapping.

Results for the UK stand in marked contrast to those of the US. For the period prior to 1926 β coefficients are negative and are significant at conventional levels even when the bootstrap technique is used as the method of estimation. However R^2 is low with a maximum of only 0.061 at a three year horizon. For the period following 1926, β coefficients are positive and significant at the conventional level when estimated by the bootstrap. R^2's are high, reaching 0.62 for 3 year horizons.

Goetzmann and Jorion identify, by using the leverage measure of the regression (see Belsley, Kuh and Welsh (1980)) the large influence on their results of the major stock market collapse in 1973 and 1974 and its recovery in 1975.

They discuss two possible explanations for the shift in regime between their two sample periods which they identified for UK data. Firstly, they speculate that the stability of prices and therefore returns, results in stable dividend yields. They argue that in these circumstances, there is not much to predict[19] and not much with which to predict. The period after 1926 is much more volatile and dividend yields become useful predictors.

Alternatively, they argue, predictability can be explained in terms of survivorship. The early 1970's were a period of global social unrest. Rapidly increasing commodity prices, the Oil Crisis and the Arab-Israeli war led to global concerns regarding the long term sources of raw materials and energy as well as the stability of the International banking system. In the UK high inflation followed a relaxed monetary policy in 1972. Elections in early 1974 resulted in a socialist government which strengthened prices and incomes controls in an attempt to reduce inflation. This led to both a collapse of company profitability and also to a liquidity crisis which was heightened by company taxation being levied on "illusory stock appreciation". Share prices had been falling steadily through 1973 and 1974. In late 1974, the government announced both a relaxation of price controls, and a scheme whereby stock holding gains would no longer be taxed. The corporate liquidity crisis passed and the stock market recovered, the FT All Share Index increasing by 61% in January 1975.

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19 The use of the term 'predict' is from Goetzmann and Jorion (1995)

With the benefit of hindsight we can see that the London stock market survived this traumatic period. Data on the London Stock Exchange for the period 1871 to 1992 is therefore available for analysis while data on other exchanges which closed are unavailable. Goetzmann and Jorion argue that this results from an inevitable survivorship bias. Markets which survive, as did the London market, will be mean reverting and high dividend yields will precede both a market recovery and consequently high positive long horizon returns. Goetzmann and Jorion model the probability of survival under a number of assumptions and provide the p factors for β in only those simulations which survived throughout the sample period. Their results show increased p factors in all cases where only the survived sample is taken into account.

Goetzmann and Jorion also show that if actual future dividends are included as explanatory variables in the regression the statistical significance of dividend yield as an explanatory variable increases. They argue that this confirms the view that using variables that proxy for dividend growth exposes the information in yields about expected returns. Their approach however uses future variables and does not directly address the issue of the forecasting ability of dividend yields in univariate regressions conditional on past and present information. They suggest that other variables might be used to signal future changes in dividend growth and, in such a case, dividend yields might then prove useful for forecasting purposes. Later in this thesis the use of surveys of businessmen's optimism concerning future business conditions as predictors of future returns will be discussed.

2.11.3 Other Evidence

A number of other studies which fall outside the main stream of research into return predictability nevertheless require mention.

Campbell and Hamao (1992) found during the period 1971 to 1990 that interest based variables and dividend yields helped to forecast excess returns in both the US and in Japan. In addition, the US variables helped to forecast excess Japanese returns. Their study however does not make allowance for the methodological problems raised in Goetzmann and Jorion (1993).

Clare Thomas and Wickens (1994) report, using UK data for the mid 1960's to the early 1990's, that the Gilt-Equity Yield Ratio, the ratio of gilt edged yields to dividend yields, helps forecast future equity returns. They achieve a remarkably high $\overline{R}^2$ of 0.467 for quarterly returns. However they use "impulse dummies " in 1973 quarter 3 and quarter 4, to take account of the oil price shock; and an impulse dummy for 1975 quarter 1, to take account of the equity market boom; and an impulse dummy for 1987 quarter 4 for the 1987 crash. It is perhaps not surprising that they achieve significant explanatory power for their model and satisfactory tests diagnostics when they eliminate the 'difficult' observations which characterise stock returns and which makes the study of this data a challenging pursuit. Once again they make no allowance for the methodological problems raised in Goetzmann and Jorion.

In a recent study, Pesaran and Timmermann (1995) provide further evidence on the predictability of U.S. stock returns. From an examination of the practitioner and academic literature published prior to their sample they chose a number of variables which were claimed to forecast returns. Using monthly data from the 1954 to 1960 they then selected from these variables those which ex-post were significant in modelling monthly returns during this period. From this and the parameters generated, a model was developed which could be used to predict returns one month ahead. Both the forecasting variables and their coefficients are updated monthly to form one step ahead forecasts for the period from January 1960 to November 1992. The aim is to mimic, as far as is possible, an investment strategy which could have been formulated by an investor with the information and the tools available at the time of preparation of the forecasts. The authors claim two main advantages for their methodology. Firstly it enables them to identify which variables forecast returns and secondly it provides information on the changing importance of each variable over time. The authors found that the short term interest rate, the change in industrial production lagged two months and monetary growth lagged two months were included as explanatory variables in their regressions for virtually all of the sample period. The dividend yield was included as an explanatory variable from 1970 onwards.

Pesaran and Timmermann then develop a decision rule for switching between bonds and stocks. They claim that, after what they have considered as high transaction costs, the mean return on their portfolio exceeds the return on the market portfolio. Since their portfolio consists of time-varying combinations of stocks and bonds it is of lower risk than a portfolio of stocks.

The authors conclude that there is a relation between predictability and periods of high volatility in the markets. During the relatively calm markets of the 1960's and 1980's there were no excess gains to be made from the model. In contrast, during the more volatile 1970's there seems to have been important gains to be made. The authors argue that their findings are consistent both with incomplete learning in the aftermath of a large shock to the economy, (see Timmermann (1993)), as well as with a story where the predictability of excess returns is reflecting time-varying risk premia. The authors lean towards an explanation in which their model learns more quickly after a major shock to the economy than investors. They argue:

> *In the context of the latter it is however difficult to explain why return on the switching portfolio exceeds return on the market when the markets are volatile. It is well known that there is no theoretical reason why required returns on stocks cannot be lower during periods with relatively high volatility. For instance, risk averse investors may want to increase their savings, thereby bidding down the equilibrium returns on stocks when markets are particularly volatile. Furthermore it is quite possible that the price of risk is time-varying so that there is no constant, proportional relationship between the first and second conditional moments of stock returns. Given the existence of a risk free T-bill rate, which establishes a lower bound for nominal return, it seems difficult, however, in the context of an equilibrium model to explain the predictions of negative risk premia on the market apparent in the 1970's. On the other hand it is possible that in the event of a major regime switch in the economy, such as the one induced by the first oil shock in 1973, learning may take longer to complete than usual ... ."* Page 1225 and 1226.

At present there has been little time for comment by other researchers on the findings of the study. The out-of-sample recursive predictions made by their model would seem to overcome many of the statistical difficulties raised in previous research. Possible criticisms include the likelyhood that Pesaran and Timmermann have benefited from hindsight in their choice of forecasting variables as well as concerns over the adequacy of transaction costs which they have included.

2.11.4 Summary.

Challenges to the efficient market hypothesis which date from the pioneering work on excess volatility by Shiller and Le Roy and Porter have been fiercely contested in the academic literature. As has been stressed in this thesis, market efficiency is *per see* untestable since tests inevitably depend on the model generating returns and are hence inconclusive. (See Fama (1991)). Studies of alleged excess volatility test the rationality of prices, a volatile series, with reference to the volatility of dividends and earnings which are smooth and highly autocorrelated.

Since dividends are highly correlated, it is hardly surprising that rejections of the tests for mean reversion have been paralleled by rejection of tests for return predictability. There is a number of features which run parallel through this work.

1. Returns appear to be most predictable at longer horizons. The limited availability of data for returns of 3 or more years has forced researchers to use overlapping observations. The techniques for correcting the standard errors of their β coefficients have poor small sample properties.

2. The use of lagged returns in autocorrelation studies or of dividend yield in return forecasting regressions, results in biases since the independent variable is, or is a proxy for, a lagged dependent variable. The independent variable is determined endogenously and not exogenously as in the standard statistical models.

3 Returns are both highly non-normal and heteroscedastic. The standard corrections for heteroscedasticity have small sample properties which are poorly understood.

4 The use of overlapping observations results in serially correlated errors. The standard statistical method of correcting biases in the standard errors are inadequate. Furthermore, the use of overlapping observations violate the assumption that they are independent of one another.

Considerable emphasis has been placed on the econometric requirement that for any model to be able to reject the null hypothesis it must be significant at the 5% level. The 5% figure is more hallowed by tradition than by science. What may be more relevant is the potential of any model to generate excess returns consistently. The Pesaran and Timmermann (1995) contribution to the literature may possibly provide a model which falls into this class.

This ends the extensive review of the research literature on forecasting returns using dividend yields. The primary data chosen for my own study is taken from the Industrial Trends Survey published by the Confederation of British Industries (hereafter the CBI). The CBI has published since 1958 surveys of Businessmen's Expectations of changes in a number of key economic variables, to which we now turn our attention.

2.12 The Use of Survey Data

In contrast to the extensive literature and controversy surrounding dividend yields as predictors of returns, I have been unable, despite thorough examination of the literature, to find any reference to the use of survey data of businessmen's expectations as predictors of stock market returns.

There is a small literature concerning the use of CBI survey data in tests of the rational expectations hypothesis advanced by Muth (1961). This work is thoroughly reviewed in Pesaran (1987). Pesaran tests the rational expectations hypothesis by comparing the responses to the CBI questions on expected selling price changes with the indices of Wholesale Prices of Manufactured goods published monthly by the Central Statistical Office. Pesaran concludes that businessmen could have significantly improved the accuracy of their inflation expectations by a better understanding of the processes generating price changes and by a more 'efficient' use of the available information, especially with respect to past movements in fuel and raw material prices and changes in the effective exchange rate. Similar findings appear in Thomas (1995) who showed that agents, the businessmen completing the questionnaires, do not make efficient use of all available information in forming predictions.

Currie Dicks and Holly (1989) considered whether the use of CBI survey data would have prevented two serious errors in the forecasts published by the London Business School. They find that the CBI survey of future stocks of finished goods would have helped predict the depth of the recession in 1980, and that the survey of consumer confidence produced by EC/FT Gallop would have helped to predict the consumer boom in 1988. However, they could only have reached this conclusion after the event. If the best weighted average of their own model and the survey information had been used at the time, little improvement in their forecasts would have resulted.

Although the finding that businessmen do not necessarily process information efficiently, and that their forecasts of important economic events are capable of improvement, does not encourage a belief that the CBI series can be used to forecast stock market returns, neither does it exclude this possibility. It is at least plausible that businessmen, by direct observation of economic activity, obtain price sensitive information in advance of other potential investors. As stock exchange investment is not the primary activity of businessmen, it is conceivable that the full impact of such price sensitive information on the stock market would be subject to measurable delay.

Thus the purpose of this study is to test whether CBI data on its own or in conjunction with dividend yields can help forecast returns for horizons from 3 to 36 months on the London Stock Exchange. The next chapter considers the hypotheses, data and methodology used in this study.

CHAPTER 3

HYPOTHESES, DATA AND METHODOLOGY

3.1 Hypotheses

The literature survey described how, by the late 1980's, a number of researchers had published evidence that financial factors such as dividend yields, the default spread (the difference between the returns on high grade and on low grade bonds) and the term spread (the difference between returns on long term and short term government bonds), as well as economic variables such as industrial production, help to explain stock returns[1] in the US. Such findings do not necessary imply that the market is inefficient since the predictability of returns, as Fama and French (1989) argue, may be the result of investors requiring returns which vary with business conditions. More recently, Nelson and Kim (1993) and Goetzmann and Jorion (1993) simulated the specific characteristics of the data and found return predictability to be much weaker than originally claimed.

The purpose of this thesis is to test whether separately or jointly, dividend yields and Confederation of British Industries (CBI) Survey data of Businessmen's expectations of a number of important economic variables, are related to returns on the London Stock Exchange.

Specifically the null hypothesis is tested that the β coefficient is zero in Equations 3.1 and 3.2.

$$TR_{t,\,t+T} = \alpha_T + \beta_T GDY_t + u_{t,\,t+T} \qquad \textbf{(3.1)}$$

$$TR_{t,\,t+T} = \alpha_T + \beta_T CBI_t + u_{t,\,t+T} \qquad \textbf{(3.2)}$$

1 For example see the studies by Fama and French (1988b) and (1989), Rozeff (1984), Campbell and Shiller (1988a. and 1988b), Fuller and Kling (1990) and Hodrick (1992) and Balvers Cosimano and McDonald (1990).

where [2]

$$TR_t = \frac{TRI_t - TRI_{t-1}}{TRI_{t-1}} \times 100 \qquad \textbf{(3.3)}$$

Tr_t is the total return at period t and TRI_t is the level of the total return index at the end of period t and GDY is the gross dividend yield at time t calculated,

$$GDY = \frac{ADIV \frac{1}{(1-tax)}}{PI_t} \times 100 \qquad \textbf{(3.4)}$$

$ADIV$ is the summation of the last 12 months net dividends and PI_t is the price index at time t. CBI_t is the value of a CBI series at time t and tax is the basic rate of income tax.

In addition the marginal significance of including CBI series with the dividend yields is tested in Equation 3.5

$$TR_{t,\, t+T} = \alpha_T + \beta_T GDY_t + \beta_T CBI_t + u_{t,\, t+T} \qquad \textbf{(3.5)}$$

The rationale for dividends predicting returns has been thoroughly discussed in the literature. In the fads version[3], low dividend yields indicate a market in which excessive optimism is reflected in overly high stock prices, and high dividend yields indicate a market which is unduly depressed. Such a market is likely to revert to its fundamental value. In the efficient markets version, predictable returns merely reflect rational changes in discount rates which vary with business conditions.

Since 1957 the CBI has conducted surveys of its members expectations concerning a number of key economic variables. The surveys take the form of postal questionnaires which are sent to the chief executives of member companies towards the end of the month. They are returned to the CBI by the middle of the following month and the results have, since 1980, been published in the first week of the next month. The results are therefore based on the expectations of a large number of senior executives who may have information which is not available to the market as a whole.

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2 Since this study closely follows the methodology in Goetzmann and Jorion (1993), monthly arithmetic returns are used rather than the more usual continuously compounded returns. See Goetzmann and Jorion (1993), page 678.

3 See for example Shiller (1984, 1988) and Summers (1986).

Since they are published within two weeks of the closing date for replies, and only 4 weeks after the questionnaires reach the respondents, the CBI claim that they are an up-to-date guide to the state of manufacturing industry and a useful indicator of movements which will be shown later in the official estimates, Wood (1992).

3.2 Data

3.2.1 Returns

Two sources of return data were considered for use in this study. The first source was the London Business School which provides a database of monthly returns and the second, Datastream, which provides daily returns. Since the results of the CBI Industrial Trends Surveys are published during the month rather than at the end of the month, the Datastream daily series was used. Returns were measured from the level of the total returns index at the close of business on the day preceding the release of the survey results.

The dates on which the CBI results first appeared in the press were obtained by a careful scrutiny of the *Times* and *Financial Times* and are listed in Appendix 3. Since the results were released by the CBI on the day prior to their publication in the press, the value of the index was taken at the close of business two days prior to the date of the first mention of the CBI results in the newspapers. For example if the first mention of the CBI survey results in the press was on a Wednesday, they would have been released on a Tuesday and the index level at the close of business on the Monday was taken for calculating returns.

Two indices which reflect the general state of the stock market, were considered for use in this study, the Financial Times-Actuaries All Share Index and Financial Times-Actuaries 500 Share Index. The advantage of the All Share Index is that with over 710 constituents, it has a very broad coverage and accounts for 80% by value of the total capitalisation of the market, Financial Times (1989). The 500 index has the advantage that it more closely reflects the CBI membership which is concentrated in the industrial sectors of the market. After some investigation it was found that the choice between the two indices was unimportant since the correlation between the monthly levels of each index for the period of this study was 0.9997, and for monthly returns, 0.995. The All Share Index was used for this study. It is a price index and therefore it takes no account of dividends.

For the period prior to 1 January 1985, Datastream generates a return index from the price index by spreading annual gross dividends evenly over each working day of the year. The calculation is:

$$TRI_t = TRI_{t-1} \frac{PI_t}{PI_{t-1}} \left[1 + \left(\frac{NDY \frac{1}{(1-tax)}}{n} \right) \right] \qquad \textbf{(3.6)}$$

Where:	TRI_t	=	return index at the close of business on day t
	PI_t	=	price index at the close of business on day t
	NDY	=	is the net dividend yield on the price index
	tax	=	the basic rate of income tax.
	n	=	the number of trading days in the year

After 1st January 1985 when the ex-dividend adjustment (XD) was first available an alternative calculation is used:

$$TRI_t = TRI_{t-1} \frac{\left[PI_t + \left(XDchange \frac{1}{(1-tax)} \right) \right]}{PI_{t-1}} \qquad \textbf{(3.7)}$$

where *XDchange* is the calculated from the price fall in a constituent attributable to it becoming XD, times the number of shares in issue. For the index, the adjustment is for the sum of the XD changes in any trading day.

Therefore prior to 1st January 1985 dividends were spread evenly over the working days in the year. After that date, the return index reflects accurately the timing of dividends. While this represents a technical shortcoming with the Datastream database, the only alternative would have been to use London Business School monthly returns. The standard deviation of daily returns over the period from January 1985 to October 1993 was 0.99% while the average daily dividend yield only 0.019%. Any loss of accuracy caused by Datastream spreading dividends evenly over the year prior to 1 January 1985 is likely to be trivial in comparison with errors resulting from using monthly data in preference to daily data.

The FT-Actuaries All Share Index is based on the capitalisation of its constituents and is therefore value weighted. It is an arithmetic index and therefore serves as a reliable yardstick against which to assess portfolio performance.

Figure 3.1 on the next page shows the All Share Index of total returns for the period from January 1965 to October 1993. The index is plotted against a natural log scale so the rate of change over time can be seen. The index rose steadily until December 1972 when it reached 322. It then started to decline and reached a low of 104 in January 1975 but then rapidly recovered.

Figure 3.2, on page 100, shows that high returns were made by investors amounting to 62% in January 1975 and a further 33% in February 1975. By early March 1975 the index had recovered to 224 and since that date, the total return index has shown a more steady increase. Even the October 1987 episode is seen as only a relatively minor 'blip' on Figure 3.1. In October 1987 the market fell 22% and a further 12% in November but from that month the index continued its upward movement.

3.2.2 Dividend Yields

Dividend yields are defined in Equation 3.4 and are gross of the basic rate of income tax. During the period covered by the study there were a number of changes in the taxation of company profits and dividends. Before 1966, income tax and profits tax were levied on company profits. Dividends were deemed to be paid out of taxed income and a standard rate tax payer incurred no further liability. In 1966 the system was changed and corporation tax was introduced. Companies were charged corporation tax of 35% and in addition dividends were subjected to income tax in the hands of the recipient.

Figure 3-1

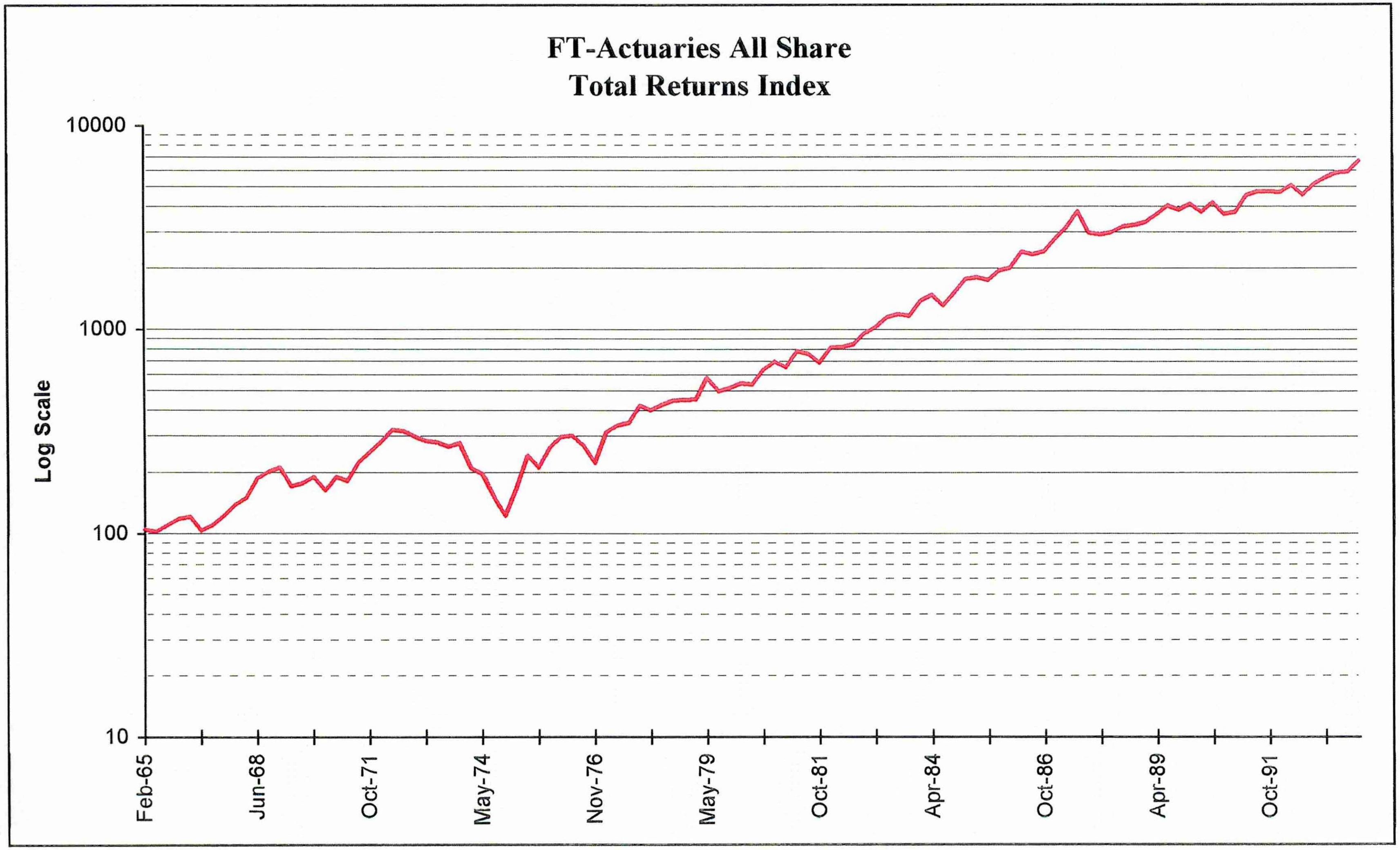
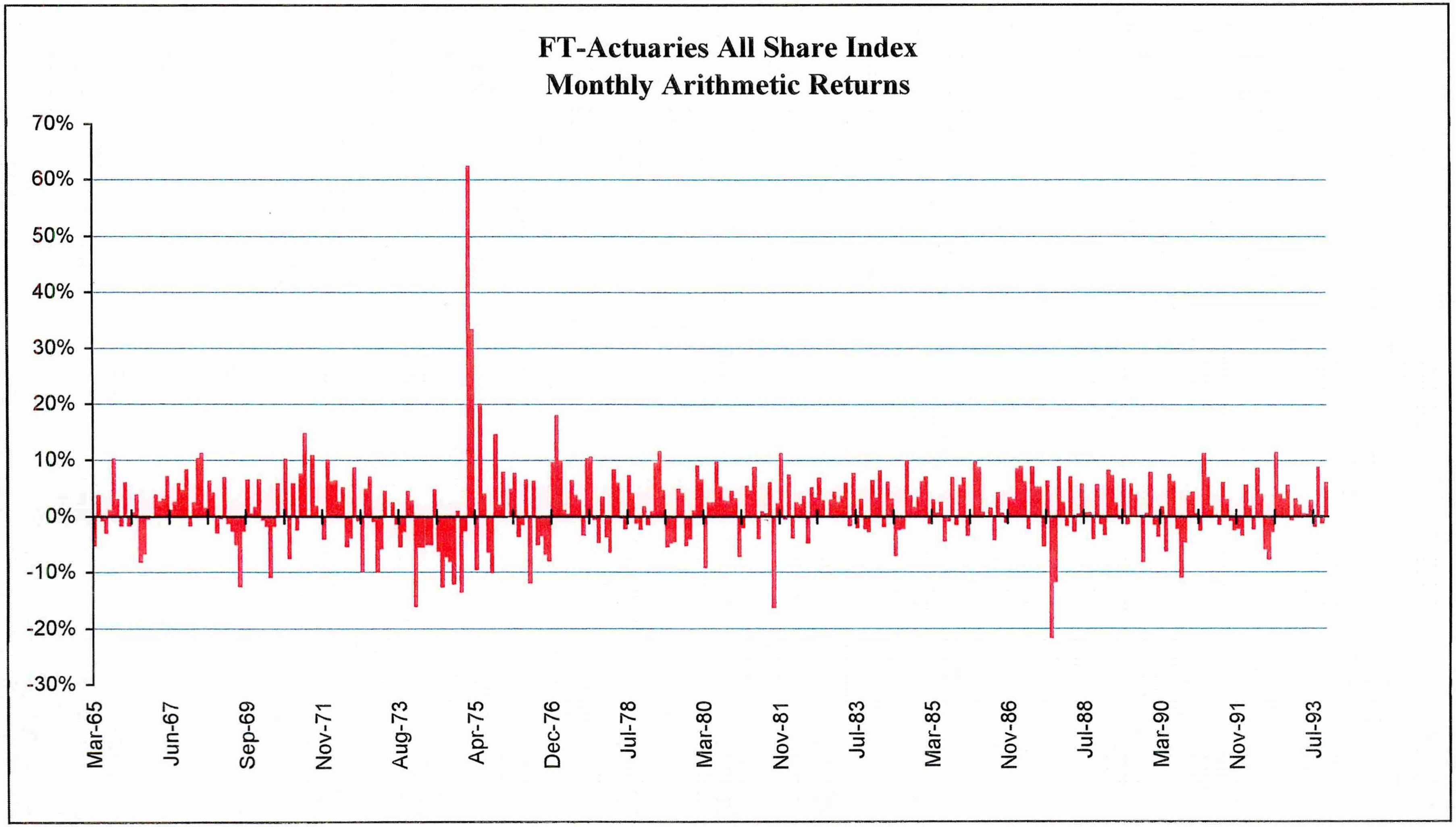

FT-Actuaries All Share
Total Returns Index
10000
1000
100
10
Log Scale
Feb-65
Jun-68
Oct-71
May-74
Nov-76
May-79
Oct-81
Apr-84
Oct-86
Apr-89
Oct-91

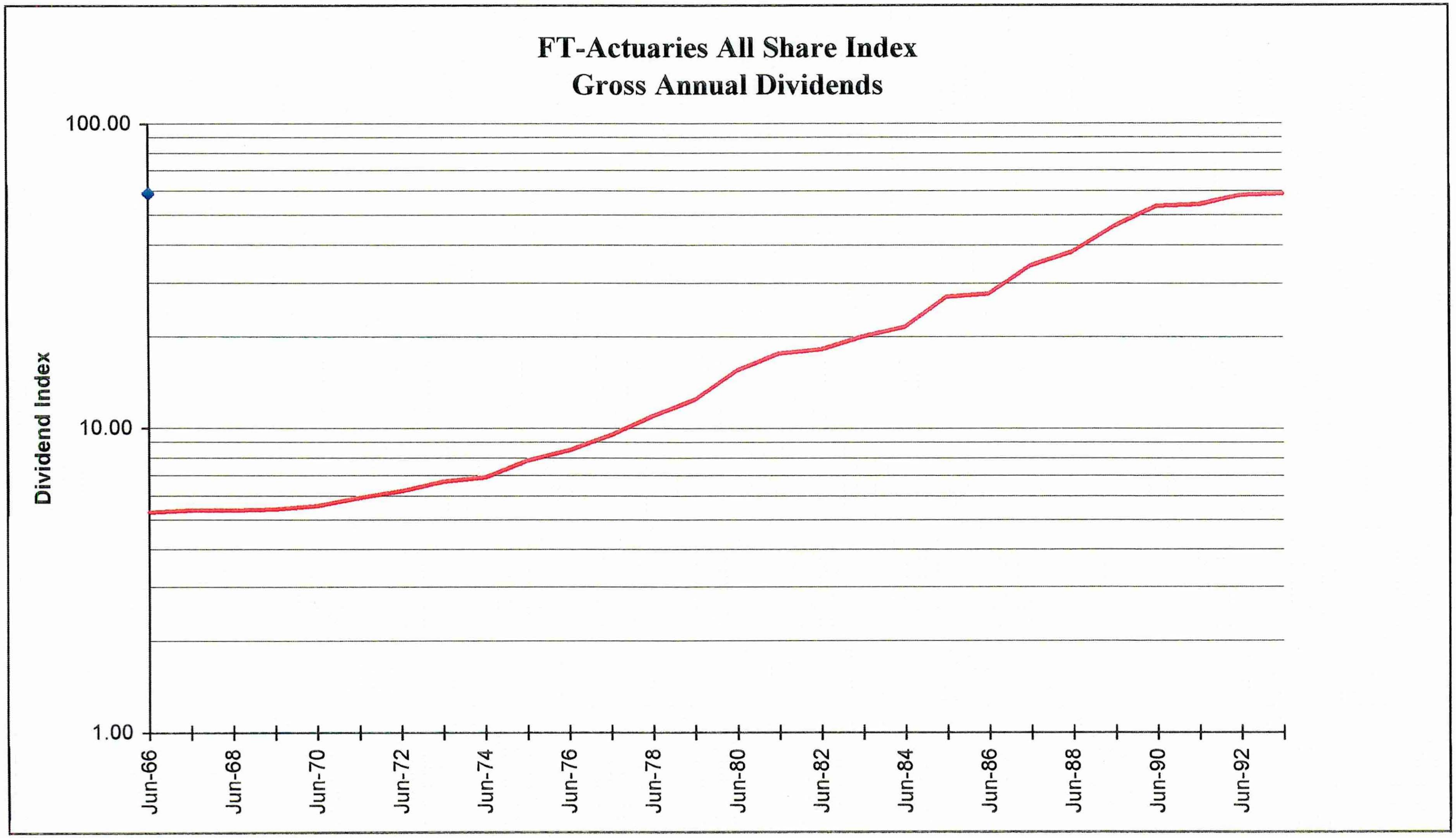
Figure 3-2


FT-Actuaries All Share Index
Monthly Arithmetic Returns
70%
60%
50%
40%
30%
20%
10%
0%
-10%
-20%
-30%
Mar-65
Jun-67
Sep-69
Nov-71
Aug-73
Apr-75
Dec-76
Jul-78
Mar-80
Nov-81
Jul-83
Mar-85
Nov-86
Jul-88
Mar-90
Nov-91
Jul-93

The purpose of the new system was to encourage retentions and to discourage payment of dividends. In 1972 there was a further change in the basis of taxation of company profits. The incoming Conservative Government wished to revert to a system which was fiscally neutral between dividends and retentions and introduced the imputation system of taxation. For the majority of companies this imposed no extra tax burden on dividend payments. Under this system, Advanced Corporation Tax is deducted from dividend payments in settlement of the shareholders' basic rate of income tax. This was later offset against the company's Mainstream Corporation Tax assessment. The imputation system's structure has remained unchanged from 1972 to the present although there have been a number of changes both in the rate of corporation tax and in the basic rate of income tax.

It is difficult to state what, if any, these changes might make to the predictive potential of dividends to forecast stock returns. The first regime, prior to 1966, under which company profits were subject to income tax and profits tax, barely features in the sample period. The second regime whereby dividends were taxed separately from company profits lasted from 1966 to 1972, only a relatively short period in the study. In the period immediately before corporation tax was introduced directors brought forward dividend payments to avoid a double liability to tax. Likewise towards the end of 1972 dividends were withheld from shareholders and paid in early 1973. Any short term retiming of dividends is unlikely to be reflected in the figure for annual dividends which is used in this study. Furthermore, it is well known that directors are reluctant to reduce dividends and hence dividends are a relatively smooth series, as shown in Figure 3.3. Dividend yield is therefore largely determined by prices. Since the imputation system was in place from 1972 to after the end of the sample period, it seems unlikely that the change in the taxation regime would have any effect on the predictive potential of dividend yields. Figure 3.3 shows the annual dividends paid on Financial Times Actuaries All Share Index plotted against a log scale.

Figure 3-3


FT-Actuaries All Share Index
Gross Annual Dividends
Dividend Index
100.00
10.00
1.00
Jun-66
Jun-68
Jun-70
Jun-72
Jun-74
Jun-76
Jun-78
Jun-80
Jun-82
Jun-84
Jun-86
Jun-88
Jun-90
Jun-92

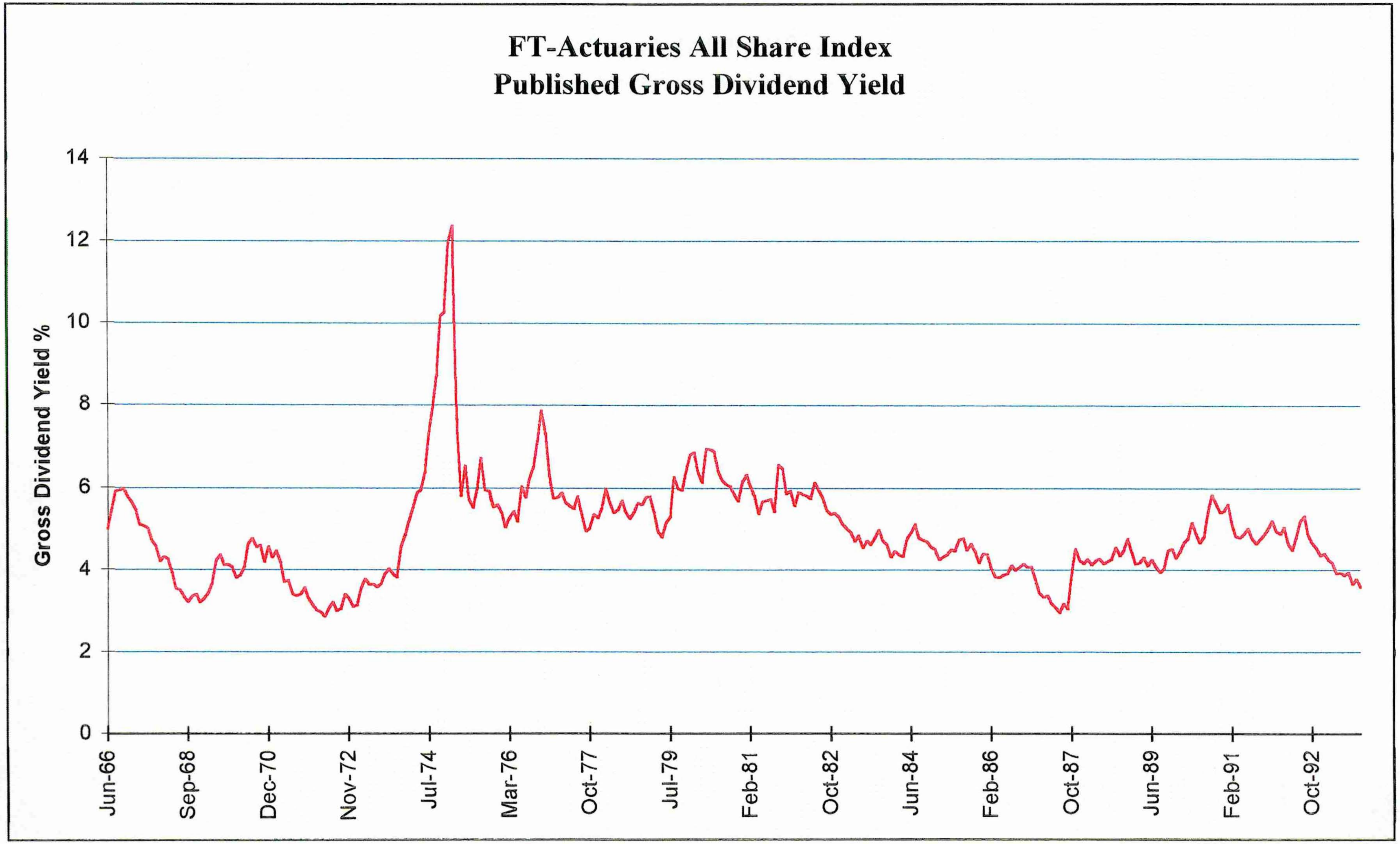
In mid-1966 statutory dividend controls were introduced and these remained in force until early 1979 with the exception of two short periods, the first being from mid-1967 to early 1968 and the second from January 1970 to September 1972. A number of relaxations to the controls were allowed. These were in respect of new issues, take-overs, and recovery situations. Exemptions were granted to investment trusts, close companies, and newly quoted companies, UK companies resident abroad for taxation and exchange control purposes, and other UK companies having 90% of their assets and earnings located abroad.

It is impossible to say what difference the imposition of dividend controls made to the level of dividend payments. Figure 3.3 on page 102, shows clearly that annual dividends are a highly autocorrelated series which in money terms has trended upwards. It is possible that an absence of dividend controls would have enabled companies to have paid higher dividends in the period from the mid-1960's to the late 1970's. There seems to be widespread agreement, however, that dividend controls were not rigidly enforced in the later part of the 1970's.

A graph of the gross dividend yield on the FT-Actuaries index is shown in Figure 3.4 on the next page.

Dividend yields started the sample period at just under 6% and fell to 2.9% in May 1972. Following the oil price shock in 1973, and a hostile political environment in 1974, they rose to a record 12.4% in January 1975. The market rapidly recovered, and by March 1975 yields had fallen to a more normal 5.8%. Dividend yields fell steadily though the early and mid-1980's to a low of 3.1% in September 1987. The crash of October 1987 caused a sharp rise and by November yields had increased to 4.5%. During the recession of the early 1990s yields continued to rise to reach another peak of 5.9% in September 1990 but fell to 3.8% by the end of the sample period. The chart clearly demonstrates that most of the volatility in dividend yields occurred during the unsettled period from the end of 1972 to mid-1975.

Figure 3-4


FT-Actuaries All Share Index
Published Gross Dividend Yield
Gross Dividend Yield %
0
2
4
6
8
10
12
14
Jun-66
Sep-68
Dec-70
Nov-72
Jul-74
Mar-76
Oct-77
Jul-79
Feb-81
Oct-82
Jun-84
Feb-86
Oct-87
Jun-89
Feb-91
Oct-92

3.2.3 Confederation of British Industries Survey Data

Since 1957 the CBI has conducted surveys of its members' expectations concerning a number of key economic variables. In 1958 there were two surveys, from 1959 to 1971, three surveys per year, and from 1972 to the present time, four surveys per year, in January, April, July and October. The surveys take the form of postal questionnaires which are sent to the chief executives of member companies towards the end of the month. They are returned to the CBI by the middle of the following month and the results have, since 1980, normally been published in the last week of the month. The results are therefore based on the expectations of a large number of senior executives who may have information both on their own company's prospects and on the business conditions in their industries, which is not available to the market as a whole. Since the surveys are published within two weeks of the closing date for replies, and only 4 weeks after the questionnaires reach the respondents, the CBI claim that they are an up-to-date guide to the state of manufacturing industry and a useful indicator of movements which will be shown later in the official estimates, (Wood 1992).

Respondents to the surveys are invited to tick boxes which categorise replies into, more, same or less. This procedure has a number of advantages. The surveys are easy to complete, a high response rate is achieved and the questionnaires are answered by senior members of staff. In a survey of a sample of regular respondents Price (1983) found that 60% of replies were signed by the chairman, managing director, finance director or other director. A further 10% were signed by the company secretary and the remainder by other senior officials, for example group financial controller or general manager. Currently the response rate is between 40 and 50%.

The survey, a copy of which appears in Appendix 16, includes 16 questions and it is summarised in the Table 3.1 below:

Table 3.1

Abbreviated Version of CBI Questionnaire

1	Optimism over the general business situation, more, same, less	**Included**
2	Optimism over export prospects more, same, less	Excluded
3	More, same or less capital expenditure on	
	a plant	**Included**
	b buildings	**Included**
4	Is your present level of output below capacity, yes, no?	Excluded
5	Present order book, above normal, normal, below normal	Excluded
6	Numbers employed, up, same, down	Excluded
7	Volume of total new orders, up, same, down	
	a trend over last 4 months	
	b expected trend over next 4 months	**Included**
8	Volume of output, up, same, down	Excluded
	a trend over last 4 months	
	b expected trend over next 4 months	
9	Volume of deliveries, up same down	Excluded
10	Volume of stocks, up, same, down	Excluded
11	Average costs per unit of output, up, same , down	Excluded
12	Average prices, up, same, down	Excluded
13	Month's production accounted for by present order book	Excluded
14	Factors likely to limit output	Excluded
15	Factors likely to limit export orders	Excluded
16	Is your capacity - more than adequate, adequate, less than adequate?	Excluded

Any decision as to which variables to include in the study is clearly judgmental. Selection of a large number of variables invites the criticism of data mining and introducing a search bias. The arguments against the use of R^2 and the t statistic as tools for the selection of variables are well summarised in Charemza and Deadman

(1992). On the other hand, the choice of a limited number of variables can lead to the charge of throwing away valuable information.

In these circumstances, four variables were chosen which appeared on an *a priori* assessment to contain information which was likely to indicate the future prospects of firms. An obvious question for inclusion was the first, 'Are you more or less optimistic about the general business situation in your industry than you were 4 months ago'. Question 3 which deals with planned changes in the level of capital expenditure on buildings and on plant, was included, since changes in expected capital expenditure might include private information regarding positive net present values of future projects and also indicate changes in business confidence. Question 7 which concerns the expectations on the levels of future orders was also included since these were more likely than any other factors to impact on future profitability. Since the answers to any of these four questions might have some predictive ability, they were all included in the study.

The precise wording[4] of the questions whose responses were included in this thesis were as follows:

Question 1. Are you more, or less optimistic than you were four months ago about THE GENERAL BUSINESS SITUATION IN YOUR INDUSTRY.

Question 3 Do you expect to authorise more or less capital expenditure in the next 12 months than you authorised in the last 12 months on:

a buildings

b plant and machinery

Question 7 **Excluding seasonal variations,** . . . what are the expected trends over the NEXT FOUR MONTHS with regard to

a Volume of total new orders, up same, down.

4 Upper case and bold are as they appear in the CBI surveys.

The replies to the CBI questionnaires are weighted by the size, measured by number of employees, of the firms responding to the survey and totalled. A score is computed by deducting the weighted figures for less from the weighted figures for more, to give what the CBI describe as the 'balance'; and this figure is included as an explanatory variable in the return forecasting regressions. Responses reporting no change in expectations are excluded from the analysis. The computation in the balance figure is shown in Equation (3.8),

$$\Delta Q_t = \sum w_i{}^{+}\Delta q_{ti}^{+} - \sum w_i{}^{+}\Delta q_{ti}^{-} \qquad \textbf{(3.8)}$$

where ΔQ_t is the balance of firms reporting more over those reporting less expressed as a percentage, w_i is a weighting depending on the relative size of respondent i to the total responding and Δq_{ti} is the reply of respondent i indicated with a + where the reply is more and a - where the reply is less, (see Thomas (1995)).

A peculiar feature of CBI survey data is that responses are ordinal. Respondents are not required to estimate the expected change in a variable but merely to indicate the change in its direction. In the rational expectations literature, a variety of methods have been used to convert the ordinal responses to those which might hypothetically have been given if the respondent had been asked to quantify his (or her) reply. Pesaran (1987) compares 4 methods of conversion of expectations of price increases with each other and also with the actual price increases as reflected in the index of 'Wholesale Prices of Manufactured Goods', published by the Central Statistical Office. Pesaran found that each method of conversion produced series which were very closely correlated with one another, coefficients ranging from between 0.940 to 0.997. The methods were also closely correlated with the actual rates of inflation which were subsequently published by the CSO, with coefficients of between 0.834 and 0.904.

Studies of rational expectations test whether managers make the optimal use of available data in forming their expectations. In this thesis the problem is different. Businessmen are not asked to forecast future returns, and to attempt to find such a conversion factor by regressing future returns on CBI data would pre-empt the purpose of this study. Furthermore, only the raw CBI balance figure is available to the market place. For this reason, the balance figures published by the CBI are used without further adjustment.

It is interesting to note the CBI position on the use of the balance figure rather than a more sophisticated transformation.

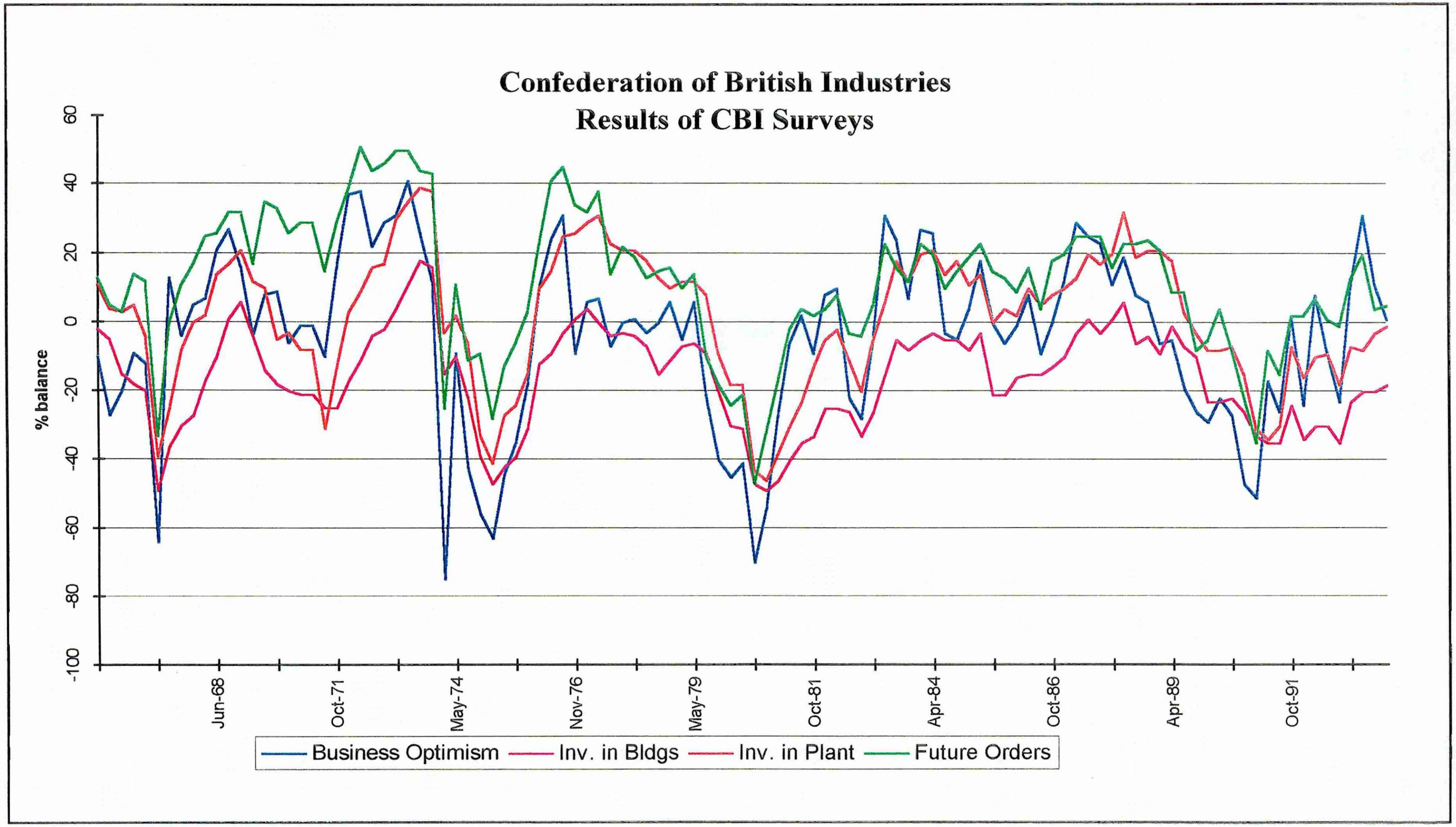
> *Despite the quantity of research that has been carried out into the use of more sophisticated variables than the balance to represent survey results, none of the methods suggested has seemed to offer sufficient improvements in understanding to justify their disadvantages in complexity and cost in comparison with the balance. For most purposes, therefore, CBI staff analysis of the Trends results has tended to use balances.* (McWilliams (1983).)

From an inspection of Figure 3.5 on the following page it is clear that all 4 measure of business confidence are closely correlated. The correlation matrix of the 4 CBI series is shown in Table 3.2 below.

Table 3.2
Correlation Matrix
CBI Series

	CBIA Business Optimism	*CBIB Investment in buildings*	*CBIC Investment in plant*	*CBID Future orders*
CBIA	1.000	0.658	0.697	0.882
CBIB		1.000	0.962	0.751
CBIC			1.000	0.782
CBID				1.000

Figure 3-5



Confederation of British Industries
Results of CBI Surveys
% balance
60
40
20
0
-20
-40
-60
-80
-100
Jun-68
Oct-71
May-74
Nov-76
May-79
Oct-81
Apr-84
Oct-86
Apr-89
Oct-91
Business Optimism
Inv. in Bldgs
Inv. in Plant
Future Orders

The series for investment in buildings and investment in plant are very closely correlated. Since all the correlation coefficients were high, above 0.6, it was decided to avoid multicollinearity by including each CBI variable in turn in the regressions. Thus Equation 3.2 becomes,

$$TR_{t,\, t+T} = \alpha_T + \beta_T CBIA_t + u_{t,\, t+T} \tag{3.9}$$

$$TR_{t,\, t+T} = \alpha_T + \beta_T CBIB_t + u_{t,\, t+T} \tag{3.10}$$

$$TR_{t,\, t+T} = \alpha_T + \beta_T CBIC_t + u_{t,\, t+T} \tag{3.11}$$

$$TR_{t,\, t+T} = \alpha_T + \beta_T CBID_t + u_{t,\, t+T} \tag{3.12}$$

and Equation 3.5

$$TR_{t,\, t+T} = \alpha_T + \beta_T DY_t + \beta_T CBIA_t + u_{t,\, t+T} \tag{3.13}$$

$$TR_{t,\, t+T} = \alpha_T + \beta_T DY_t + \beta_T CBIB_t + u_{t,\, t+T} \tag{3.14}$$

$$TR_{t,\, t+T} = \alpha_T + \beta_T DY_t + \beta_T CBIC_t + u_{t,\, t+T} \tag{3.15}$$

$$TR_{t,\, t+T} = \alpha_T + \beta_T DY_t + \beta_T CBID_t + u_{t,\, t+T} \tag{3.16}$$

where,

$CBIA$	=	the CBI balance of business optimism series,	question 1
$CBIB$	=	the CBI balance of investment in buildings	question 3a
$CBIC$	=	the CBI balance of investment in plant	question 3b
$CBID$	=	the CBI balance of future orders	question 7b

3.2.4 Time Horizon and Organisation of the Regressions

The sample period was been limited by the availability of return data from Datastream, and the publication of CBI data. Daily returns are available from Datastream from 1 January 1965. There were two CBI surveys in 1958, from 1959 to 1971 there were three surveys per year, and from 1972 to the present time, four surveys per year, in January, April, July and October.

From an econometric view point the obvious time to start the sample period would have been in 1972 when 4 surveys were published at approximately quarterly intervals. This would have resulted in losing 7 years of data, however; and it was therefore decided to start the sample period in 1965. The sample period ends in October 1993.

A decision was made to avoid as far as possible the use of overlapping observations since these lead to moving average errors in the residuals and, more importantly, they violate the assumption that observations are independent.[5]

For quarterly returns a single series was derived. Returns were measured for the three months between the quarterly surveys. For 6 months returns two series were generated. The first used the information in the January and July surveys and the second that in the April and October surveys. For annual returns, a series was generated for each of the quarterly surveys, and this procedure was also followed for 24 and 36 months returns.

This procedure results in a total of 15 series, one quarterly, two 6 monthly, four annual and four each of 2 and 3 year horizons. Since there are 5 explanatory variables, dividend yield and each of the four CBI variables, there are a total of 75 univariate regressions. In addition, returns are regressed against dividend yields and each of the 4 CBI series in turn as in Equations 3.13 to 3.16, which results in 60 multiple regressions. This totals 135 regressions. Regressions with quarterly, six monthly, and annual time horizons have non-overlapping observations. The short sample period forces the adoption of overlapping observation for time horizons greater than one year. The plan of the regressions appears in Table 3.3 on the next page.

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5 See the comments in McQueen (1992), page 4.

Table 3.3
Organisation of the Regressions

Forecasting horizon	*Series number*	*Number of observations*	*Month of CBI survey*
Non Overlapping Observations			
Quarterly returns		105	January, April, July, October
6 months returns	1 2	52	January, July April, October
12 months	1 2 3 4	26	October April January July
Overlapping Observations			
24 months	1 2 3 4	26	October April January July
36 months	1 2 3 4	26	October April January July

3.2.5 Split Sample Period

To test the structural stability of the regressions, the sample period was split into two equal length periods. This follows the methodology used by other researchers. See for example Goetzmann and Jorion (1993) and (1995). The first period starts using data from January 1965 and ends in 1979 or 1980, and the second period starts in 1980 or 1981 and runs to 1992 or 1993. Precise sample periods are determined by the dates of publication of the CBI surveys. Details appear in Appendix 15.

3.3 Methodology - Classical Ordinary least Squares

3.3.1 Criteria for a Good Model

Harvey (1989) summarises the following qualities for a good econometric model. They are:

1) *Parsimony. A simple model is preferred, other things being equal, to a more complicated model.*

2) *Data Coherence. Diagnostics should be used to check that the residuals are approximately random.*

3) *Consistency with prior knowledge. The model should be consistent with prior knowledge.*

4) *Data Admissibility. A model should be unable to predict values which violate definitional constraints. For example some variables cannot be negative.*

5) *Structural stability. As well as providing a good fit within the sample, a model should also give a good fit outside the sample. In order for this to be possible, the parameters should be constant within the sample period and this constancy should carry over into the post sample period.*

6) *Encompassing. A model is said to be encompassing if it can explain the results given by a rival formulation.*

3.3.2 Classical Ordinary Least Squares[6]

The linear multiple regression model can be written as

$$y_t = \alpha + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots \beta_n x_{nt} + u_t \qquad \textbf{(3.17)}$$

where y_t is the tth observation on the dependent variable, x_{it} is the tth observation on the ith independent variable, u_t is a disturbance term and $\beta_1, \cdots, \beta_n$ are unknown parameters and α is normally a constant.

The explanatory variables are assumed to be exogenous. For statistical purposes this means that they can be treated as though they were non-stochastic or fixed in repeated samples. This is an important assumption which has already been discussed in the literature review, and which is violated by the use of dividend yields as an explanatory variable, see Goetzman and Jorion (1993) and Nelson and Kim (1993).

Multiple regression can be formulated in matrix notation. Let $x_t = (x_{1t}, x_{2t}, \ldots, x_{kt})'$ be the k x 1 vector of observations on the independent variables at the time t, and let $\beta = (\beta_1, \cdots, \beta_k)'$ be the corresponding k x 1 vector of regression parameters. A more concise formulation of the model in terms of vector notation is given by

$$y_t = x_t'\beta + u_t \quad , \quad t = 1, \ldots\ldots, T \qquad \textbf{(3.18)}$$

$$X = \begin{pmatrix} 1 & x_{21} & \cdots & x_{k1} \\ 1 & x_{22} & \cdots & x_{k2} \\ \vdots & \vdots & & \vdots \\ 1 & x_{2T} & \cdots & x_{kT} \end{pmatrix} = \begin{pmatrix} x_{1'} \\ x_{2'} \\ \vdots \\ x_T' \end{pmatrix}$$

If $u = (u_1, \ldots, u_t)'$ denotes the T x 1 vector of disturbances, the complete model may be expressed as

$$y = X\beta + u \qquad \textbf{(3.19)}$$

The classical linear regression model satisfies the following assumptions:

1 the explanatory variables are fixed

6 The notation in this section 3.3.2 and 3.3.3 is from Harvey (1990) page 37, 38 and 45.

2 the rank of X is equal to k, in other words no exact linear relationship exists between two or more independent variables.

3 the disturbances are uncorrelated, each having a zero mean and a constant but finite variance.

Suppose $\hat{\beta}$ is an estimator of the parameter vector β. Corresponding to this vector is a set of T residuals, defined by $y_t - x_t' \hat{\beta}$, $t = 1, \ldots, T$. The ordinary least squares estimator is obtained by choosing $\hat{\beta}$ such that the residual sum of squares is minimised.

3.3.3 Properties of the Least Squares Estimator

The Gauss Markov Theorem states that when a regression model satisfies classical assumptions, the OLS estimator is the best linear unbiased estimator (BLUE) of β in the sense that the covariance matrix of any other linear unbiased estimator exceeds that of b, the least squares estimator, by a positive semi-definite matrix.

3.3.4 Tests of Significance of the Variables and of the Regression

A number of tests are available which assess the significance of the variables individually and of the regression as a whole. In this section the following notation is used.

$\hat{\beta}$	the estimated regression parameter,
β_0	the hypothesised value of β,
$S_{\hat{\beta}}$	the estimate of its standard error,
$\mathbf{y}$	the vector of the dependent variable,
$\tilde{\mathbf{y}}$	the vector of deviations from the mean of the independent variable,
$\mathbf{e}$	the vector of residuals,
T	the number of observations and
K	the number of regressors.

The t statistic

The statistical significance of the regression parameter can be tested by calculating the t statistic. For a two variable model the t statistic is given by:

$$t_{n-2} = \frac{\hat{\beta} - \beta_0}{s_{\hat{\beta}}} \qquad \textbf{(3.20)}$$

The standard econometric packages also produce the exact statistical significance, associated with an econometric result. This is the probability, p value, that the observed statistic occurs by chance and it is usual to look for p values of less than 0.05. In other words the result should be significant at the 5% level or less.

In addition, where heteroscedasticity may be present in the residuals the estimator of heteroscedastic-consistent standard errors developed by White (1980) is available.

The F- Test

A test of the joint significance of all the variables in a regression model may be based on an F-distribution. When the null hypothesis is true, the statistic

$$\frac{\tilde{\mathbf{y}}'\tilde{\mathbf{y}} - \mathbf{e}'\mathbf{e}}{(K-1)} \Bigg/ \frac{\mathbf{e}'\mathbf{e}}{(T-K)} \qquad \textbf{(3.21)}$$

has an F- distribution with $(T- K)$ degrees of freedom.

Coefficient of Multiple Correlation

A test of the overall significance of the regression is given by the coefficient of multiple correlation.

$$R^2 = 1 - \frac{\mathbf{e}'\mathbf{e}}{\tilde{\mathbf{y}}'\tilde{\mathbf{y}}} \qquad \textbf{(3.22)}$$

which lies in the range $0 \leq R^2 \leq 1$, and it may be interpreted as measuring the proportion of the variance of the independent variable which is explained by the regression. R^2 cannot decrease and will usually increase, if additional variables are introduced into the set of regressors and therefore a correction for the number of variables is required. $\overline{R}^2$,see Theil (1958), makes such an allowance and is defined:

$$\overline{R}^2 = 1 - \left(\frac{\mathbf{e}'\mathbf{e}}{(T-K)} \Big/ \frac{\tilde{\mathbf{y}}'\tilde{\mathbf{y}}}{(T-1)} \right) \qquad \textbf{(3.23)}$$

3.3.5 Alternative Measures of Model Selection.

Some authors have argued that $\overline{R}^2$ does not penalise sufficiently for loss of degrees of freedom when additional variables are added to the regression. (See for example Amemiya (1985) p. 50-51).) A number of alternative criteria for model selection have been proposed in the literature such as Akaike Information criterion (AIC), (see Akaike (1973)) and Schwarz's Bayesian Information criterion (BIC), (see Schwarz (1978))[7]. There are several equivalent formulations of these models: the ones below are those given in the *RATS* manual and which have been used for calculating the test statistics.

AIC	$T \log(\mathbf{e}'\mathbf{e}) + 2K$	**(3.24)**
BIC	$T \log(\mathbf{e}'\mathbf{e}) + K(\log T)$	**(3.25)**

The Schwarz criterion places a heavier penalty on the additional parameters and so it will never chose a model with a larger number of regressors than Akaike. Unfortunately there is no one overall agreed method. Greene (1993) states,

> *Although intuitively appealing, these measures are a bit unorthodox in that they have no firm basis in theory.* Greene (1993) page 245.

Nevertheless they are widely used as model selection criteria, as, for example, by Pesaran and Timmermann (1995).

7 There are, of course, other criteria that could be used for choosing the subset of regressors. Prominent examples are Mallows (1973) Cp criterion and Amemiya's (1980) prediction criterion. In this thesis use is made of the criteria most commonly used.

3.3.6 Diagnostic Tests of the Regression Results

A number of tests are available to examine regression residuals. Tests for serial correlation include the traditional Durbin Watson (see Durbin and Watson (1969)) test. This examines residuals only for first order autocorrelation and is not valid when a lagged dependent variable is used as an explanatory variable. In this case the *H* test, of Durbin (1970) is valid. Lagrange multiplier tests (see Godfrey (1978) and Breusch (1978)) are valid in the presence of a lagged dependent variable used as an explanatory variable and can also test for higher orders of serial correlation. Finally the Ljung-Box *Q*-statistic (see Lung Box (1978)) provides a portmanteau statistic of autocorrelation for a number of specified lags.

Other procedures exist for testing for heteroscedasticity, non normality, lack of functional form, and structural stability of the regression coefficients. While many of these tests have good properties in large samples, many lack power in the sample sizes located in this thesis and as a result misleading inferences can be drawn from their use. They are often regarded as diagnostic tests rather than tests of mis-specification. Harvey states,

> *Such tests are often termed large sample tests. This terminology indicates that the choice of the critical region can only be justified on an asymptotic basis, in contrast to the situation for exact tests. However it must be stressed that this consideration by no means precludes the use of large sample tests when the sample size is small.*
> Harvey (1990) page 156.

The residuals of the classical ordinary least squares regressions were subjected to the following diagnostic tests.

To test for serial correlation in the regression residuals three tests were used. Firstly, the Durbin Watson (1969) test was computed since it is widely used and thoroughly understood. Simulations by Granger and Newbold (1986)[8] have shown that the spurious regression problem will arise relatively infrequently if the analyst accepts only those regressions where the t or F statistics are significant and the Durbin-

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8 See page 211.

Watson Statistic does not indicate the presence of serially correlated errors. The test statistic is given by,

$$DW = \sum_{t=2}^{T}(e_t - e_{t-1})^2 \Big/ \sum_{t=1}^{T} e_t^2 \qquad \textbf{(3.26)}$$

The Lagrange multiplier test for serial correlation is valid in the presence of a lagged dependent variable. The value of the chi squared statistic is calculated from $T\left(1 - \frac{\mathbf{e}'\mathbf{e}}{\mathbf{y}'\mathbf{y}}\right)$ in the model

$$\mathbf{e} = \alpha + \mathbf{x}\beta + \mathbf{e}_{t-1\ldots t-n} + u_t \qquad \textbf{(3.27)}$$

Finally the Lung Box Q statistic, (Ljung Box (1978)), which is a portmanteau test for higher orders of correlation, is quoted. This is given by

$$T(T+2)\left(\sum_{j=1}^{M} \frac{r_j^2}{T-j}\right) \qquad \textbf{(3.28)}$$

where r_j is the jth lag autocorrelation of the residuals. M is the number of autocorrelations used, and is selected according to the formula $M = \min(T/4, 3\sqrt{T})$, with a maximum value for M of 36. The large sample distribution of Q is asymptotically χ^2 under the null hypothesis. It has low power against specific alternatives such as first order serial correlation, but can detect higher order autocorrelations.

Stock returns are well known to be both non-normal and heteroscedastic. In these circumstance heteroscedasticity may be imparted to the residuals. The Breusch-Pagan (1979) test has been adapted in Koenker (1981) to be robust to non-normality of the residuals. The chi-square statistic, TR^2 is calculated from the model.

$$\mathbf{e}'\mathbf{e} = \alpha + \mathbf{x}\beta + u_t \qquad \textbf{(3.29)}$$

where u_t are the disturbances, $\mathbf{x}_t$ is a matrix of observations on a set of K independent variables.

3.3.7 Tests of Input to the Regression

Conventional theory for least squares estimation assumes stationarity of the explanatory variables. A stationary time series is defined as one in which for any value of *t*, the series has a zero mean and a constant variance and is uncorrelated with any other variable in the sequence. A strongly stationary series is one which is, in addition, normally distributed. (See Harvey (1990), page 23.) A number of authors, of whom Phillips (1986) and Granger and Newbold (1974) are considered to be the leading authorities, have shown that when two unrelated but integrated series[9] are regressed against one another spurious correlations may result. These spurious correlations grow with sample size. Thus t and F statistics for the null hypothesis are grossly misleading. Information that such a regression is mis-specified is provided from the test of residual autocorrelation. This underlines the importance of subjecting the residuals of a regression to the tests of mis-specification which have previously been discussed.

Historically, there have been two methods of transforming data series to make them stationary. One has been to include a deterministic time trend in the regression and the other, to difference the data. If the data can be made stationary by the first method it is known as trend stationary and if it can be made stationary by differencing it is known as difference stationary. An important difference between the two series is that a difference stationary process has a variance which grows over time while the variance of a trend stationary process should remain constant over time. It should be noted at this stage that there is no overwhelming reason to suppose that economic time series can be made stationary by differencing. (See Harvey (1990) p.12.)

To detect non-stationarity the researcher using the Box Jenkins approach, should first plot his data. Most economic series show a gradual increase over time and so the means for different subsets of the data will increase, and the series is not stationary. The second test is to examine the correlogram i.e. the plot of the autocorrelation coefficients at a number of lags. Ideally, there should be no significant autocorrelation coefficients. A series can be considered stationary, however, if the size

9 An integrated series is one which can be made stationary by differencing. If first differencing is sufficient to make it stationary it is said to be integrated to the order of one or I(1). If it is stationary without differencing it is said to be an I(0) series.

of the correlation coefficients falls away quickly. Thirdly, we can test the joint hypotheses that all correlation coefficients are zero by the Ljung Box (1978) *Q* test.

More recently, further tests which enable the researcher to differentiate between a trend stationary and a difference stationary series have been developed. A series is difference stationary if it can be made stationary by first differencing and a trend stationary process is one that can be made stationary by regressing it against a linear trend.

These tests are known as unit root tests and were developed in Dickey and Fuller (1979) and (1981), and consist of estimating the model,

$$y_t = \alpha + \rho y_{t-1} + \beta t + \varepsilon_t \qquad \textbf{(3.30)}$$

where t is a time trend.

If $\rho = 1$, $\beta = 0$, it belongs to the difference stationary class, and if $|\rho| < 1$ to the trend stationary class. The term unit root is derived from the test for ρ, the autoregressive parameter being equal to 1. As has already been discussed, there are well known biases when regressing a series against its own lagged value. Dickey and Fuller (1981) have derived, by Monte Carlo simulation, the critical values of the F distribution in these circumstances. The figures at the 5% level are approximately double those given in the normal F tables.

It is possible that the error process in (3.30) above is not white noise and that the error term may be autocorrelated. To deal with this problem "augmented" Dickey Fuller (ADF) tests have been developed, (Said and Dickey (1980)). The tests involve estimating the equation,

$$y_t = \gamma + \delta t + \alpha y_{t-1} + \sum_{j=1}^{k} \theta_j \Delta y_{t-j} + e_t \qquad \textbf{(3.31)}$$

It is left to the judgement of the researcher to determine the number of lags representing the order of the autoregressive process.

Testing for unit roots is a relatively new and rapidly developing subject. The difference between a stationary and non-stationary series is not absolute but is a matter of degree. The researcher should be aware that if he regresses an I(1) series, a series which is integrated to the order of 1, against another I(1) series, spurious regressions will result in large samples. These, however, can easily be detected by the standard tests for autocorrelation in the residuals. Phillips (1986) shows that as the sample size tends towards ∞ the Durbin Watson statistic tends towards zero. In smaller samples spurious regressions are less likely to result, but in these cases the standard tests of mis-specification may not prove sufficiently powerful to alert the researcher to spurious results. Few series are perfectly stationary. The difference between an I(0) series and an I(1) series is one of degree. When the researcher is dealing with small samples he must use the appropriate numerical techniques (Monte Carlo and randomisation) which do not rely on the standard distributions to determine the significance of the appropriate test statistic.

In this thesis a number of steps are taken to detect serial correlated residuals. Firstly, the autocorrelation coefficients for the dependent and independent variables were calculated, as were the Ljung Box Q statistics. Secondly, regression residuals were examined for serial correlation using the Durbin Watson, the Lagrange Multiplier, and the Box Q tests.

Where serially correlated residuals are found, either the data must be transformed by differencing or by detrending, as appropriate; or one of the econometric methods which are available for correcting the biases caused by the serially correlated residuals must be applied.

In this research, the short data period available forces one to use overlapping observations for time horizons in excess of one year. These are well known to cause a moving average error in the residuals. The usual corrections to the standard errors of the regression coefficients are computed using the method proposed by Hansen and Hodrick (1980) in which the autocovariances are estimated from the data with the modification due to White (1980) and Hansen (1982) that allows for conditional heteroscedasticity. These are generally described as 'Generalised Method of Moments' or GMM estimators. Where the variance covariance matrix of the estimated coefficients is not positive definite, the *RATS* econometric package applies the method in Newey West (1987). As is widely known, (see for example Goetzmann and Jorion (1993) and Mudambi and Taylor (1995), these adjustments, while being asymptotically valid, have poorly understood small sample properties and are unlikely to give an adequate correction to the standard errors. In view of these difficulties the researcher needs to investigate the small-sample characteristics of these regressions by numerical analysis.

3.4 Methodology - Simulation

3.4.1 Introduction

The results of ordinary least squares regressions of returns on dividend yields are known to suffer from a number of shortcomings. Firstly, since dividends are a highly autocorrelated series, dividend yield is determined by price. Price, P_t, also determines returns as in Equation 3.32 below. If Equation 3.1 is reformulated to show both the capital return and the income return on the left hand side we have,

$$\left(\frac{P_{t+1} - P_t + GADIV_{t+1}}{P_t}\right) = \alpha + \beta \frac{GADIV}{P_t} + u_t \qquad \textbf{(3.32)}$$

where *GADIV* is the gross annual dividend.

Thus a component of the dependent variable P_t enters the equation as an explanatory variable. Since annual dividends are a highly autocorrelated series[10], the independent variable, dividend yield, is effectively determined by P_t. But, P_t also determines return, on the left hand side of the equation. Return forecasting regressions therefore may suffer from the well-known bias when a lagged dependent variable is used as a regressor. Kendall (1973), shows that the OLS estimate, although consistent, is centred at values less than 0 in finite samples, even when the slope is truly zero. Dickey and Fuller (1979) tabulate by simulation new values for the OLS t statistic under the null. The downward bias is shown to be substantial in small samples, and is of the order of (-4/n) where n is the sample size.

This problem is not confined to dividend yields. Nelson and Kim (1993) have argued that any regressor which is endogenous to the system which determines return

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10 The first order correlation coefficient for the sample data at monthly intervals is as high as 0.99.

will in general be biased. The responses of businessmen to CBI surveys are likely to be determined jointly with stock returns since unanticipated changes in macro economic factors such as interest or exchange rates will affect both series. While it is desirable to allow for the same biases in t statistics for CBI data as for dividend yields, it is not easy to model explicitly the effect on regressions involving CBI data as it is for dividend yield.

The other econometric problems which influence the results of regressions of returns on dividend yields include serial correlation in the residuals caused by the use of overlapping observations and lack of normality and heteroscedasticity in the return series. In the following sections a methodology is described which is robust to the these problems.

3.4.2 Methodology Applied to Ordinary Least Squares

To accommodate the biases caused by a lagged component of the independent variable appearing as an explanatory variable the Goetzmann and Jorion (1993) simulation methodology was followed to develop a model in which dividends could be generated as a function of the past history of returns. Daily values of The Financial Times-Actuaries All Share total return index and the capital return index were extracted from Datastream for the period from 1 January 1965 to 22 September 1994.

Total returns for the periods between the CBI surveys were calculated as in Equation 3.3 which is reproduced below.

$$TR_t = \frac{TRI_t - TRI_{t-1}}{TRI_{t-1}} \qquad \textbf{(3.33)}$$

where TRI_t is the total return index and TR_t is the total returns at period t. Capital returns are constructed in a similar manner from the FTA All Share price Index.

$$CR_t = \frac{PI_t - PI_{t-1}}{PI_{t-1}} \qquad \textbf{(3.34)}$$

where PI_t is the price index at period t and CR_t is the capital return series. Income returns, IR_t were calculated,

$$IR_t = \left[\frac{(1+TR_t)}{(1+CR_t)} - 1\right] \qquad \textbf{(3.35)}$$

Adjusted income return AIR_t was then calculated to allow for the unequal periods between the CBI surveys before 1972 as follows.

$$AIR_t = \frac{IR_t}{DA} \times \frac{365}{12} \qquad \textbf{(3.36)}$$

where DA is the number of days between CBI surveys.

A price series starting at 100, which excluded the reinvestment of dividends, was formed by setting P_0 at 100, then recursively computing P_t

$$P_t = P_{t-1} \times (1 + CR_t) \qquad \textbf{(3.37)}$$

Monthly gross dividends, GD_t were then computed

$$GD_t = AIR \times P_{t-1} \qquad \textbf{(3.38)}$$

An annual series of gross dividends, $GADIV$, was then calculated,

$$GADIV = GD_t + GD_{t-1} + \ldots.\ GD_{t-11} \qquad \textbf{(3.39)}$$

Gross dividend yield, GDY was then calculated,

$$GDY = \frac{GADIV}{P_t} \times 100 \qquad \textbf{(3.40)}$$

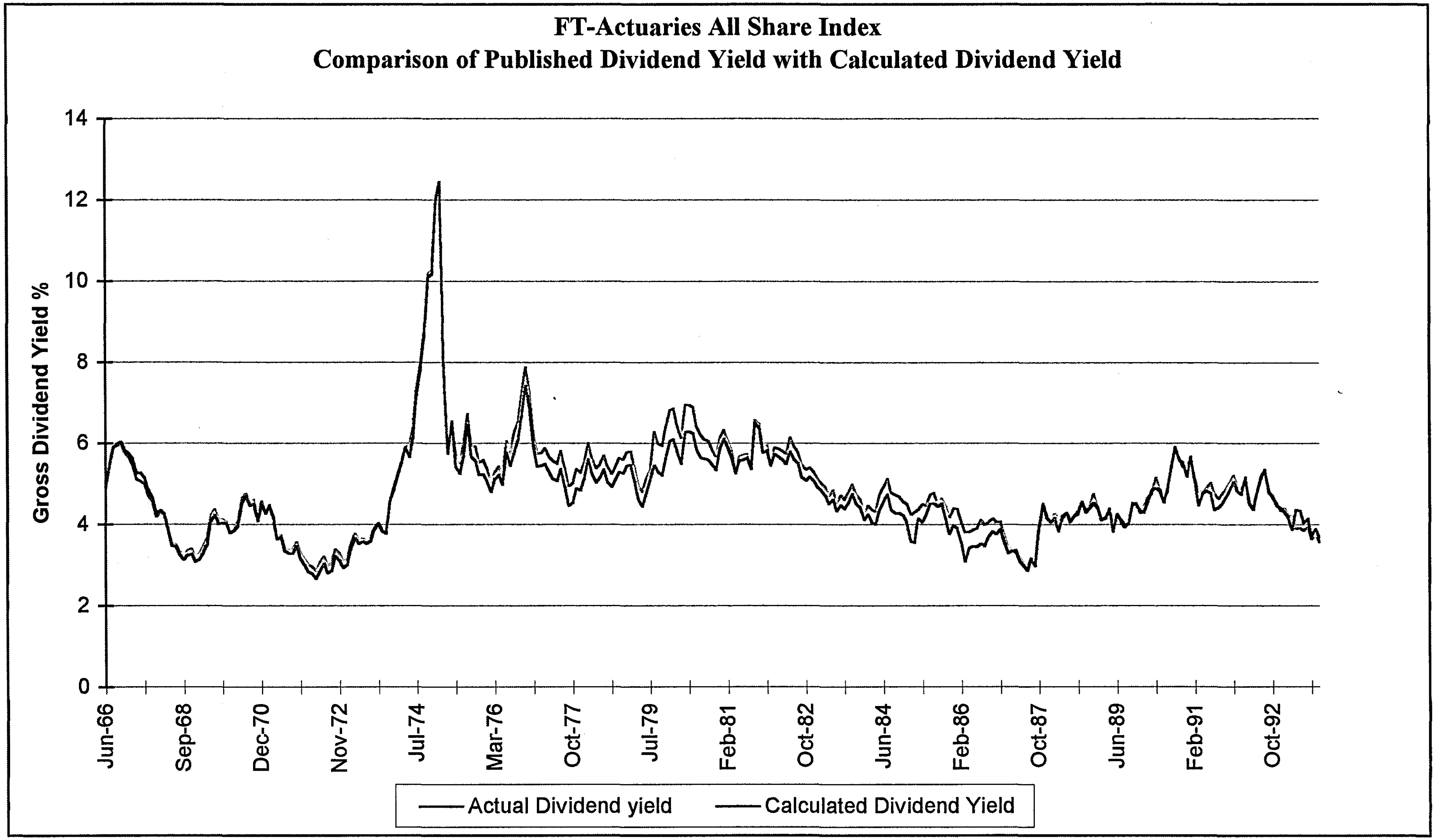
The dividend yield on the FT-Actuaries All Share Index could have been extracted directly from Datastream. The calculation described above was necessary to model the historic sequence of capital returns in calculating prices which would be used later in the randomisation tests.

Goetzman and Jorion allow for seasonality in dividends by compounding the preceding 12 months dividends at the one month treasury bill rate. The adjustment to dividends is small and is unlikely to influence significantly the results of the regressions. Dividend yields published in the *Financial Times* are calculated by taking the sum of the dividends paid in the previous 12 months and make no allowance for interest on re-invested dividends. Furthermore as described in section 3.2.1, the Datastream total return index for periods before 1 January 1985 simply spreads dividends evenly over the working days in the year as shown in Equation 3.6. To allow for seasonality in dividends by compounding them is not useful given the limitations in the data. Dividend yields are therefore calculated on the same basis as that used in the *Financial Times* and as in Equation 3.40.

From 1966 to 1971 there were only 3 CBI surveys per year, and thus the period between surveys was 4 rather than 3 months. In these circumstances, to preserve continuity of the price series, which was created by accumulating capital returns, it was necessary to pro rate the income returns, so that when accumulated as in Equation 3.39 to form an annual dividend series, they approximated the annual dividends paid on the index. Since this process assumes that dividends are paid evenly throughout the year, the constructed gross dividend yield series was compared with the actual gross dividend yield series extracted directly from Datastream. Correlation between the two series was 0.988 and the difference in explanatory power of the two series is likely therefore to be trivial. Figure 3.6 on the following page compares the actual gross dividend yields as extracted directly from the Datastream database with the series which was generated by the method described in Equations 3.33 to 3.40 above. The close similarity between the two series is apparent.

In addition, the publication of survey results only 3 times a year in the period from 1966 to 1977, and the need to maintain a continuous history of prices resulted in returns for the early part of the sample period being 1 month longer for 3 months returns, 2 months longer for 6 months returns and 4 months longer for annual returns. This unusual feature of the data will be discussed further in Chapter 4.

Figure 3-6


FT-Actuaries All Share Index
Comparison of Published Dividend Yield with Calculated Dividend Yield
Gross Dividend Yield %
0
2
4
6
8
10
12
14
Jun-66
Sep-68
Dec-70
Nov-72
Jul-74
Mar-76
Oct-77
Jul-79
Feb-81
Oct-82
Jun-84
Feb-86
Oct-87
Jun-89
Feb-91
Oct-92
Actual Dividend yield
Calculated Dividend Yield

3.4.3 Randomisation

Most methods for estimating and hypothesis testing have statistical properties which are known only asymptotically. This is true for univariate linear regression once we relax the assumption of either fixed regressors or the even stronger assumption that the error terms are normally and identically distributed. We find ourselves in this situation dealing with regressions in which dividend yields are used to explain returns. Davidson and Mackinnon (1993), describe a number of methods of dealing with this problem.

The first method is to refine asymptotic approximations. While this approach can yield valuable insights into the behaviour of estimators and test statistics, it unfortunately involves advanced mathematics and is usually applicable only to relatively simple models. Also the method tends to produce results which are both complicated and difficult to interpret. Moreover, the results are only approximations and may not be sufficiently accurate for the purpose for which they are intended.

The second approach is to investigate the finite sample properties by using Monte Carlo Experiments[11]. The software package PC Give and its associate PC Naive, (see Hendry Neale and Ericsson (1990)); enable the researcher to investigate the finite sample properties of a number of estimators or test statistics. Monte Carlo experiments assume that the researcher is able to define the Data Generating Process completely. This means that if there are exogenous variables, they or their distributions must be specified, as must the distributions of any error terms. In practice 'conventional' Monte Carlo methods are used frequently to supplement theoretical work on the properties of estimators and test statistics.

In contrast the 'bootstrap' method is specifically designed to be used in empirical work, and the name expresses the idea that the data should be allowed to "pull themselves up by their own bootstraps". The idea which was first proposed by Efron (1979) as a non-parametric technique, is implemented by performing a Monte Carlo experiment in which the error terms are drawn not from an assumed distribution but rather from the empirical distribution of their sample counter parts.

The mechanics of bootstrapping are very clearly explained in Noreen (1989). Depending on the nature of an hypothesis, a significance test provides information

11 The term Monte Carlo is reported to have originated in Metropolis and Ulam (1949).

about one of two types of random influences. The first type of hypothesis is concerned with the characteristics of the population from which a random sample is drawn. The second type of hypothesis is concerned with the relationships between variables in a sample. The sample may or may not be a random sample from a population. Noreen describes the method used to test the first type of hypothesis as Monte Carlo sampling and the method used to test the second, as randomisation. In Monte Carlo sampling the test is conducted by simulating the process by drawing, with replacement, random samples from the population. The values of the test statistic for the simulated random samples are compared to the value of the test statistic for the real sample. If the value of the test statistic for the real sample exceeds the test statistic for the random sample, at the predetermined level of significance, then the null hypothesis is rejected.

In this thesis we are concerned with the relationship between variables and so randomisation[12] is the appropriate technique. Randomisation shuffles one variable relative to another. Exact randomisation requires that all possible permutations of one variable with the other are performed.[13] In practice this is only feasible for very small sample sets. For example, assume that 10 observations of 2 variables are available, then there are 10! or roughly 3.6 million permutations of the ordering of just the first series. Clearly this technique is practical for only the smallest sample sizes. The probability distribution can be approximated however to any desired level by a process of resampling.

Noreen (1989) argues that 1,000 replications are adequate in most cases, and this seems to have provided a guide to many researchers. Kim, Nelson and Startz (1991), McQueen (1992) and Nelson and Kim (1993) used 1,000 permutations. Goetzman and Jorion (1993) used 5,000 permutations. More recently, Kennedy (1995), in a major review article entitled 'Randomisation Tests in Economics' states

> *Dwass (1957) showed that sampling 10,000 values is about 98% as powerful as full enumeration. The costs of using more than 1,000 permutations are high for Monte Carlo studies, but for empirical studies the low cost of modern computing power suggests that a larger number should be used; 10,000 permutations would not be unreasonable.* Kennedy, page 93.

12 Goetzmann and Jorion state they use bootstrapping with replacement rather than randomisation. Since they extracted 718 observations out of a total possible of 768, in practice it is difficult to see why the choice between bootstrapping and randomisation should make any difference to the empirical results.

13 Fisher (1935) first introduced the idea of an exact randomisation test.

For this study the variables were shuffled 8,000 times for each regression.[14]

Randomisation enables the calculation of the p factor, (the probability of the test statistic occurring by chance), of the statistic while allowing for the specific characteristics of the data series being studied. The procedure was carried out as follows[15]:

3.4.4 Goetzmann and Jorion Randomisation

(1) For the data set, calculate the required test statistic. In this study it is the β of the independent variables and the R^2 of the regression.

(2) Randomly shuffle total returns and capital returns.

(3) Compute a pseudo-price series starting at 100 as in Equation (3.41) below

$$P_t^* = P_{t-1} \times \left(1 + CR_t\right). \qquad \textbf{(3.41)}$$

(4) Calculate the dividend yield by dividing the actual series of annual gross dividends (see Equation 3.39) by the pseudo price series generated in Equation 3.41 above. The result is then multiplied by 100 to express it as a percentage.

(5) Compute the dependent variable future returns to the desired horizon by arithmetically compounding randomised monthly returns.

(6) Perform the regression and calculate the β of the independent variables and the R^2 of the regression. Let these results be β^*, and R^{2*}.

As the data have been shuffled at random there should be no relationship between returns and the independent variables. Furthermore, the shuffled data

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14 The author's own tests suggested that worthwhile gains might be made by increasing the replications from 1,000 to 10,000. In practice computing limitations restricted the number of replications to 8,000.

15 RATS386 Version 4.10 was used to perform the calculations.

computes dividend yield as a function of the randomised historic sequence of capital returns. Thus the peculiar feature of this data series has been preserved in the randomised data. The actual series of annual dividends is used to compute dividend yield thus preserving the highly autocorrelated feature of dividends.

(7) If $\beta^*>\beta$, or $R^2>R^{2*}$ then add 1 to x_1, or 1 to x_2, where x_1 and x_2 are counters.

(8) Repeat steps 2 through 6 n times. In this case n is taken as 8,000.

(9) Compute the empirical p[16] factor of the β, and of R^2.

$$p = \frac{x+1}{n+1} \qquad \textbf{(3.42)}$$

When regression results are estimated from the randomised data they reflect the biases which are inherent in that data. In other words they include the effects of a version of the dependent variable used as an explanatory variable, lack of normality in the return series and serial correlation in the residuals arising from the use of overlapping observations. This is a desirable feature since the same biases which occur in the OLS estimates of β and R^2 are also reflected in the randomised estimates. The proportion of times the randomised test statistic exceeds the conventional OLS test statistic, the p factor, therefore gives an estimate of the probability of the observed statistic occurring by chance. This estimate is robust to the biases described above.

As previously discussed Nelson and Kim (1993) argue that the any regressor which is endogenous to the system which determines return will be biased. Businessmen's responses to CBI surveys are likely to be determined jointly with stock returns since macro economic shocks may similarly affect both stock market returns and changes in business optimism. This suggests modelling the CBI survey data to correct for biases arising from this source. In contrast to the dividend yield series where the relationship between price and the previous history of capital returns can easily be explicitly modelled, it is not easy to model the similar effect in the CBI data. This issue will be discussed in Chapter 4 of the thesis. Randomisation of returns

16 Noreen (1989), page 17, explains that adding 1 to both the numerator and denominator ensures that the test is valid, i.e. the probability of rejecting the null when it is true is no greater than the rejection level specified for the test.

against the CBI series however does allow account to be taken of non-normality in the data and the bias caused by overlapping observations.

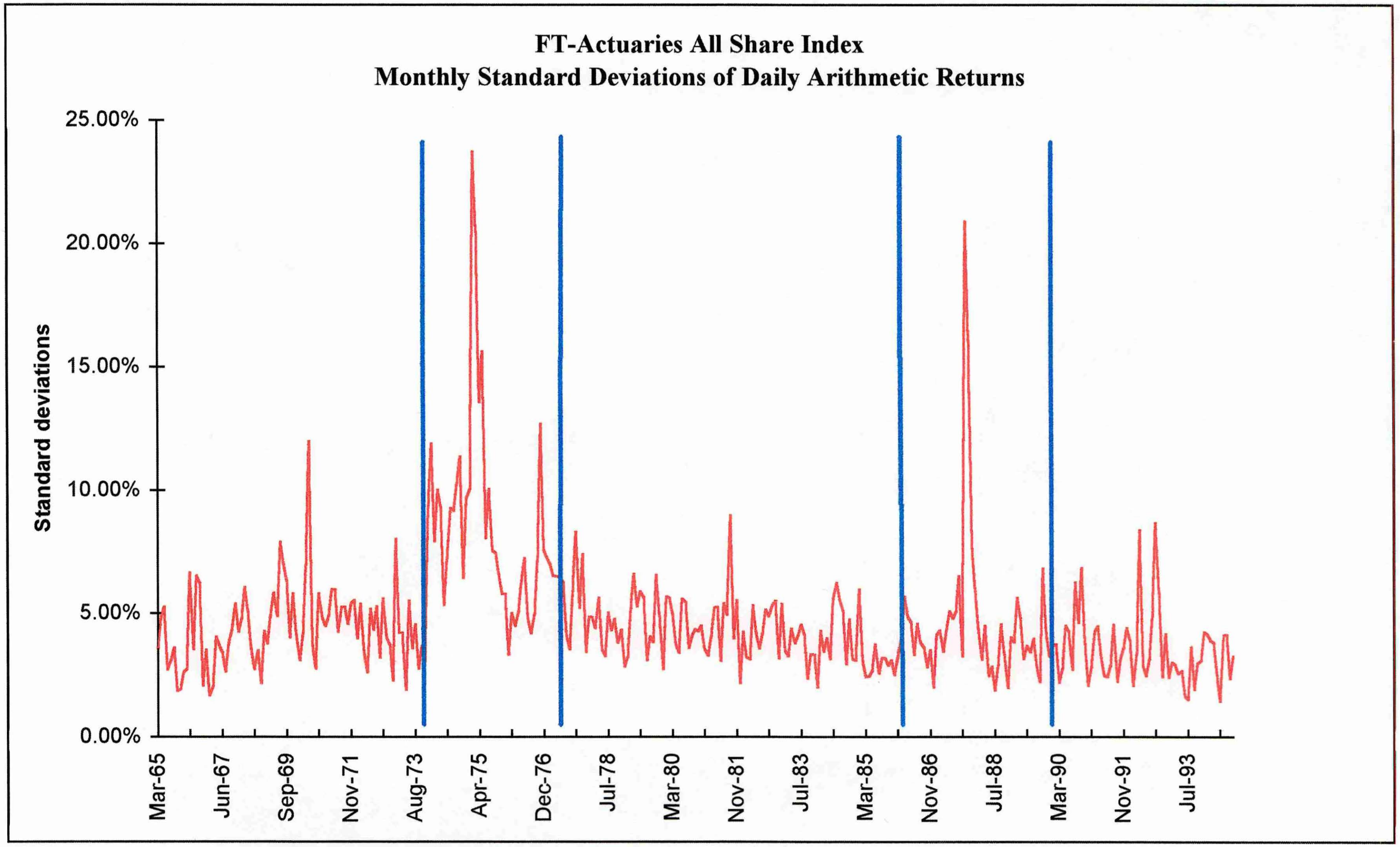
Randomisation of the data destroys the time series profile of the series of total and capital returns and the pattern of any heteroscedasticity. Two methodologies are investigated which take account of heteroscedasticity in the return series.

3.4.5 Stratified Randomised Sampling

The volatility of the UK stock market was high in 1975 following the stock market collapse in 1974 and also during the period of the October 1987 crash. (See Figures 3.1 and 3.2). Previous researchers have found that daily stock returns exhibit high heteroscedasticity but this diminishes with longer time horizons. (See Fama (1965).) Thus there are good reasons to believe that regressions errors might be expected to vary through time. While the White (1980) standard errors, which correct for heteroscedasticity, were available, these may not be reliable in the small sample sizes in this study.

The procedure in Nelson and Kim (1993) and Kim, Nelson and Startz (1991) was followed and the returns were stratified within periods of high and low volatility and shuffled randomly within these periods. By using the technique of stratified random sampling one hopes to induce into the otherwise random series of returns, the approximate pattern of heteroscedasticity found in real stock market returns. From the Figure 3.7 on page 134, five periods of high and low heteroscedasticity were identified, and these are shown in that figure. The first period ends in June 1973. The second runs from June 1973 to July 1977 and covers the turbulent period of the stock market collapse in 1974 and its recovery in 1975 and 1976. The third is the relatively stable period from the late 1970's to just before to the market crash in October 1987. The fourth period includes this episode and runs from November 1985 to January 1990, while the final includes the relatively tranquil period to the end of the sample. The total returns and capital returns were shuffled. The desired test statistics, the β coefficient and the R^2 were calculated. The process was repeated 8,000 times and the empirical p values of β and R^2 were calculated as described in (1) to (9) in 3.4.4 above.

Figure 3-7


FT-Actuaries All Share Index
Monthly Standard Deviations of Daily Arithmetic Returns
Standard deviations
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
Mar-65
Jun-67
Sep-69
Nov-71
Aug-73
Apr-75
Dec-76
Jul-78
Mar-80
Nov-81
Jul-83
Mar-85
Nov-86
Jul-88
Mar-90
Nov-91
Jul-93

3.4.6 Weighted Least Squares Randomisation

While stratified randomisation might provide some allowance for the effect of heteroscedasticity, the choice of the number and timing of periods of high and low volatility is subjective. The selection of a few periods may miss episodes of high volatility which contribute to the heteroscedasticity of the series and which are destroyed by shuffling. The choice of numerous periods effectively restricts the amount of shuffling and therefore inhibits the randomisation of the data. An alternative method of dealing with heteroscedasticity is to use weighted least squares. The methodology adopted follows closely that in McQueen (1992).

Under the null hypothesis, monthly returns are independent so the variance of long horizon returns is the sum of the variances of monthly returns. In addition, if prices follow a random walk, then β_t in Equations 3.1 and 3.2 is zero; and therefore, estimates of the standard deviation of the long horizon total returns $TR_{t,t+T.}$ are also estimates of the standard deviation of the errors, u_t.

Following French, Schwert and Stambaugh (1987), daily values of the FT-Actuaries All Share Index were used to estimate the monthly variance of stock market returns from January 1965 to October 1994. The estimate of the monthly variance is

$$\hat{\sigma}_t^2 = \sum_{i=1}^{N_t} TR_{i,t}^2 + 2\sum_{i=1}^{N_{t-1}} TR_{i,t}TR_{i+1,t}, \qquad \textbf{(3.43)}$$

where N_t is the number of trading days in the month t, $TR_{i,t}$ is the total return on the FT-Actuaries All share Index on day 1 in month t. In Equation 3.43 the cross product term adjusts for non synchronous trading of securities.

Under the null hypothesis of a random walk, the estimate of the standard deviations of the errors term in 3.1 and 3.2 is given by,

$$\hat{\sigma}_{t,t+k} = \left[\hat{\sigma}_t^2 + \hat{\sigma}_{t+1}^2 + \ldots \hat{\sigma}_{t+k}^2\right]^{\frac{1}{2}} \qquad \textbf{(3.44)}$$

The WLS randomisation test follows steps 1 to 9 above. The only difference is that the monthly returns are shuffled with their respective variance estimates. The shuffled returns and variances are then summed to form the longer horizon returns and variances. The reciprocal of the long-horizon standard deviations are used as weights, and the WLS β and correlation coefficient is recalculated for each shuffling.

3.5 Methodology - Summary

This study uses conventional ordinary least squares methodology to compute the β coefficients of the explanatory variables and also their significance. The model selection criteria, described in section 3.3.4, is then used to test for the inclusion of CBI variables with dividend yield as explanatory variables.

The significance of β is then estimated using the Goetzmann and Jorion (1993) simulation methodology described in section 3.3.4. This allows for the effect of the lagged dependent variable used as an explanatory variable, serial correlation caused by the use of overlapping future return observations and lack of normality in the return series.

Since the randomisation of the return series destroys any pattern of heteroscedasticity in the return data, further allowance is made for any bias arising from this source. Stratified randomisation as in Kim, Nelson and Startz (1991) is used to attempt to maintain approximately the same pattern of heteroscedasticity in the data. Finally the significance of β is also assessed by estimating their p factors[17] by Weighted Least Squares randomisation as in McQueen (1992).

17 p factors denote the probability of the observed statistic occurring by chance.

CHAPTER 4

RESULTS

4.1 Introduction

This Chapter presents the empirical findings of this thesis. Section 4.1 deals with the statistical features of the data, Section 4.2 discusses the results of the classical ordinary least squares regressions in a univariate context and Section 4.3 in a multivariate context. The significance of the regression coefficients and R^2 is assessed by the use of Monte-Carlo techniques in Section 4.4. Section 4.5 presents the results of the sample period split into two sub-periods, Section 4.6 identifies observations which have a large impact on the results and finally Section 4.7 provides a summary of the findings.

4.1.1 Basic Statistics

A listing of the data series used in this thesis appears in Appendix 1[1], details of basic statistics appear in Appendix 2. Appendix 3 lists the dates when the results of the CBI Quarterly surveys first appeared in the newspapers, Appendix 4 contains the autocorrelation statistics and Appendix 5 contains details of the correlation matrices. Summary tables have been extracted from these appendices which illustrate the most important features of the data. Comments have been included in the text where the figures extracted do not reflect all features that may be of interest.

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1 Daily return data was used to measure the volatility of the Financial Times-Actuaries All Share Index. For obvious reasons this series has not been reproduced.

Table 4-1

Basic Statistics for Selected Series

1966 - 1993

Series	Period	No. of obs.	Arithmetic Mean %	Std Deviation %	Minimum %	Maximum %
Stock market						
Annual Series						
Return - 12 months (1)	Jun 66 - Oct 92	26	21.5	33.9	-56.2	117.3
Div. yield - 12 m.(1)	Jun 66 - Oct 92	26	4.9	1.4	3.1	10.2
CBI						
Quarterly Series						
Business optimism	Jun 66 - Oct 93	105	-3.6	-25.3	-75.0	41.0
Investment in buildings	Jun 66 - Oct 93	105	-16.6	14.7	-49.0	18.0
Investment in plant	Jun 66 - Oct 93	105	1.1	19.5	-46.0	39.0
Future orders	Jun 66 - Oct 93	105	11.6	20.2	-47.0	51.0

(see Appendix 2 for full details)

Note: Annual series were selected for stock market data since this is the easiest to interpret. Quarterly CBI series have been shown since this reflects the interval between the publication of the CBI results

During the sample period, annual returns on the FT All Shares Index averaged 21.5% per annum and their standard deviation was 33.9%. This compares with the dividend yield series which has a standard deviation of only 1.4%. The lowest annual return was -56.2% from November 1973 to November 1974 and the highest 117.3% from November 1974 to November 1975. The lowest annual dividend yield was 3.1% in 1971 and the highest 10.2% in 1974.

The first CBI variable included in this study concerns whether respondents were more or less optimistic about the general business situation than they were four months previously. Since optimism is likely to fluctuate with the business cycle, the mean of this variable is expected to be close to zero over a long period. The actual figure of -3.6% was close to zero.

The second and third variables concern whether respondents expected to authorise more or less capital expenditure in the last 4 months than they authorised in the previous 12 months on buildings and on plant and equipment, respectively. Official statistics confirmed that expenditure on land and buildings increased during the period. It was surprising therefore that the investment in buildings series has a negative mean of -16.6% and the investment in plant series has a mean of only 1.1%. The reasons for this apparent peculiarity are not known. Although the consistent bias seems to suggest a lack of rationality among respondents, it has been suggested that some may deliberately wish to give a rather pessimistic view in their replies to the CBI questionnaires in an attempt to influence the Government's economic and taxation policy.[2]

The last question relating to the CBI data asks respondents whether the trend of the volume of future orders over the next four months is expected to be up, the same, or down. As expected in an economy which has grown in the last 25 years, the mean of the series was positive at 11.6%. This provides a contrast to the business optimism series which had a mean of slightly below zero. The reasons for this anomaly are not known. It is possible that businessmen might have been disappointed at the rate of growth in orders. Alternatively, more competitive business conditions may have lead to the expectation of reduced margins, which adversely affected business optimism. Since it is not the objective of this thesis to explain the motivation for, or the rationality of replies appearing on the CBI questionnaires, reasons for these apparent anomalies are not explored further.

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2 I am grateful to Professor A. Buckley for this helpful insight.

4.1.2 Autocorrelation Statistics

Autocorrelation coefficients together with the p factors (the marginal significance) for the Ljung Box 'portmanteau' statistics for autocorrelation for selected series appear in Table 4-2 below.

Table 4-2
Autocorrelation
1966 -1993

Return Horizon Months	Series	Coefficients Lags 1	2	3	4	Ljung Box Q - Significance (p) Lags 1	2	3	4
		Return							
		Non-overlapping observations							
3		-0.064	-0.091	0.086	-0.142	0.50	0.51	0.54	0.36
6	1	-0.024	0.054	-0.238	-0.070	0.86	0.91	0.33	0.44
12[3]	2	-0.169	-0.175	-0.070	0.107	0.36	0.41	0.59	0.68
		Overlapping observations							
24	2	0.321	-0.241	-0.147	-0.034	0.09	0.10	0.15	0.26
36	2	0.514	0.152	-0.230	-0.183	0.01	0.02	0.02	0.03
		Dividend Yield							
3		0.791	0.598	0.487	0.322	0.00	0.00	0.00	0.00
6	1	0.737	0.472	0.258	0.151	0.00	0.00	0.00	0.00
12	2	0.448	0.130	-0.041	-0.149	0.01	0.04	0.09	0.13
		CBI - Balance of Business Optimism[4]							
3		0.645	0.478	0.328	0.225	0.00	0.00	0.00	0.00
6	1	0.494	0.147	-0.139	-0.264	0.00	0.00	0.00	0.00
12	1	0.237	0.112	0.153	-0.035	0.20	0.36	0.43	0.59

(see Appendix 4.1 for full details)

---

3 The first series for annual data was highly negatively autocorrelated at 1 lag and highly positively autocorrelated at 2 lags. Since this was not typical for the other 3 annual return series, figures for series 2 have been shown in the table.

4 The other three CBI series, Investment in Buildings, Investment in Plant and Future Orders showed the same pattern of autocorrelation and therefore have not been reproduced in the table above

As expected, autocorrelation coefficients for all short horizon returns were low and none of the Box Q statistics were significant at the 5% level. At 24 months horizons, autocorrelation coefficients were positive for 1 lag, but negative at longer lags. At horizons of 36 months, correlations were positive for lags 1 and 2, but negative thereafter. Most of the Ljung Box Q statistics for longer horizon returns, were significant at the 5% level. Much of this autocorrelation can be attributed to the moving average error induced by the use of overlapping observations when computing returns for 24 and 36 months horizons.

In contrast to the return series, all dividend yield series were highly autocorrelated and most of the Ljung Box Q statistics were significant at the 5% level.

CBI data were also highly auto-correlated for the 3 and 6 months data series but less so for the annual series. It is clear from figure 3-5 that businessmen's expectations change slowly, apparently in line with the business cycle, and this is reflected in the high auto-correlation coefficients in Table 4-2.

Since returns of 24 and 36 months are highly autocorrelated, results of their regressions against other highly autocorrelated series, dividend yields and also the 3 and 6 months CBI series, may reflect the spurious correlation problem which has been extensively analysed in Granger and Newbould (1974). The researcher needs therefore to examine carefully the residuals of the regressions of returns on dividend yields for serial correlation.

The randomisation experiment following the Goetzmann and Jorion (1993) methodology specifically corrects for the biases caused by the moving average error in the residuals which results from the use of overlapping observations.

4.1.3 Correlation Matrices

The correlation matrix for the 3 months series is shown in Table 4-3 below. Correlation matrices for the longer horizons tell substantially the same story and so are relegated to Appendix 5.

Table 4-3

Correlation Matrix 3 Months Data

1966 - 1993

	Returns	**Dividend Yield**	**CBIA**	**CBIB**	**CBIC**	**CBID**
Returns	1.000	0.346	-0.230	-0.260	-0.231	-0.201
Dividend Yield		1.000	-0.650	-0.505	-0.467	-0.574
CBIA			1.000	0.658	0.697	0.882
CBIB				1.000	0.962	0.751
CBIC					1.000	0.782
CBID						1.000

CBIA is the CBI, balance of business optimism series
CBIB is the CBI, balance of investment in buildings series
CBIC is the CBI balance of investment in plant series
CBID is the CBI balance of future orders series
(see Appendix 5 for full details)

The high correlation between each of the 4 CBI series has already been discussed in Chapter 3. Each of the four CBI variables was also highly negatively correlated with dividend yield. Business optimism increases when stock prices are high and dividend yields are low. The high correlation between the CBI series and dividend yields series has an important implication for this study. Firstly, when returns are regressed on dividend yields and CBI data, multicollinearity between the explanatory variables may cause the variance explained by the regression to be shared arbitrarily by the explanatory variables. In these circumstances standard errors and their associated t statistics cannot be relied upon for assessing the significance of the coefficient of each explanatory variable. For this reason, the merit of including the CBI data with dividend yield as explanatory variables, is assessed by using the model selection criteria discussed in Chapter 3, namely $\overline{R}^2$, Akaike Information Criterion and Schwartz

Information Criterion. The high correlation of the CBI series with dividend yield suggests that the macro economic shocks which affect stock prices and hence dividend yield, also influence the level of optimism among respondents to the CBI survey. Nelson and Kim (1993) argue,

> *The presence of small sample bias is not limited to regressions of return on financial variables such as dividends or earnings which are directly related to share valuations. Regression of return on the lagged value of any variable that is endogenous to the system which determines return in general will be biased, even if the true conditional expectation of return does not depend on the lagged predictor.*

As discussed in Section 3.4.4 it is not easy to model any implicit effect of a lagged regressor in the form of a CBI variable. Nevertheless, since the regression of returns on CBI data involve biases arising from the use of overlapping observations and non-normality in the data, randomisation is applicable to the four CBI series as well as to dividend yield.

4.2 Classical Ordinary Least Squares

4.2.1 Introduction

Tables 4-4 to 4-8 show the results of the regression of returns on dividend yields and each of the 4 CBI series. To avoid unnecessary detail, the results of only 2 of the 4 possible series have been shown for each of the 12, 24 and 36 months time horizons. Selection has been based on the series with the highest and lowest $\overline{R}^2$ for the particular time horizon to illustrate the range of results. The reader who wishes to examine the full results is referred to Appendix 6. Underneath each table a summary shows the number of series out of the total of 15 for which the t values are significant at the 1% and the 5% levels[5]. While this is interesting it does not provide a direct test of the hypothesis that $\beta = 0$ for all time horizons. This aspect is left to Section 4.4.5 where the p factors for the regression coefficients for all 15 series are discussed.

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[5] Table 2.3 described the 15 series.

4.2.2 Dividend Yields

Table 4-4 shows a summary of the results of the regression of returns on dividend yields.

Table 4-4

Regressions of Returns on Dividend Yields

$$TR_{t,\,t+T} = \alpha_T + \beta_T GDY_t + u_{t,\,t+T}$$

1966 -1993

Return Horizon Months	Returns following CBI survey	Series	β	β t	β p	$\bar{R}^2$	Durbin Watson	B.P p
			Non-overlapping return observations					
3			3.927	3.738	0.000	0.111	1.94	0.002
6	Jan & July	1	4.710	2.496	0.016	0.093	1.85	0.313
6	Apr & Oct	2	10.665	5.199	0.000	0.346	1.75	0.236
12	October	1	17.634	5.556	0.000	0.544	2.10	0.534
12	July	4	9.553	2.497	0.020	0.173	1.81	0.127
			Overlapping return observations					
24	January	2	18.039	4.130	0.000	0.401	1.11*	0.012
24	April	3	19.933	3.686	0.001	0.344	1.37	0.061
36	October	1	33.505	8.256	0.000	0.745	1.19*	0.050
36	April	3	25.251	3.819	0.001	0.371	1.02*	0.173

Number of series, out of 15, with significant coefficients - see Appendix 6.1

Number significant at 1%	**13**
Number significant at 5%	**15**

Full details appear in Appendix 6.1

Notes:

1 The $\beta\, p$ column shows the marginal probability of β calculated by using classical ordinary least squares. No adjustment has been made to the p values for heteroscedasticity or for serial correlation. These corrections appear in Table 4-12.

2 B.P. is the Breusch Pagan (1979) test for heteroscedasticity.

3 Durbin Watson Test. * indicates significant at 5% level.

4 The Lagrange Multiplier test for 1st order serial correlation gave rather similar results to those given by the Durbin Watson test. The Ljung Box Q test for serial correlation in many cases did not give a significant test statistic even for those series which used overlapping observations where there are strong *a priori* reasons for believing serial correlation to be present in the residuals. Details of the results of these two tests appear in Appendix 6.1.

5 Figures for R^2 appear in Appendix 6.1.

Table 4-4 shows, in common with other studies, for example Fama and French (1988b) and Goetzmann and Jorion (1993), both $\overline{R}^2$ and β increasing with the time horizon. Test statistics vary considerably depending on selection of the data series. For example, if the series with a return horizon of 6 months following the publication of CBI surveys in January and July is chosen, $\overline{R}^2$ is only 0.093. The April and October series however, give an $\overline{R}^2$ of 0.346. Even with 36 months horizon data, differences are marked, $\overline{R}^2$ reaches a remarkable 0.745 for the series following the publication of the CBI October survey, while the $\overline{R}^2$ for the series following the April survey is only 0.371. Using conventional OLS methodology the p value for all 15 series was significant at the 5% level and as many as 13 out of 15 series were significant at the 1% level.

As expected, the Durbin Watson test gives a warning of the serial correlation due to the use of overlapping observations in all the 24 and 36 months the series, and all the statistics fell to unacceptably low levels. The results of these series need therefore to be treated with caution.

The Breusch Pagan test indicated the presence of heteroscedasticity in some of the series. For example, the test statistic for the 3 months series was significant at the 1% level. It is possible that some of the heteroscedasticity in returns may not be present in the series of longer term returns, and this results in non-significant test results. Alternatively, the poor small sample properties of the Breusch Pagan test may fail to detect heteroscedasticity in longer horizon returns where the number of observations is small.

4.2.3 Confederation of British Industries - Business Optimism

Table 4-5

Regressions of Returns on CBI - Business Optimism

$$TR_{t,\,t+T} = \alpha_T + \beta_T CBIA_t + u_{t,\,t+T}$$

1966 -1993

Return Horizon Months	Returns Following CBI survey	Series	β x 10	β t	β p	$\overline{R}^2$	Durbin Watson	B.P p
			Non-overlapping observations					
3			-1.163	-2.394	0.018	0.044	2.04	0.016
6	Jan & July	1	-0.845	-1.077	0.287	0.003	2.00	0.359
6	Apr & Oct	2	-3.374	-2.851	0.006	0.121	2.18	0.028
12	January	2	-1.900	-1.333	0.195	0.030	2.22	0.167
12	July	4	-3.816	-2.066	0.050	0.116	1.85	0.441
			Overlapping observations					
24	January	2	-4.954	-2.903	0.008	0.236	0.97*	0.091
24	July	4	-3.527	-1.250	0.224	0.023	1.30	0.205
36	October	1	-15.117	3.626	0.001	0.346	2.01	0.063
36	April	3	-4.814	-1.456	0.159	0.046	0.77*	0.025

* Indicates significant at 5% level

Number of series, out of 15, with significant coefficients

Number significant at 1%	**3**
Number significant at 5%	**7**

Full details appear in Appendix 6.2. For explanatory noted see Table 4-4.

The CBI Business Optimism variable, showed only a modest relationship with future returns. Only 7 of the t statistics for the full series of 15 regressions were significant. $\overline{R}^2$ at 0.044 for 3 months returns, was significant at the 5% level. At longer horizons the results were mixed. For example the $\overline{R}^2$ for 36 months data for the October series amounted to 0.346 and was significant at the 1% level. In contrast the $\overline{R}^2$ for the April series amounted to only 0.046 with a p value of 0.159. In general, high $\overline{R}^2$ at longer horizons must be viewed with caution since the use of overlapping observations is likely to cause serial correlation in the residuals[6]. In addition, it is dangerous to draw inferences selectively from a number of series. For the moment, the test statistics are reported, and no conclusions are drawn concerning the relationships between the variables.

The signs of the coefficients for all time horizons were the opposite of those expected. Increasing business confidence seems not to be associated with positive returns but with negative returns. These results therefore do not support the hypothesis that businessmen have private information which is only slowly revealed in security prices. It is more consistent with the over- reaction hypothesis. The model predicts that when businessmen are confident, stock prices are high and can be expected to fall (and vice versa).

6 The Durbin Watson statistic of 2.01 for the October series indicates that it is not possible to reject the hypothesis of no serial correlation. This is reinforced by the results of the Lagrange multiplier and the Lung Box *Q* statistic. See Appendix 6.2. The Breusch Pagan test statistic of 0.063 suggests the possibility of heteroscedastic residuals.

4.2.4 Confederation of British Industries - Investment in Buildings

Table 4-6

Regression of Returns on CBI -Investment in Buildings

$$TR_{t,\,t+T} = \alpha_T + \beta_T CBIB_t + u_{t,\,t+T}$$

1966 - 1993

Return Horizon Months	Returns following CBI survey	Series	β x 10	β t	β p	$\bar{R}^2$	Durbin Watson	B.P p
			Non-overlapping observations					
3			-2.268	-2.736	0.007	0.059	2.17	0.871
6	Jan & July	1	-3.817	-2.856	0.006	0.123	2.16	0.431
6	Apr & Oct	2	-5.103	-2.688	0.009	0.107	2.34	0.368
12	October	1	-8.290	-1.991	0.057	0.106	3.12	0.856
12	January	2	-7.578	-3.065	0.005	0.252	2.17	0.997
			Overlapping observations					
24	January	2	-9.140	-2.679	0.013	0.205	1.35	0.187
24	April	3	-5.117	-1.280	0.213	0.026	1.80	0.231
36	January	2	-12.830	-2.637	0.015	0.206	1.09*	0.975
36	July	4	-8.304	-1.224	0.233	0.021	0.96*	0.483

* Indicates significant at 5% level

Number of series, out of 15, with significant coefficients

Number significant at 1%	4
Number significant at 5%	9

Full details appear in Appendix 6.3. For explanatory notes see table 4-4.

The Investment in Buildings variable shows rather stronger test statistics than the CBI business optimism series. For horizons of up to 12 months, the t statistics were significant at the 1% level for 4 out of 5 of the regressions shown in Table 4-6. For longer horizons the relationship was less strong. Only 3 of the eight series shown in Appendix 6.3 for 24 and 36 months horizons were significant at the 5% level. As for the Business Optimism Series, the signs of the β coefficients were all negative for the Investment in Buildings series. The Durbin Watson test statistic for the 36 months return horizons indicates serially correlated residuals.

4.2.5 Confederation of British Industries - Investment in Plant

Table 4-7

Regression of Returns on CBI -Investment in Plant

$$TR_{t,\,t+T} = \alpha_T + \beta_T CBIC_t + u_{t,\,t+T}$$

1966 - 1993

Return Horizon Months	Returns following CBI survey	Series	β x 10	β t	β p	$\bar{R}^2$	Durbin Watson	B.P p
			Non-Overlapping observations					
3			-1.520	-2.413	0.017	0.044	2.14	0.706
6	Jan & July	1	-2.382	-2.340	0.023	0.081	2.12	0.603
6	Apr & Oct	2	-3.291	-2.220	0.030	0.070	2.30	0.292
12	October	1	-5.233	-1.549	0.134	0.053	3.12	0.909
12	January	2	-5.316	-2.864	0.009	0.224	2.16	0.605
			Overlapping Observations					
24	January	2	-7.032	-2.835	0.009	0.227	1.22	0.174
24	April	3	-3.074	-1.017	0.320	0.001	1.73	0.168
36	January	2	-9.102	-2.547	0.018	0.193	1.02*	0.867
36	July	4	-1.754	-0.340	0.737	-0.040	0.94*	0.881

* Indicates significant at 5% level

Number of series , out of 15, with significant coefficients

Number significant at 1%	2
Number significant at 5%	6

Full details appear in Appendix 6.4. For explanatory notes see table 4-4.

Although the investment in plant variable, was very closely correlated with the investment in buildings series (a correlation coefficient of 0.962), it was rather less closely associated with future returns. Even so t statistics were significant at the 5% level in 4 out of 5 of the series shown above for regressions for horizons under 12 months. As for the Business Optimism and the Investment in Buildings series, the signs of all the β coefficients were negative for the Investment in Plant Series. The Durbin Watson test statistic for the 36 months return horizons indicates serially correlated residuals.

4.2.6 Confederation of British Industries - Future Orders

Table 4-8

Regression of Returns on CBI - Future Orders

$$TR_{t,\,t+T} = \alpha_T + \beta_T CBID_t + u_{t,\,t+T}$$

1966 - 1993

Return Horizon Months	Returns following CBI survey	Series	β x 10	β t	β p	$\overline{R}^2$	Durbin Watson	B.P p
			Non-Overlapping Observations					
3			-1.274	-2.086	0.039	0.031	2.08	0.640
6	Jan & July	1	-1.418	-1.459	0.151	0.022	2.04	0.816
6	Apr & Oct	2	-2.961	-1.932	0.058	0.049	2.26	0.695
12	October	1	-3.648	-1.052	0.303	0.004	3.14	0.676
12	April	3	-5.205	-2.098	0.047	0.120	2.18	0.515
			Overlapping Observations					
24	January	2	-7.371	-3.553	0.002	0.326	1.14*	0.059
24	July	4	-4.677	-1.435	0.165	0.043	1.37	0.086
36	January	2	-10.151	-3.523	0.002	0.332	1.30	0.434
36	April	3	-9.672	-2.702	0.013	0.215	0.96*	0.062

* Indicates significant at 5% level

Number of series , out of 15, with significant coefficients

Number significant at 1%	**2**
Number significant at 5%	**6**

Full details appear in Appendix 6.5 For explanatory notes see table 4-4.

The CBI Future Orders variable was rather weakly related to future returns. In only 2 out of the 5 series for returns of 12 months and under shown in Table 4-8 above, were the t statistics significant. In contrast with the other CBI variables this series gave high $\overline{R}^2$ for the four, 36 months series. In view of the high serial correlation in 3 of 4 of these series, it is dangerous to draw inferences from these results.

4.2.7 Summary of Univariate Regressions

Table 4-9 below enables a comparison to be made of the $\overline{R}^2$ for the regressions of returns on dividend yields and each of the 4 CBI series which were reported in Table 4-4 to Table 4-8.

Table 4-9

Summary of $\overline{R}^2$ for Univariate Regressions

Equations 3.1 and 3.9 to 3.12

1966 - 1993

Return Horizon Months	Returns following CBI survey	Series	Dividend Yield	CBI Business Optimism	CBI Investment in Building	CBI Investment in Plant	CBI Future Orders
		Equations	3.1	3.9	3.10	3.11	3.12
			Non overlapping observations				
3			0.111**	0.044*	0.059**	0.044*	0.031
6	Jan & July	1	0.093*	0.003	0.123**	0.081*	0.022
6	Apr & Oct	2	0.346**	0.121**	0.107**	0.070*	0.049
12	October	1	0.544**	0.114	0.106	0.053	0.004
12	January	2	0.272**	0.030	0.252**	0.224**	0.081
12	April	3	0.282**	0.087	0.131*	0.099	0.120
12	July	4	0.173*	0.116*	0.190*	0.086	0.091
			Overlapping observations				
24	October	1	0.388**	0.165*	0.087	0.044	0.073
24	January	2	0.401**	0.236**	0.205*	0.227**	0.326**
24	April	3	0.344**	0.043	0.026	0.001	0.055
24	October	4	0.344**	0.023	0.106	0.011	0.043
36	October	1	0.745**	0.346*	0.142*	0.101	0.183*
36	January	2	0.554**	0.176**	0.206*	0.193*	0.332**
36	April	3	0.371**	0.046	0.067	0.005	0.215*
36	July	4	0.429**	0.058	0.021	-0.040	0.119

* Indicates significant at 5%, ** indicates significant at 1%.

Number of series , out of 15, with significant coefficients

Significant at 1%	13	3	4	2	2
Significant at 5%	15	7	9	6	6

Full details appear in Appendices 6.1 to 6.5

It is clear from Table 4-9 that, before adjusting for the biases which may affect the results, dividend yields have a strong relationship with future returns at all time horizons. Thirteen out of 15 series had $\overline{R}^2$ significant at the 1% level. In contrast CBI data were relatively weakly related to future returns. Of the 4 CBI series, investment in buildings had higher $\overline{R}^2$ than the other 3 CBI series.

The statistical difficulties which may bias the results which have been reported in the tables above are:

1. the effect on the t statistics of a lagged variable, dividend yield,
2. the effect on the t statistics of a lagged variable, correlated with dividend yield and determined by the same exogenous factors, namely each the four CBI series,
3. serial correlation in the residuals caused by the use of overlapping observations,
4. heteroscedasticity and non-normality in the return series.

Whilst randomisation is used to correct for the first three biases, weighted least squares estimates of the regression parameters provide robust results in the presence of heteroscedasticity. Before the results of the randomisation tests are given, the ability of the CBI variables to add to the explanatory power of dividend yields within an OLS framework is examined.

4.3 Multiple Regression

Full details of the regression of returns on dividend yields and on each of the four CBI variables are summarised in Appendix 8.1 to 8.4. Since dividend yields were more closely related to future returns than were the CBI data, the high collinearity between the explanatory variables heavily influences the results. Dividend yields capture most of the explained variance, leaving the t statistics of the CBI variables to be insignificant at the 5% level. Table 4-10 summarises the statistics for the business optimism variable. Other CBI variables gave similar results and full details appear in

Appendices 8.1 to 8.4. Examination of these Appendices shows that out of a total of 60 regressions, none of the coefficients of the CBI variables was significant at the 5% level.

Table 4-10

Multiple Regressions of Returns on Dividend Yields and CBI Data[7]

$$TR_{t,\,t+T} = \alpha_T + \beta_T DY_t + \beta_T CBIA_t + u_{t,\,t+T}$$

1966 -1993

Return Horizon Months	Returns following CBI survey	Series	Dividend Yields β	Dividend Yields β p	CBI - Business Optimism β x 10	CBI - Business Optimism β p	$\bar{R}^2$	Significance of F
			Non-overlapping observations					
3		1	3.863	0.006	-0.044	0.943	0.102	**
6	Jan & July	1	5.833	0.025	0.676	0.501	0.119	*
6	Apr & Oct	2	11.177	0.000	0.397	0.773	0.360	**
12	October†	1	21.291	0.000	3.409	0.221	0.555	**
			Overlapping observations					
24	October†	1	14.526	0.010	-0.100	0.976	0.414	**
36	October†	1	32.921	0.000	-0.542	0.884	0.756	**

*** indicates significant at the 5% level, ** indicates significant at the 10% level.**

†*(Only the first series is shown for 12, 24 and 36 months horizons, for full detail see Appendix 8.1)*

The model selection methods discussed in 3.3.5 provide more robust criteria for the inclusion of additional variables.

Table 4-11 below, shows for each variable the number of series for which adding CBI data as an explanatory variable improves the explanatory power of the model. For example the addition of the business optimism variable to dividend yield as an explanatory variable increased $\bar{R}^2$ in only 5 out of the 15 series.

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7 For the 12 month, the 24 month and 36 months series only the 1st series for each time horizon is shown.

Table 4-11

Model Selection Criteria

Number of series, out of 15, in which the addition of CBI data enhanced the selection criteria

1966 - 1993

	Criteria		
	$\overline{R}^2$	**Akaike Inf. Criteria**	**Schwartz Inf. Criteria**
Business optimism	5	0	0
Investment in buildings	5	3	0
Investment in plant	5	0	0
Future orders	2	0	0
Total (out of 60 series)	17	3	0

Full details appear in Appendix 9.1 and 9.2

The results demonstrate that even when the least stringent criterion $\overline{R}^2$ is applied, a CBI variable would have been included in only 17 out of 60 regressions. With the more demanding Akaike and Schwartz criteria, CBI data would only have qualified for inclusion three and zero times, respectively. The results dramatically indicate that whilst CBI data may have very modest explanatory power on their own, they add little to the ability of dividend yields to explain future returns. The reason is clear. Dividend yields, before allowing for the statistical limitations of the analysis so far, are closely correlated with future returns, while CBI data are relatively poorly correlated with future returns of returns. High collinearity between the two explanatory variables ensures that in a multiple regression framework only a small proportion of the explained variance is attributed to the CBI variables.

4.4 Tests for Significance of the Regression Coefficients and for R^2.

4.4.1 Introduction

This section presents the marginal significance (p factors) for the regression coefficients and for R^2 using both conventional OLS estimation as well as that based on the simulation models described in 3.4.4 to 3.4.6, for the Dividend Yield and the CBI Business Optimism variables. Tables 4-12 and 4-13 give the results for the Dividend Yield variable and Tables 4-14 and 4-15 for the CBI Business Optimism variable. Since the results of the other 3 CBI variables were rather similar to those of the business optimism variable, details of their p factors appear only in Appendix 10. Tables 4-16 and 4-17, however, summarise for each of the 5 variables, the number of series for which significant regression coefficients at the 5% level were identified. For the 12, 24 and 36 months time horizons only the first series is shown in the tables.

4.4.2 Dividend Yields

The marginal significance of the p factors for the β coefficient of the dividend yield variable has been estimated by four randomisation methods. The results appear in columns 7 to 10 in Table 4-12. Column 7 shows the p factor calculated by randomly shuffling the return series but leaving the original dividend yield series. This allows for the effects of the serial correlation induced by overlapping observations and the impact of non-normality in the return series. No allowance at this stage is made for the presence of a lagged regressor. Column 8 shows the p factors estimated by using the Goetzmann and Jorion (1993) methodology which generates dividend yield as a function of the randomised series of historic returns. This methodology therefore allows for the presence of a lagged regressor. The last two columns allow for the presence of heteroscedasticity, in column 9, by estimating the p factors while stratifying the sample into periods of high and low volatility and, in column 10, by basing the estimation on weighted least squares as in McQueen (1992).

Table 4-12

Dividend Yields, 1966 -1993

p factors for significance of β

1 Return Horizon Months	2 Returns following CBI surveys	3 β	4 O.L.S p	5 HCSE p	6 HHNW p	7 Simple random p	8 G&J random p	9 G&J with stratified random p	10 G&J with W.L.S random p
3		3.93	0.000	0.008		0.002	0.047	0.251	0.116
6	Jan & July	4.71	0.016	0.006		0.021	0.207	0.675	0.080
6	Apr & Oct	10.67	0.000	0.000		0.001	0.010	0.061	0.020
12	October✝	17.63	0.000	0.000		0.001	0.029	0.109	0.052
24	October✝	14.63	0.000	0.002	0.002	0.020	0.396	0.895	0.163
36	October✝	33.51	0.000	0.000	0.000	0.005	0.184	0.455	0.251
		---------------- *App.6* -----------				------------------ *App 10.1.1* --------------			

Number of series, out of 15, with significant coefficients - see Appendix 10.1.1

	4	5	6	7	8	9	10
Number significant at 1%	**13**	**15**		**6**	**0**	**0**	**0**
Number significant at 5%	**15**	**15**		**14**	**3**	**0**	**2**

✝ *(Only the first series is shown for 12, 24 and 36 months horizons, full detail see in Appendix 10.1)*

Notes:

1. Column 4 headed OLS gives the p factor for the t value of the β regression coefficient.
2. Column 5 headed HCSE shows the p factor for the t value for the White (1980) heteroscedasticity adjusted standard errors.
3. Column 6 headed HHNW shows the p factors for the t values of the standard errors adjusted for heteroscedasticity and serial correlation by the method of Hansen (1982) and Newey West (1987).
4. Column 7 shows the p factor where returns are randomised but the actual dividend yield is used as the explanatory variable. Columns 8 and 9 show the p factor of the OLS β where the methodology described in Chapter 3.4.4 to 3.4.5 is used. Column 10 headed G & J with WLS random shows the p factor of the weighted least squares, β occurring where the methodology described in 3.4.6 is used

As discussed in Section 4.2.2, the conventional p factors for the t test for β for the dividend yield variable are less than 0.01 in 13 out of the 15 series. The remaining two series have p factors of between 0.01 and 0.05. The General Method of Moments (GMM) corrections appearing in columns 5 and 6 headed HCSE and HHNW make little difference to the p factors. While these corrections are asymptotically valid, their performance in small samples is poorly understood.[8] Column 7, headed simple randomisation, allows for the effect of non-normality in the return series data and also for the serial correlation induced by the overlapping residuals. It is clear from the results in Table 4-12, and as reported in Goetzmann and Jorion (1993), that the standard GMM adjustments do not adequately allow for serial correlation in the residuals and cannot be relied upon in the small samples found in this study. At the 1% level, the number of series with statistically significant coefficients falls from 15 with OLS estimation to 6 with simple randomisation. The results, nevertheless, are strong and at the 5% level, 14 out of 15 series have statistically significant coefficients.

The results in column 8 are based on the Goetzmann and Jorion (1993) methodology described Chapter 3.4.3 and 3.4.4. This methodology is robust to serial correlation in the residuals and to the effect of the lagged dependent variable, but not to heteroscedasticity. The resultant p factors show a dramatic increase and only 3 out of 15 regression coefficients were significant at the 5% level. It is important therefore, as reported in Goetzmann and Jorion, to model explicitly the presence of a lagged dependent variable where this is present as an explanatory variable.

Stratified randomisation, (see Section 3.4.5), attempts to allow for the pattern of heteroscedasticity by restricting the shuffling of the data so that the approximate pattern of heteroscedasticity is preserved. The results shown in column 9 of Table 4-12 indicate substantial increases in the p factors. None of the 15 series had significant regression coefficients at the 5% level. The weighted least squares randomisation which follows the methodology in McQueen (1992), described in Section 3.4.6, allows for the specific form of heteroscedasticity in the data. Its use in combination with the Goetzmann and Jorion methodology again gave very weak results, only 2 out of the 15 series having significant regression coefficients at the 5% level. Application of the randomisation methodology in conjunction with allowances for heteroscedasticity

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8 The literature contains a number of alternative methods of estimating the standard errors in the presence of overlapping observations, see Kotecha and Yadav (1995) for a review. Since none of them are found to make adequate adjustment, they are not examined in this thesis

therefore greatly weakens the evidence that the regression coefficients are statistically significant at the 5% level.

Table 4-13 below reports the p factors for the significance of R^2.

Table 4-13

Dividend Yield, 1966 - 1993

p factors for significance of R^2 [9]

1 Return Horizon Months	2 Returns following CBI surveys	3 R^2	4 O.L.S R^2 p	5 Simple random p	6 G & J Random p	7 G & J with stratified random p	8 G & J with W.L.S random p
3		0.120	0.000	0.002	0.101	0.085	0.146
6	Jan & July	0.111	0.016	0.015	0.179	0.583	0.030
6	Apr & Oct	0.359	0.000	0.000	0.001	0.003	0.002
12	October	0.563	0.000	0.000	0.001	0.005	0.012
24	October	0.414	0.000	0.000	0.124	0.368	0.016
36	October	0.756	0.000	0.000	0.006	0.018	0.016
		Appendix 6.1		*-------------- Appendix 10.2.1 --------------*			
Number of series, out of 15, with significant coefficients							
Number significant at 1%			**13**	**13**	**3**	**2**	**3**
Number significant at 5%			**15**	**15**	**4**	**3**	**11**

†*(Only the first series is shown for 12, 24 and 36 months horizons, full detail see in Appendix 10.2)*

Notes:

1 The column headed OLS R^2 is the p factor for the R^2 as assessed in the traditional F test.

2 Column 5 shows the p factor where returns are randomised but the actual dividend yield is used as the explanatory variable. Columns 6 and 7 show the p factor of the OLS R^2 where the methodology described in Chapter 3.4.2 to 3.4.5 is used. Column 8 headed G & J with WLS random shows the p factor of the weighted least squares R^2 occurring where the methodology described in 3.4.6 is used.

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9 For the figures in the OLS column, the significance of the β coefficient is measured by the t test. The t value is β/SE where SE is the coefficient's standard error. The significance of R^2 is measured by an F test which assesses the significance of the variance explained to the total variance. The value of the F equals t^2 and so the significance of t is always the same as the significance of F. (see Noreen (1989), page 30). The equivalence however does not extend to randomisation. In randomisation we can test two hypotheses. Firstly, how frequently can the OLS β be exceeded in the randomised experiment and, secondly, how frequently the R^2 can be exceeded in the randomised experiment.

The results for simple randomised (column 5), Goetzmann and Jorion randomised (column 6) and the stratified randomised shuffling (column 7) in Table 4-13, show the probability of achieving an R^2 equal to or greater than that estimated by the conventional ordinary least squares methodology. The WLS random (column 8) shows the probability of achieving an R^2 equal to or greater than that estimated by the weighted least squares methodology. It is clear once again that the adoption of the Goetzmann and Jorion methodology considerably weakens the support for the hypothesis that there is a relationship between future returns and dividend yields.

4.4.3 CBI Business Optimism

Table 4-14 shows the β coefficients and their p factors estimated by the different methods for the CBI Business Optimism Series and Table 4-15 provides similar information for R^2. As previously discussed, it is not easy to model explicitly any biases in the regression statistics arising from the CBI series being correlated with dividend yields and being determined by the same exogenous factors as returns. No allowance for this effect has therefore been made in the results reported below.

Table 4-14

CBI - Business Optimism, 1966-1993

p factors from randomisation tests for β

Return Horizon Months	Returns following CBI surveys	OLS β	O.L.S p	HCSE p	HHNW p	Simple random p	Stratified random p	W.L.S random p
3		-1.163	0.018	0.043		0.009	0.017	0.125
6	Jan & July	-0.845	0.287	0.422		0.178	0.198	0.151
6	Apr & Oct	-3.374	0.006	0.290		0.002	0.004	0.114
12	October †	-5.771	0.051	0.091		0.013	0.016	0.082
24	October †	-6.508	0.025	0.026	0.093	0.081	0.074	0.146
36	October †	-15.117	0.001	0.006	0.039	0.017	0.007	0.060
			---------- *Appendix 6.2* ----------			---------- *Appendix 10.1.1* ----------		

Number of series, out of 15, with significant coefficients -

		O.L.S p	HCSE p	HHNW p	Simple random p	Stratified random p	W.L.S random p
Number significant at 1%		**3**	**1**		**2**	**2**	**0**
Number significant at 5%		**7**	**7**		**4**	**6**	**0**

†*(Only the first series is shown for 12,24 and 36 months horizons. For full details see Appendix 10.1.1)*

When the regression coefficients were estimated by classical ordinary least squares methodology 7 of the 15 β coefficients for the CBI business optimism series were significant at the 5% level. Simple randomisation resulted in higher p values and lower levels of significance. None of the regression β coefficients were significant in the weighted least squares randomisation. The conclusion seems clear. Although the CBI optimism series showed some relationship with future returns when estimated by OLS, this relationship was shown to be weaker when allowance was made for the specific peculiarities of the data.

Table 4-15

p factors from randomisation tests for R^2

CBI - Business Optimism 1966-1993

Return Horizon Months	Returns following CBI surveys	R^2	O.L.S R^2 p	Simple random p	Stratified random p	W.L.S random p
3		0.057	0.018	0.013	0.032	0.241
6	Jan & July	0.027	0.287	0.239	0.364	0.257
6	Apr & Oct	0.137	0.006	0.007	0.010	0.238
12	October †	0.150	0.051	0.051	0.064	0.151
24	October †	0.200	0.025	0.047	0.069	0.195
36	October †	0.374	0.001	0.042	0.004	0.036
		------ *Appendix 6.2* ------		---------- *Appendix 10.2.1* ----------		
		Number of series , out of 15, with significant coefficients -				
Number significant at 1%			**3**	**1**	**1**	**0**
Number significant at 5%			**7**	**7**	**3**	**1**

†(Only the first series is shown for 12, 24 and 36 months horizons. For full detail see Appendix 10.2.1)

The number of series with significant R^2 at the 5% level, fell from 7 using ordinary least squares to only 1 using the WLS randomisation. It is clear that the evidence which suggests that the CBI business optimism series has a significant relationship with future returns, is greatly weakened when allowance is made for heteroscedasticity and the other unusual features of the data.

4.4.4 CBI - Investment in Buildings, Investment in Plant and Future Orders

The statistical significance of β and R^2 for the remaining three CBI series also fell when their p factors were estimated using randomisation. Rather than burden the reader with voluminous statistics, Table 4-16 below, gives details of the number of series for each variable for which the β coefficient was significant at the 5% level, when estimated by ordinary least squares and by the three versions of randomisation.

Table 4-16

Number of series with significant β coefficients at the 5% level

1966 -1993

	O.L.S p	HCSE p	Simple random p	G & J Random p	Stratified random p	W.L.S random p
Dividend yields (out of 15 series)	**15**	**15**	**14**	**3**	**0**	**2**
Business optimism	7	7	4		6	0
Investment in buildings	9	10	7		7	7
Investment in plant	6	6	5		7	2
Future orders	6	6	3		4	0
Total CBI series (out of 60 series)	**28**	**29**	**19**		**24**	**9**

See Appendix 10.1.1 to 10.1.3 for further details

Two main conclusions can be drawn from these data. Firstly, the number of series for which the β for the dividend yield variable was significant at the 5% level fell when their p factors were estimated by randomisation. When specific allowance was made for the presence of the lagged variable only 3 out of the 15 series had significant β's at the 5% level. This fell to 0 and 2 when allowance was made for heteroscedasticity.

Secondly, the number of series for which the 4 CBI variables had significant coefficients at the 5% level also fell when their p values were estimated by simple randomisation. None of the coefficients for the CBI business optimism variable were significant when estimated by WLS randomisation. The Investment in Buildings series had 7 series, out of 15, with significant coefficients. Allowing for data mining bias, this evidence of an association between the CBI survey results and future returns. seems very weak.

Table 4-17 shows the number of series for which R^2 is significant under the OLS and the randomisation methodologies.

Table 4-17

Number of series for which R^2 is significant at 5% level

1966 - 1993

	O.L.S p	Simple random p	G & J random p	Stratified random p	W.L.S random p
Dividend yields	**15**	**15**	**4**	**3**	**11**
Business optimism	7	7		3	1
Investment in buildings	9	9		7	8
Investment in plant	6	6		5	0
Future orders	6	5		3	0
Total CBI Series	**28**	**27**		**18**	**9**

See Appendix 10.2.1-3 for further details.

Table 4-17 gives similar results to those in Table 4-16. The number of series for which dividend yield was significantly related to future returns fell from 15 to 4 under GJ randomisation. Only 9 of the CBI series out of a possible 60 (15 series and 4 variables) had significant R^2 when WLS randomisation was used as the method of estimation.

4.4.5 Summary

While the number of series which bears a significant relationship with future returns is of interest, it does not directly provide a test of whether for all time horizons there is a relationship between returns and the explanatory variables. Most researchers, for example Goetzmann and Jorion (1993) and Fama and French (1988b), are content to examine the evidence provided by a number of series and derive conclusions from these. Provided the results are sufficiently strong this methodology is unlikely to be disputed.

To test the hypothesis that $\beta = 0$ jointly for all time horizons, the weighted average p values for each time horizon and for all the 15 time horizons were computed. For example, for annual data where there are 4 series, the p values for each series are summed and divided by 4. Full details of the results appear in Appendix 10.3.1 and 10.3.2. They are summarised in Table 4-18 below.

Table 4-18

Weighted average of p factors for β

Months	OLS p	Simple Random p	G&J random p	Stratified random p	WLS random p
		Dividend Yields			
3 to 12	0.006	0.011	0.097	0.343	0.064
24 to 36	0.000	0.043	0.278	0.704	0.250
3 to 36	0.003	0.028	0.193	0.535	0.163
		CBI - Business Optimism			
3 to 12	0.098	0.068		0.076	0.132
24 to 36	0.092	0.129		0.095	0.243
3 to 36	0.095	0.100		0.086	0.191
		CBI - Investment in Buildings			
3 to 12	0.020	0.018		0.022	0.040
24 to 36	0.097	0.220		0.238	0.124
3 to 36	0.061	0.125		0.137	0.085
		Investment in Plant			
3 to 12	0.051	0.031		0.031	0.070
24 to 36	0.235	0.239		0.222	0.330
3 to 36	0.149	0.142		0.133	0.209
		CBI - Future Orders			
3 to 12	0.108	0.065		0.081	0.127
24 to 36	0.062	0.120		0.122	0.230
3 to 36	0.084	0.094		0.103	0.181

The table neatly condenses the voluminous collection of statistics relating the 5 series examined. The conclusions are clear. β's of regressions of returns on dividend yields are significant when estimated by ordinary least squares even at the 1% level. When their significance is estimated by any of the four randomisation methods p values well in excess of conventional levels are reported. The evidence indicates that we are unable to reject the null hypothesis of $\beta = 0$ for the dividend yield series.

Despite a number of individual CBI series returning significant test statistics, when the p values are pooled, even when ordinary least squares is the method of estimation, significant test statistics are not generated. When p values are estimated by randomisation they substantially increase. Once again we are unable to reject for each of the four CBI variables the hypothesis that $\beta = 0$.

4.4.6 Distributions of Randomised p Values

Table 4-19 shows details of the distributional characteristics for the weighted least squares randomisation for the dividend yield variable and the CBI business optimism variable.

The skewness statistic for the dividend yield variable increases with the return horizon. This is reflected in the increased empirical p value for longer horizon returns. For example the OLS and the WLS p values for the 36 months series were both 0.000. However, when the empirical p value was estimated by WLS randomisation, it increased to 0.251. It is clear that when an allowance has been made for the effect of dividend yield as a lagged dependent variable, its empirical distribution is significantly positively skewed.

Rather different results were achieved for the CBI business optimism series. The empirical distribution of β was negatively skewed. None of the values for the skewness statistic were statistically significant however.

Table 4-19
Weighted Least Squares Randomisation of Total Returns, 1966 - 1993
Fractiles of Statistics

Horizon Months	Series	Mean	Std. Dev.	Median	Skewness	0.750	0.900	0.950	0.990	Observed WLS Statistic	WLS p value	Empirical WLS p value
				Dividend Yields - Distribution of β coefficients						*See Appendix 7.1*	*7.1*	*10.1.1*
3		1.009	0.538	0.923	0.718**	1.336	1.741	2.015	2.429	1.696	0.004	0.116
6	Jan & July	2.228	1.293	1.989	0.974**	3.010	3.938	4.697	5.972	4.159	0.001	0.080
6	Apr and Oct	2.176	1.253	1.969	0.964**	2.884	3.908	4.462	5.901	5.345	0.000	0.020
12	October	4.593	2.966	3.965	1.347**	6.148	8.562	10.047	14.002	9.999	0.001	0.052
24	October	10.829	6.523	9.557	1.308**	13.952	19.352	23.284	33.177	16.280	0.000	0.163
36	October	19.113	11.178	17.031	1.336**	24.660	33.940	39.580	52.489	24.674	0.000	0.251
				Confederation of British Industries - Business Optimism - Distribution of β coefficients †								
						0.250	**0.100**	**0.050**	**0.010**			
3		-0.0021	0.0339	-0.0017	-0.0116	-0.0255	-0.0470	-0.0587	-0.0803	-0.0413	0.265	0.125
6	Jan & July	-0.0033	0.0761	0.0043	0.0041	-0.0560	-0.0983	-0.1271	-0.1725	-0.0842	0.266	0.151
6	Apr and Oct	0.0026	0.0882	0.0033	-0.1063	-0.0577	-0.1136	-0.1451	-0.2034	-0.1068	0.237	0.114
12	October	-0.0018	0.2042	-0.0003	-0.0260	-0.1435	-0.2677	-0.3362	-0.4499	-0.2948	0.174	0.082
24	October	0.0006	0.4052	0.0127	-0.1636	-0.2450	-0.5410	-0.6975	-0.9724	-0.4332	0.154	0.146
36	October	-0.0135	0.6142	-0.0040	-0.0810	-0.3945	-0.7954	-1.0536	1.5619	-0.9923	0.018	0.060

* indicates significant at 5%, ** indicates significant at 1% level.

† Note, since β for the Business Optimism series is negative, the lower portion of the distribution has been shown.

4.5 Split Sample Results

4.5.1 Introduction

To test the structural stability of the regressions, the sample was split into two sub-samples of approximately equal-length. The first period starts in January 1966 and ends in the 1979/80[10], and the second period starts in 1980/81 and ends in 1992/93. Section 4.5.2 gives the ordinary least squares estimates of the β and R^2 for the Dividend Yield variable, Section 4.5.3 for the CBI Business Optimism variable and Section 4.5.4 provides a summary of the results for all 5 variables included in this study. Finally, Section 4.5.5 compares the p factors estimated by ordinary least squares with their empirical distribution.

4.5.2 Dividend Yields

Results for the Dividend Yield variable for selected series appear in Table 4-20 below.

Table 4-20

Split Sample Results - Dividend Yields

$$TR_{t,\,t+T} = \alpha_T + \beta_T GDY_t + u_{t,\,t+T}$$

		β			R^2		
Return Horizon Months	**Returns following CBI survey**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**
3		3.927**	4.404**	3.126	0.120	0.156	0.058
6	Jan & July	4.710*	5.200*	4.804	0.111	0.163	0.071
6	Apr & Oct	10.665**	12.308**	4.138	0.359	0.440	0.075
12	October†	17.634**	19.611**	4.695	0.563	0.648	0.070
24	October†	14.634**	15.749**	10.158	0.414	0.478	0.194
36	October†	33.505**	35.691**	24.927*	0.756	0.860	0.406
		App. 6.1	*--- App 12.1 ---*		*App. 6.1*	*--- App 12.1 ---*	

* indicates significant at the 5% level, and ** indicates significant at the 1 % level.
The significance of R^2 is the same as that of β.

Number of series , out of 15, with significant t values.

Significant at 1%	**13**	**11**	**0**
Significant at 5%	**15**	**15**	**2**

†*(Only the first series is shown for 12, 24 and 36 months horizons)*

---

10 Precise sample periods are determined by the dates of publication of the CBI surveys. Details appear in Appendix 15.

R^2 for the regression of returns on dividend yield show a dramatic reduction from the first to the second period. In the first period, from 1966 to 1980, R^2 reached 0.648 for the 12 month horizon. Since this figure has been estimated using independent observations, it is not distorted by the moving average error in the residuals which affects the 24 and 36 months series. The 36 months horizon shows a remarkable R^2 of 0.860. In contrast to the first period, R^2's are low for the second period, only 2 out of the 15 series having R^2's significant at the 5% level. Both these R^2's are for 36 months returns and both have unacceptably low Durbin Watson scores of 0.713 and 0.719 respectively (see Appendix 12).

It is clear from the evidence in Table 4-20 above that there are major structural differences between the first and second sub-samples and that the strong association between dividend yields and future returns which was reported in Table 4-4 can be attributed entirely to the influence of the first sub-period.

4.5.3 CBI - Business Optimism

Table 4-21 shows the results of the regression of returns on the CBI business optimism variable for the two sub-samples.

Table 4-21

Split Sample - Results

Confederation of British Industries - Business Optimism

		β			R^2		
Return Horizon Months	**Returns following CBI survey**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**
		x 10	**x 10**	**x 10**			
3		-1.163*	-1.265	-0.991	0.053	0.059	0.043
6	Jan & July	-0.845	-0.907	-0.882	0.023	0.033	0.013
6	Apr & Oct	-3.374**	-5.318*	-1.146	0.137	0.210	0.058
12	October†	-5.771	-12.472*	1.043	0.150	0.387	0.031
24	October†	-6.508*	-12.099*	-0.025	0.200	0.417	0.000
36	October†	-15.117**	-25.725**	-2.609	0.374	0.661	0.038
		App 6.2	*App 12.1*	*App 12.1*	*App 6.2*	*App 12.1*	*App 12.1*

* indicates significant at the 5% level, and ** indicates significant at the 1 % level.
The significance of R^2 is the same as that of β

†*(Only the first series is shown for 12, 24 and 36 months horizons, full detail see in Appendix 12.1)*

Number of series , out of 15, with significant test statistics

Significant at 1%	**3**	**2**	**0**
Significant at 5%	**7**	**7**	**0**

The statistical significance of the β coefficients for the CBI business optimism series also show a marked deterioration between the first and the second sub-samples. In the second period none of the test results were significant at the 5% level. The signs of the regression coefficients are unstable and reference to Appendix 12 reveals that most p factors were above 0.5. The evidence strongly suggests that in the second period there is no relation between future returns and the results of the CBI surveys.

4.5.4 Summary

Similar results are presented in Appendix 12 for the remaining three CBI Series. Once again, to avoid displaying unnecessary detail, the summary below gives the number of series (out of the total of 15) which are significant for dividend yields and for each of the four CBI variables.

Table 4-22

Split Samples - Summary of Results for all variables

Number of series , out of 15, for which R^2 is significant at 5% level

	1966 to 1993	1966 to 1980	1981 to 1993
Dividend yields	15	15	2[11]
Business optimism	7	7	0
Investment in buildings	9	7	0
Investment in plant	6	6	0
Future orders	6	3	0
	28	**23**	**0**
Full results appear in:	*Appendix 6*	*Appendix 12*	

Table 4-20, 4-21 and 4-22 above, all powerfully demonstrate that any relationship between returns and the explanatory variables is entirely a phenomenon of the first sub-period which runs from 1966 to 1980.

11 These regressions had unsatisfactory Durbin Watson Test Statistics.

4.5.5 Randomisation and Split Sample Results.

The Goetzmann and Jorion (1993) randomisation methodology which applied to dividend yield was repeated for the sub-samples. To limit extensive computing the p factors were calculated for only the 3 months horizon, the two six monthly series and the October series for 12 months, 24 months and 36 months returns. The p values for β for the dividend yield variable are summarised in Table 4-23.

Table 4-23

Split Sample - Dividend Yields

p factors for β for OLS and simple randomisation methods for split sample

		OLS p			**G & J Randomisation p**		
Return Horizon Months	**Returns following CBI survey**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**
3		0.000	0.003	0.099	0.047	0.197	0.276
6	Jan & July	0.016	0.041	0.187	0.207	0.504	0.372
6	Apr and Oct	0.000	0.000	0.166	0.010	0.080	0.450
12	October †	0.000	0.001	0.384	0.029	0.146	0.704
24	October †	0.000	0.009	0.152	0.396	0.756	0.700
36	October †	0.000	0.000	0.035	0.184	0.409	0.479
		App. 6.1	*---- App 12.1 ----*		*App. 10.1*	*---- App 13.1 ----*	

Number of series, out of 6, with significant t values.

Significant at 1%	**5**	**5**	**0**	**0**	**0**	**0**
Significant at 5%	**6**	**6**	**0**	**3**	**0**	**0**

†*(Only the first series is shown for 12, 24 and 36 months horizons.)*

Table 4-23 clearly shows that the Goetzmann and Jorion randomisation increases the p factors for β, both for the whole sample and also for each of the sub samples. Even in the first sub sample, which includes the turbulent period from 1973 to 1975 and for which all OLS results were significant at the 5% level (see Appendix 12.1) the p factors of the regression coefficient are substantially increased by randomisation; and none is significant. The same is true for the second sub-sample. This result suggests that the biases which affect the p values of the regression coefficients are more pronounced in small samples.

Table 4-24 shows the p value for the CBI Business Optimism variable computed by simple randomisation. The right hand columns of Table 4-24 show the p factors for the CBI Business Optimism series for the whole sample period as well as for each sub-sample.

Table 4-24

Split Sample - CBI - Business Optimism

***p* factors for β for OLS and simple randomisation methods for split sample**

		OLS *p*			**Simple Randomisation *p***		
Return Horizon Months	**Returns following CBI survey**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**
3		0.018	0.079	0.140	0.009	0.025	0.131
6	Jan & July	0.287	0.376	0.575	0.178	0.081	0.310
6	Apr and Oct	0.006	0.019	0.227	0.002	0.003	0.231
12	October †	0.051	0.023	0.563	0.013	0.046	0.387
24	October †	0.025	0.017	0.992	0.081	0.003	0.494
36	October †	0.001	0.001	0.564	0.017	0.080	0.395
		App 6.2	--- *App 12.1* ---		*App 10.1.1*	--- *App 13.1* ---	
		Number of series, out of 6, with significant *t* values.					
Significant at 1%		2	1	0	2	2	0
Significant at 5%		4	4	0	4	4	0

† *(Only the first series is shown for 12, 24 and 36 months horizons,)*

The OLS p factors for the sub-period 1966 to 1980 are significant for 4 of the 6 series in Table 4-24 above. Simple randomisation also shows 4 out of 6 series to be significant. In the second sub-period none of the coefficients are significant under either methodology.

The conclusions remain unchanged. While the CBI optimism variable was weakly related to returns in the first period, in the second period we are unable to reject the null hypothesis, using either OLS or simple randomisation, that there is no relationship between CBI optimism data and future returns.

Once again, the results strongly confirm that any relationship which exists between CBI data and returns is entirely a phenomenon of the first sub-period. The simple randomisation process was repeated for each of the other CBI variables in the study. The conclusions which can be derived from the OLS results remain unchanged. Any relation between future returns and any of the CBI variables is entirely a feature of the first sub-period.

We now examine the impact of individual observations on the results which have been reported.

4.6 Influential Observations

4.6.1 Methodology

Some econometric texts suggest that regression residuals and the fitted values be examined as a method to detect outliers. There are two major problems with this approach. Firstly, OLS residuals do not all have the same variance and, secondly, and more importantly, the OLS residuals do not reveal the explanatory power of any individual observation. Belsley et al. (1980) show graphically the effect that a number of different outliers may have on the results of a regression. One outlier may fit well with the other data in a regression and therefore have a small residual but it may have a very large impact on both the regression coefficients and on the explanatory power of the regression.

Belsley et al. (1980) argue that although much can be learned through examination of the residuals, this method nevertheless fails to show directly what the estimated model would be if a subset of the data were modified or set aside. They have developed a measure which they describe as the leverage measure of the regression. This is given by:

$$h_i - \tfrac{1}{n} = \tilde{h}_i = \tilde{\mathbf{x}}_i(\tilde{\mathbf{X}}^T\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{x}}_i^T \qquad (4.1)$$

where $\mathbf{X}$ is the n x p matrix of explanatory variables, and the matrix is transposed by the superscript T. $\widetilde{\mathbf{X}}$ indicates the matrix formed by centring the columns of $\mathbf{X}$ about their respective column means.

They suggest 3 different methods by which influential observations might be identified. They argue that as with all empirical procedures, this question is ultimately answered by judgement and intuition in choosing reasonable cut-offs most suitable for the problem at hand guided wherever possible by statistical theory. The three methods are external scaling, internal scaling and gaps. For external scaling they argue that a suitable cut-off would be that where $h_i > 2\sqrt{(p/n)}$, where p equals the number of regressors and n equals the number of observations in the sample. For external scaling they suggest the interquartile range $\widetilde{s}$ for each series is computed. Extreme values are those which exceed (7/2) $\widetilde{s}$. If these diagnostics were Gaussian they would occur less than 1% of the time. Finally they suggest that the researcher identifies points at which the diagnostic measure appears to be singularly different from the others.

The leverage measure of the regression was estimated for the regressions for horizons of 3, 12 and 36 months for dividend yields and the CBI optimism series. The results are presented in Figures 4-1 to 4-4.

4.6.2 Dividend Yields

The leverage measure of the regression of 3 months returns on dividend yields were calculated using the Micro-Fit package. The results are shown in Figure 4-1 on the following page. The graph dramatically demonstrates that the most important observations occurred in the period prior to May 1975. Figure 4-2 shows the leverage measure for the regression of dividend yields on 12 months returns. A very similar pattern is shown in Figure 4-2 as in Figure 4-1. When the procedure was repeated for 36 months returns, a pattern virtually identical to that shown in figure 4-2 was revealed. The graph is therefore not presented in the thesis.

An analysis of the data from which Figure 4-1 was derived revealed that the most influential observation followed the CBI survey published in November 1974. The FT Actuaries All-Share index fell from a peak of over 220 in August 1972 to 76.5 in November 1974. Further modest falls occurred in December 1974 and January 1975 when the index reached a low of 63.2. In February 1975 the index recovered to 101.9 an increase of 61%. It is clear that the effect of this one episode heavily influences the results of this study.

Figure 4-1

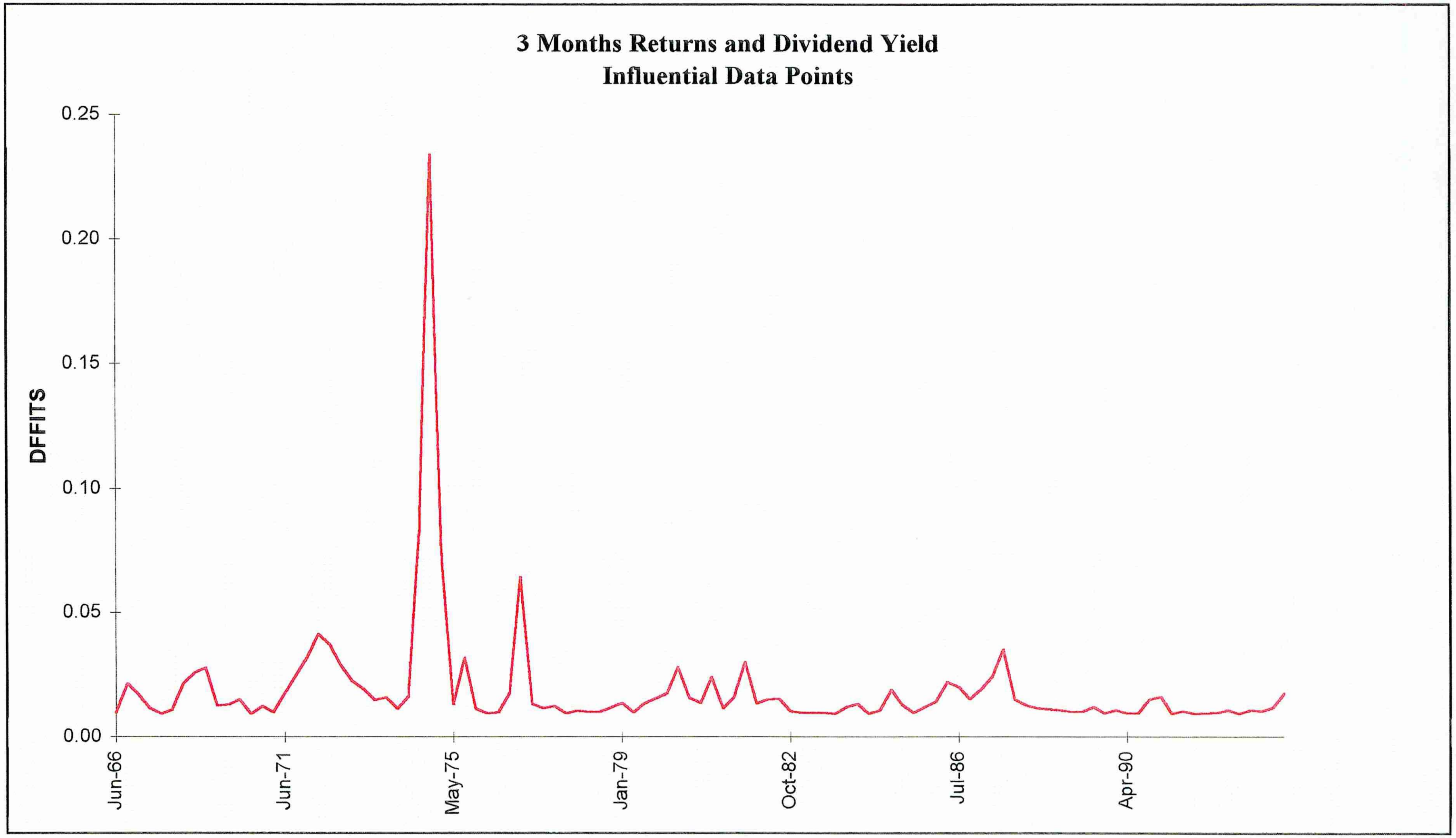
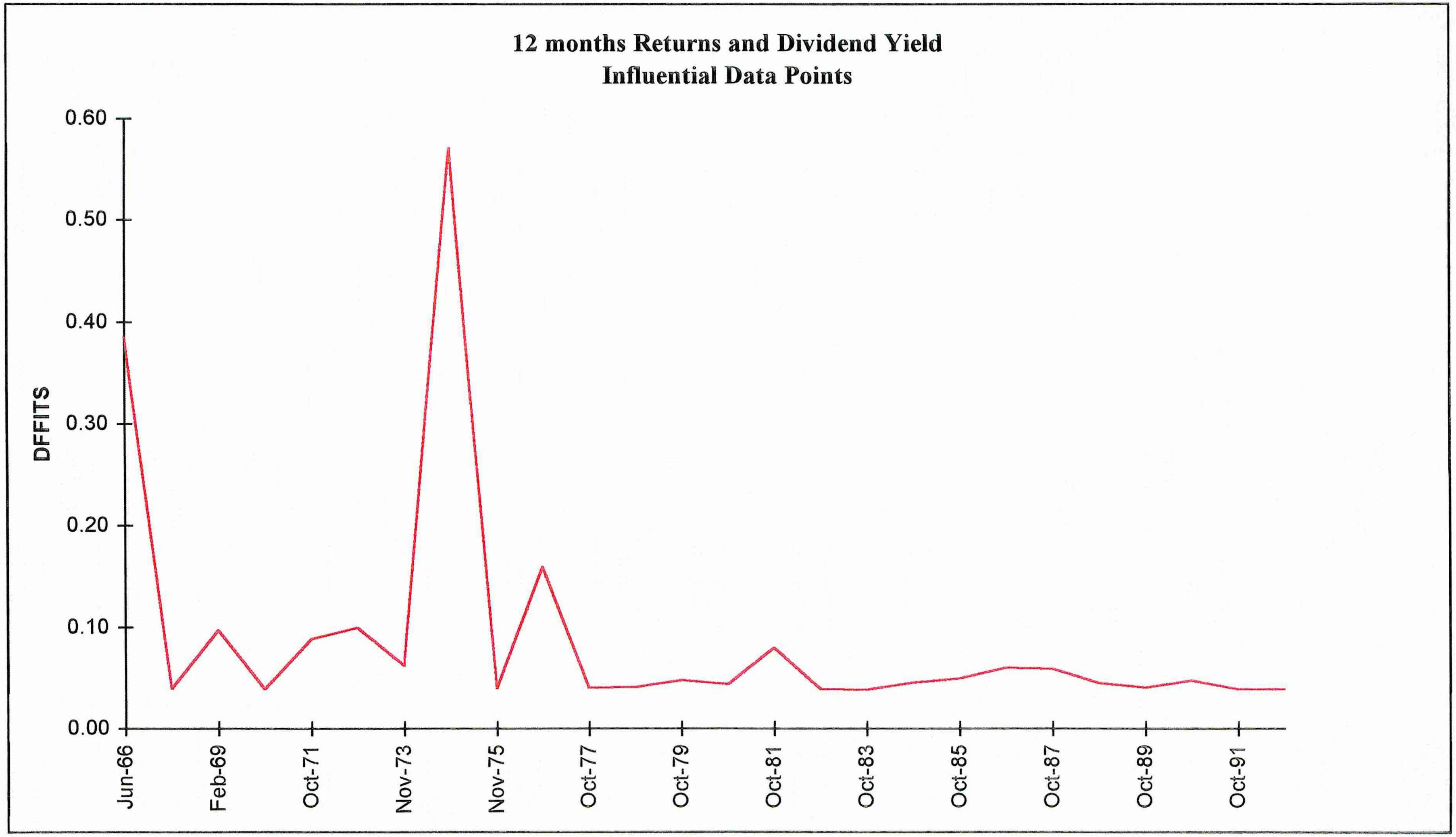

3 Months Returns and Dividend Yield
Influential Data Points
DFFITS
0.25
0.20
0.15
0.10
0.05
0.00
Jun-66
Jun-71
May-75
Jan-79
Oct-82
Jul-86
Apr-90

Figure 4-2



12 months Returns and Dividend Yield
Influential Data Points
DFFITS
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Jun-66
Feb-69
Oct-71
Nov-73
Nov-75
Oct-77
Oct-79
Oct-81
Oct-83
Oct-85
Oct-87
Oct-89
Oct-91

4.6.3 Confederation of British Industries Data

Figure 4-3 shows the leverage measure for the regression of the CBI Balance of Business Optimism series on three months returns. The figure indicates that the observation including the results of the April 1980 survey was extremely influential in the regression and that most of the R^2's can be explained by this observation. The regression R^2 of 5.1% was significant at the 5% level. All four CBI business optimism series had been falling since October 1979. The stock market showed a considerable rally from April 1980, the FT All Share Price Index increasing from 242.8 to 282 in the 3 months period. The negative relationship between the change in business confidence and future returns would be consistent with an hypothesis that the market takes a longer term view of business prospects than is exhibited in the surveys of business confidence.

Figure 4-4 shows the leverage measure for the regression of the CBI business optimism on 12 months future returns for the October series. The chart shows two influential observations. The first follows the publication of the CBI survey in November 1974 and the second follows the publication of the October 1980 survey. The peaks reflect the recoveries of the market in 1975 and also in 1980 which were described in the preceding paragraphs.

Figure 4-3

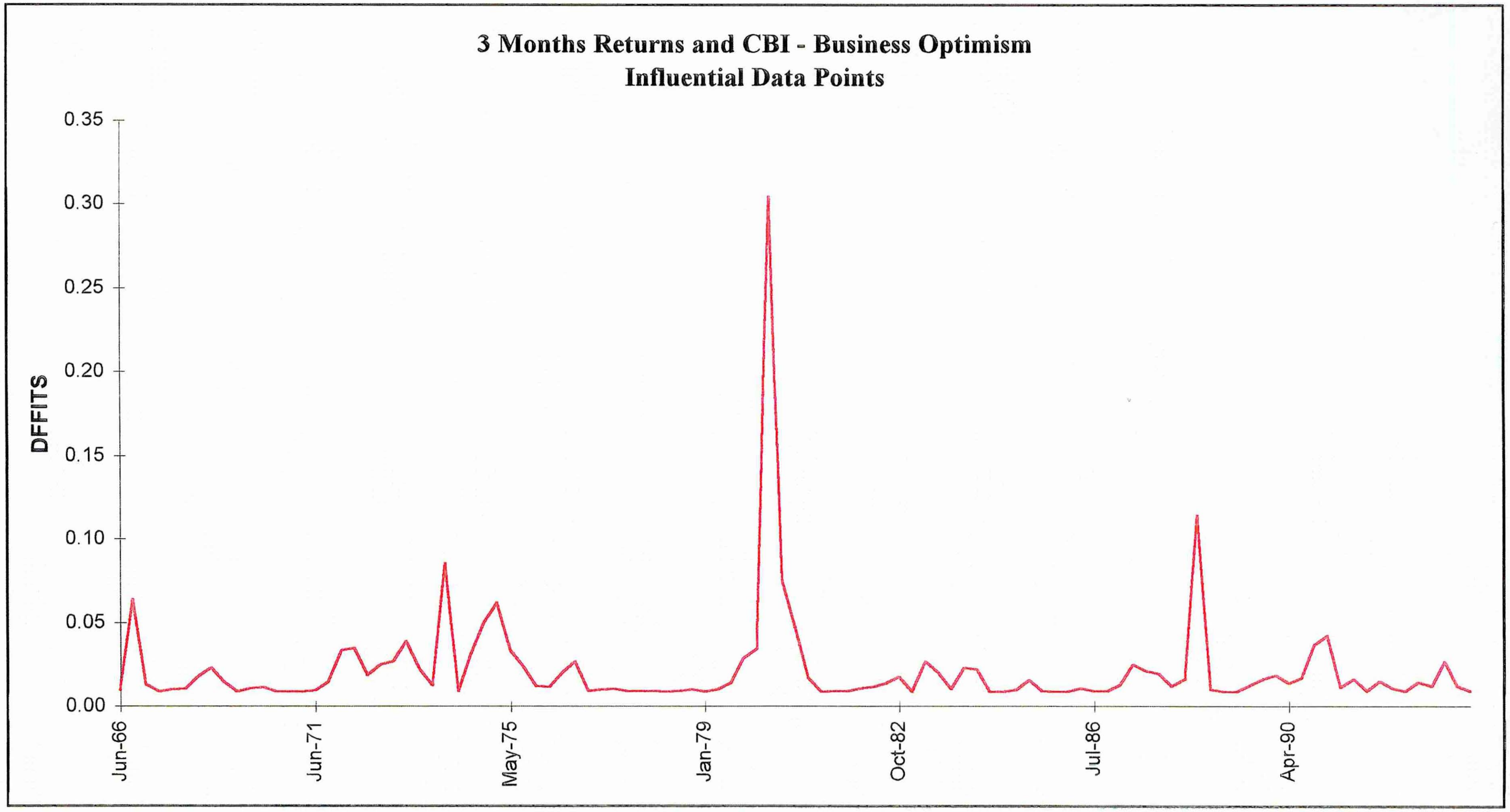
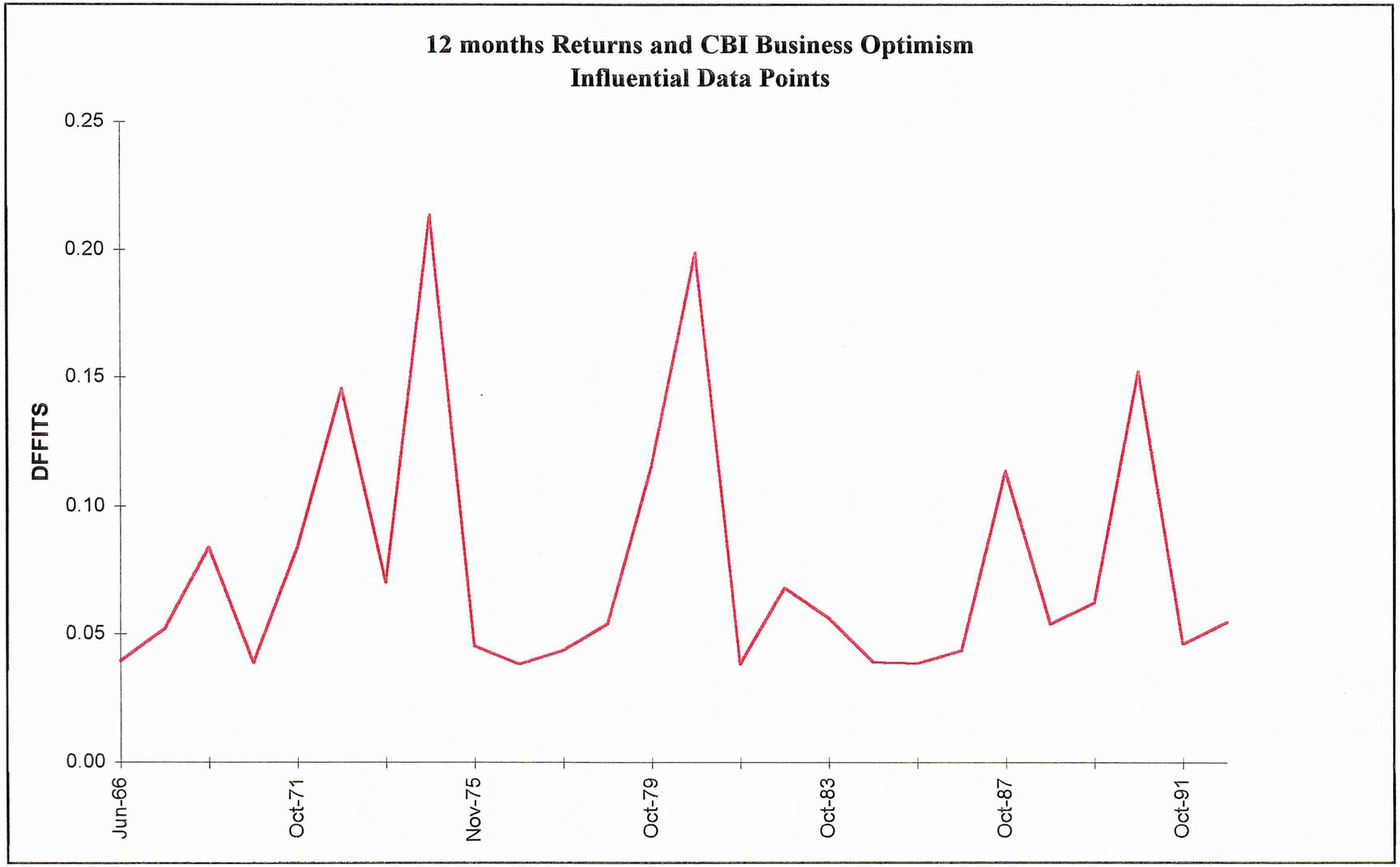

3 Months Returns and CBI - Business Optimism
Influential Data Points
DFFITS
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Jun-66
Jun-71
May-75
Jan-79
Oct-82
Jul-86
Apr-90

Figure 4-4


12 months Returns and CBI Business Optimism
Influential Data Points
DFFITS
0.25
0.20
0.15
0.10
0.05
0.00
Jun-66
Oct-71
Nov-75
Oct-79
Oct-83
Oct-87
Oct-91

15 series ranges from between 0.163 for WLS randomisation to 0.535 for the stratified randomisation.

In the first sub-period from 1966 to 1980 ordinary least squares estimation revealed remarkably high R^2 of as high as 0.757 for 3 year horizons (see Appendix 12.1.1). During this period all 15 series had significant coefficients at the 5% level. In the second period from 1981 to 1993, R^2 was much lower and only 2 out of 15 series showed a statistically significant relationship between dividend yields and future returns. Thus OLS methodology reveals that any statistically significant relationship between dividend yields and future returns is almost entirely a feature of the turbulent period from 1966 to 1980. When the leverage measure developed by Belsley et al. (1980) was implemented, the period following November 1974, when the Financial Times Actuaries All Share Index fell to 76.5, was shown to be the dominant influence on the regression results for 3, 12 and 36 months horizons.

4.7.3 Confederation of British Industries Survey Data

In contrast to the dividend yield variable, the four CBI variables showed only a modest relationship with future returns. When estimated by OLS, out of a total of 60 regressions, (4 variables and 15 series), 28 had β coefficients significant at the 5% level. See Table 4-16. This was reduced to 19 and 9 respectively when estimation was by simple randomisation and weighted least squares randomisation. Table 4-18 showed that for the entire 15 series, the p factors generated by conventional ordinary least squares and by randomisation were not significant for any of the 4 CBI variables. When the sample was split into two, any modest relationship between CBI data and future returns was shown to be entirely attributable to influence of the first period. The leverage measure was calculated for the regression of 3 months future returns on the CBI Business optimism series. As for dividend yields, the period following the publication of the November 1974 survey was found to be influential. For longer return horizons, both this period and also that following the October 1980 CBI survey were found to be influential.

15 series ranges from between 0.163 for WLS randomisation to 0.535 for the stratified randomisation.

In the first sub-period from 1966 to 1980 ordinary least squares estimation revealed remarkably high R^2 of as high as 0.757 for 3 year horizons (see Appendix 12.1.1). During this period all 15 series had significant coefficients at the 5% level. In the second period from 1981 to 1993, R^2 was much lower and only 2 out of 15 series showed a statistically significant relationship between dividend yields and future returns. Thus OLS methodology reveals that any statistically significant relationship between dividend yields and future returns is almost entirely a feature of the turbulent period from 1966 to 1980. When the leverage measure developed by Belsley et al. (1980) was implemented, the period following November 1974, when the Financial Times Actuaries All Share Index fell to 76.5, was shown to be the dominant influence on the regression results for 3, 12 and 36 months horizons.

4.7.3 Confederation of British Industries Survey Data

In contrast to the dividend yield variable, the four CBI variables showed only a modest relationship with future returns. When estimated by OLS, out of a total of 60 regressions, (4 variables and 15 series), 28 had β coefficients significant at the 5% level. See Table 4-16. This was reduced to 19 and 9 respectively when estimation was by simple randomisation and weighted least squares randomisation. Table 4-18 showed that for the entire 15 series, the p factors generated by conventional ordinary least squares and by randomisation were not significant for any of the 4 CBI variables. When the sample was split into two, any modest relationship between CBI data and future returns was shown to be entirely attributable to influence of the first period. The leverage measure was calculated for the regression of 3 months future returns on the CBI Business optimism series. As for dividend yields, the period following the publication of the November 1974 survey was found to be influential. For longer return horizons, both this period and also that following the October 1980 CBI survey were found to be influential.

4.7.4 Dividend Yields and Confederation of British Industries Data

The model selection criteria described in 3.3.5 were used within the framework of ordinary least squares to test whether the addition of CBI data as an explanatory variable was justified under the criteria. In a total of 60 regressions, the addition of CBI data was justified in only 17 regressions when $\overline{R}^2$ was the criterion. This fell to 3 regressions with the Akaike Information Criterion and zero with the Schwartz Criterion. It was later shown that when the p factors of β in Equations 3.1. and 3.2 were estimated by weighted least squares randomisation, it was impossible to reject the null hypothesis at conventional levels in all but a tiny minority of series.

4.7.5 Conclusions

Section 3.2.3 explained that the classical linear regression model should satisfy the following assumptions:

1. The explanatory variables are fixed
2. The rank of X is equal to k, in other words no exact linear relationship exists between two or more independent variables.
3. The disturbances are uncorrelated, each having a zero mean and a constant but finite variance.

Furthermore, Section 3.3.1 quoted Harvey (1989) who summarised the qualities of a good econometric model, stated:

5. *Structural stability. As well as providing a good fit within the sample, a model should also give a good fit outside the sample. In order for this to be possible, the parameters should be constant within the sample period and this constancy should carry over into the post sample period.*

The regression of returns on dividend yields and on CBI survey data leads to a number of econometric difficulties and to violations of the assumptions on which ordinary least squares regressions are based. Chapter 3 of this thesis described the randomisation methodology which was used to allow for a lagged version of the dependent variable as the explanatory variable, for serial correlation induced by overlapping observations and for the heteroscedastic and non-normal pattern of stock returns. When these corrections were made, it was not possible to reject the null hypothesis that $\beta = 0$ for either Equations 3.1 or 3.2. Furthermore OLS regression coefficients which were significant in the first sample period at the 5% levels, were insignificant in the second period. The explanatory power of the regressions which appeared from conventional estimation to be high in the first period, was very low in the second period. It therefore seems unlikely that the regressions based on Equations 3.1 and 3.2 can give good out of sample predictions.

CHAPTER 5

CRITICISMS OF THIS STUDY AND COMPARISONS WITH OTHER STUDIES

5.1 Introduction

Chapter 4 showed that when OLS was the method of estimation, dividend yields were strongly related to returns at all time horizons. Allowance for the violations of the assumptions on which OLS is based, in particular for the effect of the lagged regressor, caused statistical significance to disappear. CBI data were rather more weakly related to returns. For both dividend yields and CBI data, the relationship which existed was shown to be entirely a feature of the first period which ran from 1966 to 1980.

Chapter 5 considers possible challenges to the econometric findings in this study and also compares its results with those of other studies.

5.2 Possible Criticisms of this Study

5.2.1. Arithmetic v.'s Continuously Compounded Returns

This study followed Goetzmann and Jorion (1993) in deriving long horizon returns by arithmetically compounding monthly returns. Continuously compounded returns however are more widely used in empirical studies. To test whether the conclusions of this study might be altered by using continuously compounded returns in preference to arithmetic returns, as the dependent variable, the regressions in equations 3.1 and 3.9 were re-estimated.

Appendix 14 shows the full results. Table 5-1 summarises the figures for the 3 and 36 months return horizons.

Table 5-1

Regressions of Returns on Dividend Yields

$$TR_{t,\,t+T} = \alpha_T + \beta_T GDY_t + u_{t,\,t+T}$$

Return Horizon Months	Returns following CBI Survey	Arithmetic returns β	βp	R^2	Log. returns β	βp	R^2
			1966 - 1993				
3		3.927	0.000	0.120	3.521	0.002	0.094
36	October	33.505	0.000	0.756	20.294	0.000	0.546
		see Appendix 6.1			*see Appendix 14.1*		
			1966 - 1980				
3		4.404	0.003	0.156	3.911	0.010	0.122
36	October	35.691	0.000	0.860	21.994	0.001	0.645
		see Appendix 12.1			*see Appendix 14.1*		
			1981 -1993				
3		3.126	0.099	0.058	3.256	0.080	0.060
36	October	24.927	0.035	0.406	15.266	0.040	0.390
		see Appendix12.1			*see Appendix 14.1*		

As expected β coefficients for the dividend yield variable were a little lower when returns were based on its continuously compounded form, as was R^2. The p factors for the β coefficients were slightly higher. Differences however were small and not likely affect the conclusions of this study.

Table 5-2 below shows the results for the business optimism series.

Table 5-2

Regressions of Returns on CBI - Business Optimism

$$TR_{t,\ t+T} = \alpha_T + \beta_T CBIA_t + u_{t,\ t+T} \qquad \textbf{(2.9)}$$

Return Horizon Months	Return following CBI Survey	Arithmetic returns β	βp	R^2	Log. returns β	βp	R^2
				1966 - 1993			
3		-0.116	0.018	0.053	-0.104	0.029	0.046
36	October	-1.512	0.001	0.374	-0.965	0.003	0.339
		see Appendix 6.2			*see Appendix 14.2*		
				1966 - 1980			
3		-1.265	0.079	0.059	-1.111	0.107	0.050
36	October	-25.725	0.001	0.661	-15.644	0.004	0.546
		see Appendix 12.1			*see Appendix 14.2*		
				1981 -1993			
		Arithmetic returns			**Log. returns**		
3		-0.991	0.140	0.043	-0.971	0.139	0.04
36	October	-2.609	0.564	0.038	-1.853	0.048	0.05
		see Appendix 6.2			*see Appendix 14.2*		

The log based model shows only a very slightly weaker relationship between future returns and the explanatory variables. Furthermore, the inferences which can be drawn from data for the whole sample, can also be drawn from the sub-samples. Both the log and the arithmetic models show significant test statistics in the first period. In the second period, test statistics are generally insignificant in both models. In short, the findings of this thesis are not materially affected by the method of compounding returns.

5.2.2 Excess Returns

This study in common with Goetzmann and Jorion (1992) and (1995) has tested the hypothesis that the explanatory variables forecast returns rather than excess returns. The series of returns were highly volatile. Annual returns, for series 1, varied from a high of 117.3% to a low of -56.2% (see Table 4-1), with a standard deviation of 33.9%. In contrast, the treasury bill interest rate series is relatively stable. Returns on 90 day treasury bills varied from a low of 4.4% per annum in November 1971 to a high of 16.3% in March 1980, with a standard deviation of only 2.9%. Therefore there are strong *a priori* reasons for believing the replacement of returns by excess returns would make little difference to the results in this study. This study follows the approach adopted by Goetzmann and Jorion in using returns as the dependant variable. There are good grounds for believing that the findings for returns are equally applicable to excess returns[1].

5.2.3 Dividends

Section 3.4.2 of this thesis showed how the dividend yield variable was calculated from the underlying capital and income return series extracted from Datastream. Since CBI surveys took place only 3 times a year until 1972, returns for periods prior to that year covered 4 months for quarterly data, 8 months for the 6 monthly series and 16 months for annual data. To derive the annual series of dividends in the period prior to 1972 it was necessary to pro rata the dividends calculated from the capital and income return series. Figure 3.6 showed that the simulated series of dividend yields closely matched the series of published dividend yields extracted directly from the Datastream database. The correlation between the two series was 0.988. Nevertheless, as a check on the effect of using a simulated series rather than the actual series, the regression of returns on dividend yields for a 12 month horizon was re-run, dropping data before October 1971, which included rather longer returns than in the rest of the sample, and then replacing the unequal return periods with periods of precisely 12 months. The results are shown in rows 3 and 4 of Table 5-3.

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1 In an earlier version of this work, both returns and excess returns were regressed on dividend yields. As expected, R^2 was slightly higher for returns than for excess returns.

Table 5-3

Regression of Returns on Dividend Yield.

Sensitivity to Return and Dividend Assumptions

12 months horizon - series 1

		β	βp	R^2
1	Base case (as Table 4-4)	17.6	0.000	0.563
2	Actual dividend yield	17.0	0.000	0.554
3	Returns from October 1971	17.4	0.000	0.621
4	Annual return observations	17.2	0.000	0.549

The first row shows the results published in Table 4-4[2]. The second row substitutes the actual dividend yield extracted directly from Datastream for the derived dividend yield which was used in this study. The third row uses data from this study but ignores the first five annual observations which incorporated return data for non standard periods. The final row, replaces the first five observations of the data series which included returns for periods in excess of 12 months with data for at exactly annual periods.

Table 5-3 demonstrates that the results are robust even when allowance is made for peculiarities in the data and for a non-standard econometric approach.

In chapter 3.2.2 taxation and government controls of dividends were discussed. The dividend series is relatively smooth, (See figure 3.3), and does not appear to have been influenced greatly by the changes in tax regime over the 28 years of this study. The imputation system of taxation, which was introduced in 1972, has remained in operation throughout the last 21 years of data in this study. Dividend controls were applied intermittently in the early part of this study but were finally abandoned in early 1979. Regressions of returns on dividend yields are dominated by prices since

2 Computations were checked by extracting the FT Actuaries All-Share Return and the Price Indices directly from Datastream. The Microfit package was used to estimate the regressions in the table 5-3.

dividends are a highly autocorrelated series and any minor changes to the dividend stream seem unlikely to greatly influence the results of this study. Section 4.6.2 demonstrated that the regression results were heavily influenced by the recovery of the market in early 1975.

To test whether the relationship between future returns and dividend yields was determined by the specific properties of the dividend yield series or whether a simple time trend would equally well explain future returns, the series of *GADIV* (annual dividends) was replaced with a linear trend starting at the figure for annual dividends in 1966 and ending with the figure for 1993. This trend was divided by the price as in equation 3.40 to give a pseudo dividend yield. Returns for selected horizons were regressed on the pseudo dividend yield series and the results are shown in Table 5-4 below.

Table 5-4
Regression of Returns on 'Trended' Dividend Yields

1966 - 1993

		Reported results			Trended dividends		
Return Horizon Months	**Returns following CBI Survey**	β	βp	R^2	β	βp	R^2
3		3.927	0.000	0.120	0.637	0.030	0.045
6	Jan & July	4.710	0.016	0.111	0.477	0.354	0.017
6	Apr & Oct	10.665	0.000	0.359	2.016	0.002	0.174
12	October	17.634	0.000	0.563	3.764	0.003	0.320
24	October	14.634	0.000	0.414	3.057	0.019	0.217
36	October	33.505	0.000	0.756	7.903	0.000	0.487

see Appendix 6.1

It is clear that a simple time trend, in combination with a lagged version of the dependent variable, the current value of the index, explains a high proportion of future returns. Table 5-4 shows an R^2 as high as 0.487 for 36 months returns. As Nelson and Kim (1993) have observed, the longer the horizon and the greater the overlap in the return series, the more the return series resembles a price series which itself approximates a random walk. This is reflected in the unit root tests in Appendix 4.2

where the Dickey Fuller and the Augmented Dickey Fuller tests approach the 5% critical level for the 36 months return series. Furthermore, the dividend yield series also shows statistics approaching the 5% critical level. It is possible that at least some of the apparent relationship between dividends yields and long horizon future returns is related to the spurious regression which arises from regressing one random walk on another random walk (See Phillips (1986)). Moreover, Nelson and Kang (1984) have shown that the regression of a random walk on time will produce R^2 values of around 0.44 regardless of sample size when, in fact, the mean of the variable has no relationship with time. In the case of a random walk with drift, that is when $\beta \neq 0$, the R^2 will be higher regardless of sample size. The researcher is alerted to the potential problem by the unacceptably low level of the Durbin Watson test statistics for regressions of returns on the explanatory variables at longer horizons.

Another possible criticism that can be levelled at the methodology used in this study is omission of interest on dividends received throughout the year. Since dividend payments have seasonal peaks, their payment dates and interest accrued on them might possibly influence the statistical significance of their coefficients. In chapter 3 (see 3.2.1), the method by which Datastream calculated dividends, was described. Prior to 1st January 1985 dividends were spread evenly over the trading days of the year. Thus for a major part of this study no meaningful allowance for seasonal dividends can be made. Furthermore, since the data in this study are dominated by the characteristics of the return series there seems to be little reason to believe that minor tinkering with the dividend series is likely to make a substantial difference to the results. Nevertheless, to assess the magnitude of the difference that might be made by the inclusion of interest on dividends, the simplifying assumption was made that all dividends were received mid-year.[3] Treasury Bill interest was added to the dividends series. A selected sample of regressions were re-estimated and their results appear in Table 5-5 below.

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3 The distribution of dividends for the period after 1st January 1985 was derived from Datastream data. The seasonal pattern is modest.

Table 5-5

Effect of Interest on Dividends

1966 - 1993

		Reported results			With Interest on Dividends		
Return Horizon Months	**Return following CBI Survey**	β	βp	R^2	β	βp	R^2
3		3.927	0.000	0.120	3.660	0.000	0.118
6	Jan & July	4.710	0.016	0.111	4.426	0.016	0.111
6	Apr & Oct	10.665	0.000	0.359	9.928	0.000	0.353
12	October	17.634	0.000	0.563	16.507	0.000	0.556
24	October	14.634	0.000	0.414	13.772	0.019	0.413
36	October	33.505	0.000	0.756	31.621	0.000	0.759

Appendix 6.1

It is clear from the table that the inclusion of interest in the computations is likely to make only a trivial difference to the results.

5.2.4 Econometric Issues

This study has followed closely the methodology adopted in the mainstream literature in financial economics, starting with Fama and French (1988b) and (1989) and continuing through Nelson and Kim (1993) and Goetzmann and Jorion (1993). Returns have been regressed on dividend yields and on CBI data.

Some econometric models incorporate lags of explanatory variables. On *a priori* grounds there seemed to be little justification for inclusion of lags of either dividend yield or CBI data in return forecasting regressions. Nevertheless, the inclusion of lagged dividend yields and lagged CBI data was tested, for a few selected series by using the $\overline{R}^2$, AIC and SIC criteria which were described in 3.3.5. The results appear in Table 5-6 below.

Table 5-6

Classical Regressions Results - Lagged Explanatory Variable - Model Selection Criteria 1966 - 1993

		$\overline{R}^2$			Akaike Inf. Criteria			Schwartz Inf. Criteria	
Return Horizon Months	**Returns following CBI surveys**	**Div. yield**	**Lag Div. yield**		**Div. yield**	**Lag Div. yield**		**Div. yield**	**Lag Div. yield**
					Dividend Yield				
3		0.115	0.110		1001.1	1002.8		1006.4	1010.7
6	Jan & July	0.087	0.088	*	475.8	476.7		479.6	482.5
6	Apr & Oct	0.356	0.343		502.1	504.1		506.0	510.0
12	October	0.545	0.580	*	239.9	238.7	*	242.3	242.4
24	October	0.406	0.411	*	234.2	234.9		236.5	238.4
36	October	0.755	0.747		229.1	230.7		231.3	234.2
					CBI - Business Optimism				
3		0.044	0.036		1021.3	1023.2		1026.7	1031.1
6	Jan & July	0.003	0.037	*	489.9	489.2	*	493.9	495.0
6	Apr & Oct	0.121	0.112		529.1	530.5		533.0	536.4
12	October	0.114	0.081		266.7	268.6		269.2	272.3
24	October	0.165	0.201	*	253.4	253.2	*	255.9	256.9
36	October	0.346	0.319		262.8	264.7		265.2	268.2

Notes:

1 The criterion is to maximise $\overline{R}^2$ and to minimise the Akaike or Schwartz information criteria. Where the inclusion of the CBI series is indicated by the statistic, the series is marked by an *.

2 The statistics in the dividend yield columns are slightly different from the figures in Appendix 6.1. It was necessary to drop the first observation where a lagged variable was not included in the regression so that the statistics covered the same time-frame as those where a lagged explanatory variable was included.

The inclusion of a lag of the dividend yield variable was only justified for three of the 6 series using the $\overline{R}^2$ criterion. This falls to one series and none with the Akaike and the Schwartz criteria respectively.

The inclusion of a lag of the CBI Business Optimism series was justified for only two of the six series by the $\overline{R}^2$ and the Akaike criteria and for none of the series by the Schwartz criterion. Any gains to be achieved by including lagged explanatory variables would seem to be small. In common with the substantial research on the association between dividend yields and returns in financial economics literature they were therefore considered no further in this study.

5.2.5 Randomisation v.'s Bootstrapping

This study employs approximate randomisation to estimate the empirical distribution of β [4]. In contrast Goetzmann and Jorion use bootstrapping. Noreen (1989) page 6, emphasises that randomisation is the appropriate technique when the hypothesis is concerned with the relationship between variables. Randomisation simply shuffles one variable to determine the number of occasions when the specified relationship between it and another variable may be exceeded. Thus for this study, returns are randomly shuffled and regressed on dividend yields or CBI data. With bootstrapping, samples of returns are taken, with replacement, at random from the return series and regressed on the dividend yield series.

The use of randomisation has an effect which is particular to the Goetzmann and Jorion model. In section 3.4.4 the creation of a pseudo price series by cumulating the historic series of capital returns was described. Since the product of a series of numbers does not depend on the ordering of the series, this has the effect that the last pseudo price under randomisation is the last price in the series. As actual dividends are used as the denominator in the dividend yield calculations, the last dividend yield in the randomised series is the actual dividend yield. In this respect the series is not truly randomised. Since there are over 330 monthly observations in the sample period, it was not considered that this would be likely to make a material difference to the results. Romano (1989) showed that under general conditions randomisation and bootstrapping were asymptotically equivalent and concluded that randomisation may be preferred because it ensures desired size in finite samples.

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4 Approximate randomisation uses a set number of shuffles to determine whether the specified relationship might occur by chance. Full randomisation shuffles the series to include all possible permutations.

To test whether bootstrapping made any difference from randomisation to the empirical results in this study, the Goetzmann and Jorion (1993) methodology for the dividend yield series was replicated using bootstrapping, and the empirical p values for β were calculated and compared with the p values generated by randomisation. The results are as shown in Table 5-7 below.

Table 5-7

Randomisation v.s Bootstrapping

Dividend Yields, 1966 -1993

***p* factors for tests for significance of β**

1 Return Horizon Months	2 Returns following CBI surveys	3 β	4 O.L.S p	8 G&J random p	9 G&J with bootstrap p
3		3.93	0.000	0.047	0.058
6	Jan & July	4.71	0.016	0.207	0.177
6	Apr & Oct	10.67	0.000	0.010	0.024
12	October	17.63	0.000	0.029	0.042
24	October	14.63	0.000	0.396	0.311
36	October	33.51	0.000	0.184	0.184
		-- App.6	*--*	*10.1.1*	

It is apparent that the differences are small and are of little consequence to either the results or to the inferences which can be drawn from them.

5.3 Comparison with Other Published Studies

Fama and French (1988b) provided the seminal research on the relationship between dividend yields and future returns. They make insufficient allowance for a number of econometric issues which have been discussed in this study. As already discussed the methodology in this study follows closely that in Goetzmann and Jorion (1993) and (1995). Inevitably, direct comparison between this study and others is difficult since data are taken from the different markets and different sample periods. Time horizons for returns and methodological differences also may create difficulties.

5.3.1 Fama and French (1988b)

Figures extracted from Table 3 of Fama and French (1988b), which are based on OLS regression, are compared with figures from this study, in Table 5-8 below.

Table 5-8

Comparison with Fama and French (1988b)

Fama and French, 1957 - 1986					This Study, 1966 -1993		
Return Horizon Months	**Beta**	**Beta t**	**R^2**	**Returns following CBI Survey**	**Beta**	**Beta t**	**R^2**
3	2.33	2.78	0.05		3.52	2.41	0.09
12	9.32	3.02	0.22	October	13.87	5.52	0.39
24	16.40	4.04	0.45	October	12.63	2.43	0.32
36	17.12	4.12	0.51	October	20.29	4.69	0.55

See Appendix 14.1 for full details

1 Returns are continuously compounded

2 For 24 and 36 months returns the Fama and French t values are adjusted for autocorrelation in the residuals by the method of Hansen and Hodrick (1980).

3 The t values in my study are adjusted for heteroscedasticity and serial correlation by the method of Hansen (1982) and Newey West (1987). The OLS t values in my study are very close to the t values published above.

4 Both Fama and French (1988b) and this study use overlapping observations for 24 and 36 months horizons.

Despite the difficulties previously mentioned the figures for the two studies are very similar. Table 5-8 above shows for 3 out of the 4 series shown, only slightly higher β coefficients and R^2's than Fama and French.

5.3.2 Goetzmann and Jorion (1993) and (1995)

Goetzmann and Jorion (1993) and (1995) extend the work of Fama and French by specifically allowing for the biases to the β coefficient caused by a lagged variable. They use bootstrap estimates to adjust their p factors for biases arising from serially correlated residuals generated by the use of overlapping observations. My study extends their work by specifically allowing for hetroscedasticity, by stratified random sampling as well as the use of weighted least squares. Table 5-9 reports Goetzmann and Jorion (1993) U.S. results for the period 1959 to 1990. Table 5-10 reports Goetzmann's (1995) results from 1927 to 1992 based on UK data and Table 5-11 presents the results of this study for comparable time horizons.

Table 5-9

Goetzmann and Jorion (1993)

US data - S&P 500 Index - 1959 - 1990

Return Horizon Months	Beta	β *t* OLS	β *t* HHNW	R^2	Empirical *p* value β	Empirical *p* value R^2
12	8.76	11.04	4.46	0.277	0.137	0.022
24	14.40	14.29	4.32	0.363	0.243	0.057
36	19.74	17.15	4.90	0.459	0.309	0.081

Table 5-10

Goetzmann and Jorion (1995)

UK data - Barclays-DeZoete-Wedd Index - 1927 - 1992

Return Horizon Months	Beta	β *t OLS*	β *t HHNW*	R^2	Empirical *p* value β
12	13.20	6.54	3.98	0.405	0.016
24	18.59	6.80	7.22	0.427	0.045
36	31.56	10.03	12.38	0.623	0.033

Table 5-11
This Study, 1966 - 1993

Return Horizon Months	Returns following CBI surveys	β	R^2	Empirical *p* value OLS β	Empirical *p* value WLS β
12	October	17.63	0.563	0.029	0.052
	January	11.54	0.301	0.127	0.096
	April	15.30	0.311	0.052	0.023
	July	9.55	0.211	0.204	0.061
24	October	14.63	0.415	0.396	0.163
	January	18.04	0.426	0.268	0.240
	April	19.93	0.372	0.211	0.222
	July	18.19	0.371	0.264	0.211
36	October	33.51	0.756	0.184	0.251
	January	28.54	0.574	0.274	0.322
	April	25.25	0.399	0.361	0.348
	July	28.75	0.454	0.265	0.242
Full details see Appendix		*6.1*	*6.1*	*10.1*	*10.1*

Notes

1 All long horizon returns have been calculated by arithmetic compounding monthly returns.
2 Goetzmann and Jorion use overlapping returns at all horizons to derive more powerful test statistics.
3 Goetzmann and Jorion's dividend yields include interest on dividends reinvested during the year.
4 The HHNW t values are adjusted for heteroscedasticity and serial correlation by the method of Hansen (1982) and Newey West (1987).

As might be expected, there appear to be some differences between the results generated by this study and those in Goetzmann and Jorion (1993) which reflects US data. In particular the β coefficients and the R^2's are higher for UK data.

A comparison of the results of Goetzmann's and Jorion's (1995) study, which includes UK as well as US data for sub-sample period from 1927 to 1992, with those of this study, show a number of interesting features. Firstly, the results of Goetzmann and Jorion's OLS regressions for UK data are rather similar to those of my study which covers the shorter period, 1966 to 1993. Secondly, the results in this thesis show that when the randomisation methodology is used to estimate the significance of the regression coefficients for the shorter UK series, the empirical p values substantially increase and are no longer significant at conventional levels.[5] On initial inspection, this seems a surprising result since the sample period in this study focuses on the highly volatile epoch in the 1970's where OLS regression showed R^2 typically in excess of 0.5 and highly significant β coefficients. This period includes the observations which the DFFITS measure showed to be influential in determining the results (See Figures 4-1 and 4-2). In this period one might expect to find significant regression coefficients even using the randomisation methodology.

The intuitive explanation for this apparent anomaly is clear. The Goetzmann and Jorion (1995) study includes the relatively stable period from 1927 to 1965 as well as the turbulent period from 1966 to 1992. Table 5-12 summarises the basic

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5 As a check on my computer program and calculations, the Barclays-DeZoete-Wedd series was obtained and Goetzmann and Jorion's 1927 to 1992 sample period results were replicated. My OLS results were virtually identical to those in the Goetzmann and Jorion study. The empirical p factors in this study were extremely close to those in Goetzmann and Jorion's (1995) study.

statistics for the return data and Figure 5-1 shows a plot of returns for the BZW data from 1927 to 1992.

Table 5-12

Basic Statistics

BZW Series, 1927 to 1992

Annual Arithmetic Returns

	1927 to 1965	1966 to 1992	1927 to 1992
	%	%	%
Mean	10.2	20.2	14.3
Standard deviation	17.4	34.8	26.2
Maximum	54.8	149.5	149.5
Minimum	-15.5	-49.4	-49.4

Note. Data in the table above is taken from the BZW series which is based on annual intervals starting at 1st January. Data in other tables in this thesis have been determined by the dates of publication of the CBI series. This accounts for the small difference between these figures and those shown elsewhere.

The sample period, 1966 to 1993, includes the market slump of 1973 and 1974 as well as the dramatic rebound in 1975. The more the sample period focuses on this turbulent period, the higher the OLS β' s and R^2. In such a short sample period, when returns are randomised, low returns generate both low prices and also high dividend yields in the randomised series. There is then a high probability, especially in regressions with long horizons, that this will be followed by the 1975 rebound. The randomised model will then generate very high β's and R^2 and will loose power to reject the null hypothesis. Thus the empirical p factor for the β coefficient will increase and the regression coefficients will be shown not to be significant. An examination of Table 4-23, an abbreviated version of which is reproduced on page 200, as Table 5-13, illustrates this argument. Ordinary least squares p factors are shown to be significant for all series for the turbulent period from 1966 to 1980. In the Goetzmann and Jorion version of randomisation these p values dramatically increase. The increase is particularly marked for longer time horizons.

Table 5-13

Dividend Yields

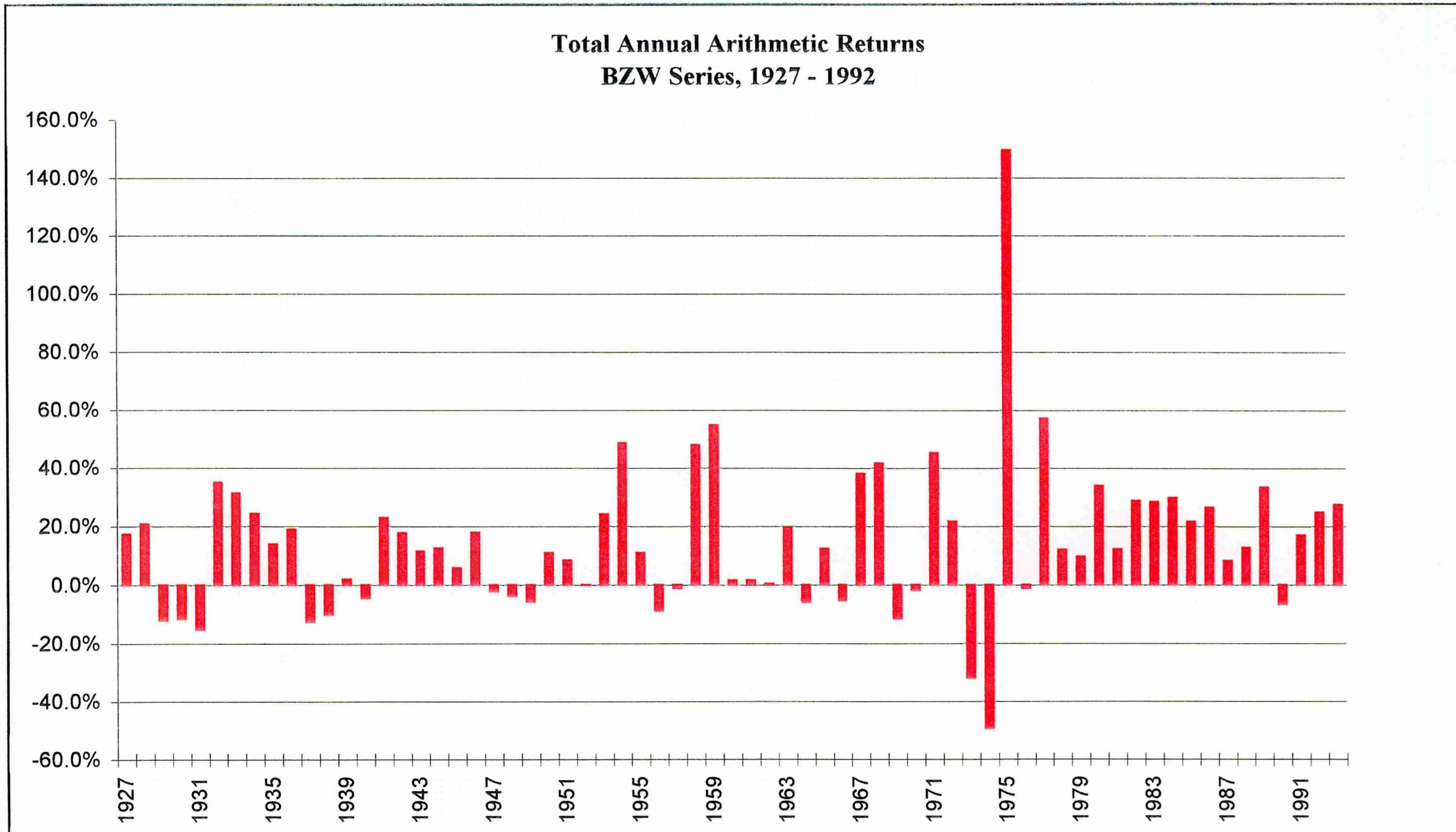
Split Sample - Empirical p Factors

		OLS p			**G & J Randomisation p**		
Return Horizon Months	**Returns following CBI survey**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**	**1966 to 1993**	**1966 to 1980**	**1981 to 1993**
3		0.000	0.003	0.099	0.047	0.197	0.276
12	October †	0.000	0.001	0.384	0.029	0.146	0.704
24	October †	0.000	0.009	0.152	0.396	0.756	0.700
36	October †	0.000	0.000	0.035	0.184	0.409	0.479
		App. 6.1	*---- App 12.1 ----*		*App. 10.1.1*	*----App 13.1.1 ----*	

†*(Only the first series is shown for 12, 24 and 36 months horizons.)*

Nevertheless, in the sample period 1966 to 1993 the empirical p values for return horizons of 3 months and 12 months are significant. In the shorter 1966 to 1980 period even these become insignificant despite the high β and R^2 in this period, (See Table 4-20). It is clear for the data in this series that the p factors for the β coefficients tend to be very much weaker as the sample size shortens.

Figure 5-1


Total Annual Arithmetic Returns
BZW Series, 1927 - 1992
160.0%
140.0%
120.0%
100.0%
80.0%
60.0%
40.0%
20.0%
0.0%
-20.0%
-40.0%
-60.0%
1927
1931
1935
1939
1943
1947
1951
1955
1959
1963
1967
1971
1975
1979
1983
1987
1991

CHAPTER 6

CONCLUSIONS

6.1 Introduction

This thesis has examined both the power of dividend yields and CBI surveys of businessmen's opinion concerning prospective business conditions to explain future returns on the London Stock Exchange for horizons from 3 to 36 months. The sample period is from 1966 to 1993.

The study found a highly significant relationship between dividend yields and future returns for all time horizons when estimation was by ordinary least squares. The relationship between the CBI variables and future returns was, however, considerably weaker than for dividend yields. Nevertheless, statistically significant coefficients were detected at a number of time horizons. When allowance was made for the peculiarities of the data series by estimating the significance of the regression coefficients by randomisation[1], few coefficients of either series remained significant. Furthermore, when the sample period was split into two sub-samples, the first from 1966 to 1980 and the second from 1981 to 1993, significant statistics for both the dividend yield and the CBI series were confined to the first period. Further investigation indicated that the market's dramatic recovery in January and February 1975 was highly influential in the results.

Early studies such as Kendall (1953) suggested that stock and commodity prices appeared to follow random walks and hence were unlikely to be predictable. Later, Fama (1965) provided evidence that daily returns on a number of leading US shares were uncorrelated at lags of 1 to 16 days. Rather similar evidence was provided for shares on the London Stock Exchange by Dryden (1970). Rigorous testing of the

1 As in Goetzmann and Jorion (1993).

Efficient Market Hypothesis followed the development of the Capital Asset Pricing Model which explained the return generating process in competitive markets.[2] Numerous studies failed to reject the hypothesis in both its weak and semi-strong forms and the EMH remained the cornerstone of finance teaching on both undergraduate and post-graduate finance programmes. In 1978 Jensen remarked at a seminar called to discuss market efficiency, "I believe there is no proposition in economics which has more solid evidence supporting it than the Efficient Market Hypothesis". (See, Jensen (1978).) This proved to be a high point for the EMH paradigm for since the mid-1970's evidence of a number of apparent anomalies to the EMH was published.

A direct challenge to the EMH appeared in Shiller (1981) who argued that, the US stock index from 1871 to 1979 was more volatile than could be attributed to the volatility of fundamentals such as dividends[3]. Shiller (1984) and (1988) maintained that this excess volatility reflected fashions and fads amongst investors which influenced the level of stock prices.

If stock prices were too volatile, then long stock prices series should be negatively autocorrelated. Fama and French (1988a) found such negative autocorrelation. Long term autocorrelation also suggests that fundamentals might be used to forecast future returns. Stock prices in an efficient market should be optimal estimators of the corresponding series of discounted future dividends. If the market is significantly influenced by fashions and fads then present stock prices might be expected to drift away from their fundamentals. Dividend yields would then be high when stock prices are artificially depressed, and low when stock prices are artificially high.

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2 See section 2.1.5.2 and Sharpe (1964), Lintner (1965) and Treynor (1965).

3 Shiller assumed constant discount rates in his early study. See section 2.9 for a full discussion.

In a further study, Fama and French (1988b) regressed future returns on dividend yields and found R^2's of as high as 0.64 for four year returns. Return predictability by itself, however, is insufficient evidence to enable rejection of market efficiency since it might imply merely that the investors' risk premium changes with the business cycle. In this sense market efficiency is untestable since it depends on the unobservable rates of return required by investors which reflect time-varying risk premia.

Subsequently, Goetzmann and Jorion (1993) found for US data, that after adequate allowance was made for the various statistical problems which affect 'return forecasting regressions'[4], the relationship between dividend yields and future returns was no longer statistically significant at the 5% level.

The organisation of this chapter is as follows. Section 6.2 considers the hypotheses, data and methodology, section 6.3 the results, section 6.4 the contribution to knowledge, section 6.5 the historical setting, section 6.6 the limitations of the study and section 6.7 makes suggestions for further research. Finally section 6.8 adds some concluding comments.

6.2 Hypotheses, Data and Methodology

When work on this thesis commenced in 1991 it seemed likely from evidence published in US studies that dividends might predict returns in the UK. Given the possibility of a relationship between dividend yields and future returns, it was decided also to test whether CBI survey data of their members' views of future business conditions might also be a useful predictor of returns. The likelihood that other researchers were examining the connection between future returns and dividend yields provided additional motivation for the inclusion of CBI data as an unexplored ingredient in this study.

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4 These include the effect of a lagged version of the dependent variable used as an independent variable, serial correlation in the residuals and non-normality in the return series.

The CBI sends questionnaires each quarter to their members, who presumably have access to confidential information regarding their own companies' prospects which may not be available to the market as a whole. Since these businessmen may not necessarily be active participants in the stock market, it was at least plausible that their private information might not be reflected by stock prices until after a measurable delay.

The objectives of this study were to test the null hypothesis that the β coefficients were zero in the equations 6.1 and 6.2 for time horizons of between 3 and 36 months. Sample data was for the period from 1966 to 1993, the beginning of which was determined by the availability of the CBI series.

$$TR_{t,\,t+T} = \alpha_T + \beta_T GDY_t + u_{t,\,t+T} \qquad \textbf{(6.1)}^{5}$$

$$TR_{t,\,t+T} = \alpha_T + \beta_T CBI_t + u_{t,\,t+T} \qquad \textbf{(6.2)}$$

where TR_t is the total return at period t and GDY is the gross dividend yield at time t and CBI_t is the value of a CBI variable at time t.

In addition the model selection criteria, $\overline{R}^2$, Akaike Information Criterion and Schwartz Information Criterion were used to determine whether the CBI series should be included in equation 6.3,

$$TR_{t,\,t+T} = \alpha_T + \beta_T GDY_t + \beta_T CBI_t + u_{t,\,t+T} \qquad \textbf{(6.3)}$$

Total capital return and total income return data were extracted on-line from Datastream. From this data, the series of monthly capital returns and monthly dividends were derived. Annual dividends were accumulated from the sum of the last twelve months' dividends, and dividends yields were calculated by dividing annual dividends by a price index derived from the sum of the historic capital returns. (See, 3.4.2.)

[5] Equations 6.1, 6.2 and 6.3 are equations 2.1, 2.2 and 2.5 respectively. They are reproduced above for convenience.

Data for four CBI series which were considered on *a priori* grounds to be related to future returns were obtained directly from the CBI. These series were Balance of Business Optimism, Balance of Investment in Buildings, Balance of Investment in Plant and the Balance of Future Orders.

To overcome the numerous problems which afflict return forecasting regressions, this research followed the procedure in Goetzmann and Jorion (1993) by modeling the price component of dividend yields as a function of the randomised series of historic capital returns. In addition, allowance was made for heteroscedasticity by the method of stratified randomisation as in Kim, Nelson and Startz (1991) and weighted least squares randomisation as in McQueen (1992). (See, 3.4.4 to 3.4.6.)

6.3 Results

6.3.1 Introduction

The publication of Goetzmann and Jorion's (1995) paper in the Autumn issue of the Journal of Business has, pre-empted some of the findings of this study although the vast majority of the results of this thesis were generated well before the Goetzmann and Jorion paper appeared. There are a number of important differences, however, between this study and Goetzmann and Jorion (1995), and these provide some useful insights into the operation of their model. Furthermore, this study includes an additional set of variables in the form of the CBI data. Goetzmann and Jorion cover a very long sample of UK data from 1871 to 1992, which they split into two periods; the first from 1871 to 1926 and the second from 1927 to 1992. This thesis concentrates on UK data for the period between 1966 to 1993, which should be of greater interest to market participants than the longer data series used by Goetzmann and Jorion since it reflects more recent economic and political conditions. The length of the sample was determined by the availability of the CBI data series.

6.3.2 Dividend Yields

In a market which arguable is influenced by fashions and fads, dividend yields may be low when prices are overly high and high when prices are unduly depressed. Alternatively predictable returns may merely reflect changing business conditions and shifts in the risk premia required by investors. This study finds that for the 1966 to 1993 period that:

1. Ordinary least squares methodology generates significant β coefficients for the regression of future returns on dividends yields, (Table 4.4).

2. When estimation was by simple randomisation[6], coefficients of 14 out of the 15 series were still significant at the 5% level. It is clear that serial correlation in the residuals and non-normality in the return series, only slightly biases the statistical significance of β, (Table 4-12).

3. Application of Goetzmann and Jorion methodology caused a dramatic loss of statistical significance, only 3 out of 15 series remaining statistically significant, (Table 4-12 and 4-18). It is clear that the appropriate modeling of the effect of price, which is a determinant of future returns and of dividend yields, causes this dramatic loss of significance.

4. Allowance for the effect of heteroscedasticity by stratified randomisation and weighted least squares randomisation makes only a

[6] This did not model the effect of the lagged regressor but allowed for serial correlation in the residuals and non-normality in the return series.

modest difference to the p values and does not alter the conclusions of this study, (Table 4-12).

5 The statistical significance of β, as shown by OLS was entirely a feature of the turbulent period from 1966 to 1980. This relationship was not apparent in the 1981 to 1993 period, (Table 4-20).

6 The recovery of the market in early 1975 was highly influential in the results, (Figures 4-1 and 4-2).[7]

7 The regression coefficients which were highly significant during the first period from 1966 to 1980 when estimated by OLS, became insignificant when the estimated by the Goetzmann and Jorion method. (Table 4-23).

6.3.3 Confederation of British Industries Survey Data

The results of the CBI Surveys into Industrial Trends include the opinions of businessmen who are not professional participants in the market place but who through their intimate knowledge of their own companies private affairs may possess market sensitive information. The possibility that the results of the surveys contained information which may only gradually become disseminated in the market place was considered. The results of this study revealed:

1 Ordinary least squares regression showed for most series, β not to be significant, (Table 4-5 to 4-9).

[7] Goetzmann and Jorion (1995) identify this event in their 1927 - 1992 sample.

2 The signs of the regression coefficients were opposite from those hypothesised, and high returns followed lower business confidence and vice versa. The relationship, however, was not statistically significant at the conventional level, (Table 4-5 to 4-9).

3 When the p values were estimated by simple randomisation, they were shown to be higher than when estimation was by Ordinary Least Squares. (Table 4-14).

4 Since all the four CBI series were highly correlated with dividend yields and determined by the same exogenous macro-economic shocks[8], it is likely that the effect of applying the Goetzmann and Jorion methodology to CBI series will be similar to its effect with dividend yields. We have seen that in the case of dividend yields statistical significance of the regression coefficients was dramatically reduced. The effect of this adjustment is likely therefore to reduce even further the already weak statistical significance of coefficients of the CBI series and strengthen the negative findings of this study regarding these variables.

5 Weighted least squares randomisation showed very few significant coefficients, (Table 4-16).

6 A division of the sample into two sub-periods, the first from 1966 to 1980 and the second from 1981 to 1993, revealed that the coefficients of 28 series out of a possible 60 were significant in the first period, but no coefficients were significant at the 5% level in the second period, (Table 4-22).

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[8] See Nelson and Kim (1993).

7 Figure 4-3 demonstrated that the observation for April 1980 was highly influential in the regression of 3 months future returns on the CBI Business Optimism series. The Balance of Business Optimism declined dramatically that month and the figure of -70% was the second highest in the sample period. The market increased by 18% in the following 3 months. This might suggest that the market took a longer term view and perhaps foresaw the recovery which was to come in the 1980's while businessmen who completed the questionnaires based their optimism on the business situation over the following months. (See section 3.2.3 for the CBI Questionnaire.)

6.4 Contribution to Knowledge

6.4.1 Background

In the late 1980's the financial economics literature suggested that that long horizon stock returns in US markets were predictable[9]. Some interpreted this predictability[10] as evidence contrary to market efficiency while others interpreted it as merely a reflection of time-varying expected returns[11].

In the early 1990's studies based on US data, began to appear which suggested that the apparent predictability of long horizon returns was illusory. Two main criticisms of the return forecasting literature, feature in these studies. The first was that when allowance was made for the peculiarities inherent in the stock return series, the statistical significance of the regression coefficients in previous studies was found to have been overstated[12]. The second concerned the stability of the regression

9 See Chapter 3 footnote 1 for the references.
10 For example Shiller(1988).
11 For example Fama and French (1989) and Cochrane (1991).
12 For example Goetzmann and Jorion (1993) and Nelson and Kim (1993).

coefficients over time. Predictability was shown only to be a feature of particular periods.[13].

This thesis has examined the power of dividend yields and CBI surveys of businessmen's opinion concerning prospective business conditions to explain future returns on the London Stock Exchange for horizons from 3 to 36 months. The addition of CBI variables is especially relevant in light of the recommendation of Goetzmann and Jorion (1995) that researchers investigating the relationship between dividend yields and future returns should attempt to incorporate forecasts of dividend growth. It is a plausible proposition that future growth in dividends might be correlated with indicators of business confidence. Since the empirical work on this study was completed before Goetzmann and Jorion (1995) was published, no attempt was made to examine directly the relationship between changes in business confidence and future dividend growth. Instead, the CBI series were included directly in the return forecasting regressions. This provides a more immediate test of the ability of CBI data to forecast returns.

6.4.2 Contribution

The thesis adds to the growing body of evidence based on US studies which suggests that lack of power of dividend yields to predict future returns comes from two sources. Firstly, the O.L.S. results which were significant in the first period from 1966 to 1980 were insignificant in the second period from 1981 to 1993[14]. It was also shown that the results were heavily influenced by the dramatic rise in the stock-market in 1975.

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13 Kim Nelson and Startz showed that return autocorrelation was only a feature of the 1926 to 1946 period.

14 While this suggests the possibility of a structural break between the two periods the Chow (1960) test was unable to reject the null hypothesis of the equality of regression coefficients.

Secondly, randomisation as in Goetzmann and Jorion (1993) dramatically reduced the statistical significance of the dividend yield variable. Interestingly, Goetzmann and Jorion (1995) find, using annual data in the UK from 1927 to 1993, that their randomised results still show statistical significance. It is possible that their model lacks power to reject the null hypothesis when applied to the shorter and more turbulent 1966 to 1993 period.

The results for the CBI surveys are rather weaker than those for dividend yields. For the whole sample even with estimation by OLS, the significance of the regression coefficients was weak. This significance deteriorated when the coefficients were estimated by simple randomisation. As for the dividend yield variable, all statistical significance was a feature of the 1966 to 1980 period and none for the later period. The results strongly suggest that the use of CBI data to develop trading rules which attempt to forecast future returns for the time horizons included in this study are unlikely to be successful. The finding that the signs of the coefficients of the CBI variables were opposite from those hypothesised may suggest that business confidence, as reflected in the replies to the CBI survey questions, relates to short term conditions which may be temporarily depressed while the stock market takes a longer term perspective and stock prices anticipate a recovery. Modest future returns may therefore be associated with high business confidence and vice-versa.

This study represents one of the few examples of randomisation using financial data. (See Kennedy (1995) for a review.) It extends the Goetzmann and Jorion (1993) methodology by using stratified randomisation as in Kim Nelson and Startz (1991) and weighted least squares randomisation as in McQueen (1992).

It was shown that for the data in this study, the choice between randomisation and bootstrapping makes no difference to the conclusions, (Table 5-7).

In retrospect given the competitive nature of stock markets and the vast existing literature which supports the EMH it would have perhaps been surprising if evidence rejecting the null hypothesis of market efficiency had been uncovered in this thesis. This thesis adds to the body of literature which suggests that the estimation of the statistical significance of return forecasting regressions by OLS which use dividend yields as predictors provides unreliable estimates. The researcher must resort to the appropriate numerical methods such as randomisation to determine statistical significance.

The CBI series were shown to be only very weakly related to future returns. This raises the question of whether this data adds information not already known by knowledgeable investors. Section 6.7 suggests a number of possible avenues for further research.

This research also adds to the evidence that the results of return forecasting regressions both in the UK and in the US are heavily influenced by periods of turbulent activity such as the 1930's in the US or the early 1970's in the UK. Given the length of the data series available these are relatively isolated events.

6.5 Historical Setting Reflected in the Data and Results

Since the results of this study are dominated by the events of the turbulent period from 1972 to 1975, it is important to understand the unique combination of events which lead to the greatest bear market in the history of the London Stock Exchange.

Economies throughout the Western world boomed in 1972, and this led to rapid increases in commodity prices. To control inflation, a prices and incomes policy was introduced in the UK. The combination of an administration which was unsympathetic to industry[15], rapidly rising prices, price control and the taxation of unrealised holding gains on stocks, resulted in a corporate liquidity crisis. This together with the Oil Crisis in the Autumn of 1973, led in turn to falling stock prices. The crisis continued until December 1974 when the BZW cost of living adjusted share price index had fallen to its lowest level since 1921.

During the Autumn of 1974 the government became aware of the increasing plight of industry and of possible redundancies arising from corporate failure. As a result of these concerns they introduced stock relief[16] and relaxations in the Price Code in an emergency budget in November 1974. Following these measures, the All Share Index increased by 61% in January and a further 32% in February 1975, by which time it had recovered most of the losses incurred over the past year.

The evidence of psychologists that agents place too much emphasis on irrelevant information and over-react to recent events and news, was discussed in section 2.6.3. (See Tversky and Kahneman (1963).) De Bondt and Thaler (1985) have argued that companies become temporarily undervalued because of such over-reaction. In contrast Merton (1987) dismisses the studies of psychologists and argues that individuals are unlikely to make these errors when repeatedly making important decisions which they are allowed discuss with their colleagues. In retrospect, the collapse of the market may appear irrational and to have resulted from the over-reaction hypothesis described in De Bondt and Thaler (1985). Investors who had the insight that the Government would be forced to review its policy towards industry to prevent corporate collapse and mass unemployment and who were prepared to risk their funds in November 1974 were rewarded with exceptional returns.

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15 A White Paper was published in August 1974 setting out plans for extending state ownership to unspecified key sectors of industry. In the meantime Dennis Healey had promised to "squeeze the rich until the pips squeak".

16 Stock relief allowed companies when calculating their tax liability, subject to a number of restrictions, to deduct the increase in stock values from their profits.

The situation facing investment professionals in the Autumn of 1974 can be argued to be unlike any other which they faced throughout their careers. In these circumstances they may have lacked the experience needed to help them form rational expectations of future events.

An efficient market advocate can argue that the uncertainties facing investors in the Autumn of 1974 were sufficient to justify exceptionally high discount rates. The budget of November 1974 may have removed a number of uncertainties thus reducing required rates of return and enabling analysts to revise their forecasts of future dividend streams.

The purpose of reporting this historical narrative is to indicate the uniqueness of the circumstances surrounding the market collapse in 1973 and 1974 and its recovery in early 1975. This one event has been shown to have been highly influential on the Ordinary Least Squares statistics. In retrospect, it seems perhaps self-evident that reliance on one major event does not make for robust statistical inference.

6.6 Limitations of this Study

This thesis has applied the methodology included in three major studies in the US, those of Kim Nelson and Startz (1991), McQueen (1992) and Goetzmann and Jorion (1993), to data taken from the London Stock exchange. In addition, any benefit to be gained from the use of lags of explanatory variables has been considered. It is of course possible that some alternative econometric specification may reveal a relationship between future returns and the explanatory variables. In view of the results of this study, this seems unlikely, however.

It could be argued that the choice of CBI variables was arbitrary and that it would have been possible to select the answers to other questions included in the survey for analysis. The evidence provided by this thesis suggests it is unlikely that other variables would perform better. Choosing explanatory variables from the large number which are available could merely serve to introduce a data mining bias into the study.

An opponent of efficient markets might argue that coefficients do not have to be statistically significant at the 5% level for market participants to develop rules which generate excess returns. They can point to the stability of regression coefficients shown both in Table 4-20 and Appendix 12. The conventional requirement that the null hypothesis can be rejected at the 5% level sets a high, and some would argue, unrealistic test in the context of a competitive market place in which there are at least strong 'a priori' reasons for believing that any gains which can arise may be transitory. This thesis has not set out to test trading rules which claim to generate excess profits as in, for example, Pesaran and Timmermann (1995) which uses US data.

This study does not examine the immediate impact of the announcement of CBI results on returns. This is suggested below as an avenue for additional research.

6.7 Recommendations for Further Research

The relationship between dividend yields and future returns has now been examined carefully for the UK and the US stock markets in a number of published studies. It would not be difficult to extend the methodology in this thesis to other markets. The shortness of the available data series in most other markets, however, may prove to limit the usefulness of such studies.

The Pesaran and Timmermann (1995) study based on US data uses a number of variables, including dividend yields, to make one step ahead forecasts of monthly returns. The authors claim to have derived a profitable trading rule based only on *ex* *ante* information. A replication of this study in the UK may give further useful insights and would enable an assessment to be made both of the timing and of the economic significance of any excess returns arising through the use of an econometric model.

Little is known about the market's immediate reaction to the announcement of the CBI results. In particular, it would be interesting to study the direction of causality between stock returns and the level of Business Optimism as reflected in the CBI survey data. It is possible that favourable economic news may cause both higher stock prices and as well as increased business optimism. It is also possible that information feeds from the stock prices to business optimism and not vice versa as hypothesised in this thesis. In view, however, of the findings of the very extensive literature into event studies and in particular of those which examine macro-economic events, see for example Pearce and Rowley (1985), it seems unlikely that that this avenue of research would reveal evidence rejecting market efficiency.

CBI survey data disaggregated by industry sector is available , on subscription, in machine readable form from the early 1980's. The relationship between this data and stock returns for industry sectors may merit research.

6.8 Conclusion

The evidence provided in this thesis does not enable the rejection of the null hypotheses that no relationship exists between dividend yields or CBI data and future returns. This research therefore confirms the considerable body of evidence which is consistent with market efficiency in its weak and semi-strong forms. Nevertheless, as discussed in section 2.7 of the thesis, failure to reject a null hypothesis is not equivalent to its acceptance. Furthermore, failure to reveal conventional levels of statistical significance does not imply that successful trading rules cannot be derived from the use of either dividend yields or of the CBI data. The major difference in the explanatory power of the OLS regressions between the 1966 to 1980 and the 1981 to 1993 sub-periods does not give any encouragement to the notion that they can.

While further econometric research concerning stock market efficiency is likely to be interesting, the researcher should be aware that the evidence of this dissertation reinforces the view that price anomalies are exceedingly rare and transitory. They are extremely difficult to measure even with the best of statistical methods.

References

Ackert, L. F. and B. Smith. (1993). "Stock Price Volatility, Ordinary Dividends, and Other Cash Flows to Shareholders". Journal of Finance, vol. 48, no.4, 1147 - 60.

Aharony, J. and I. Swary. (1980). "Quarterly Dividend and Earnings Announcements and Stockholders' Returns, an Empirical Analysis". Journal of Finance, vol. 35, 1-12.

Akaike, H. (1973). "Information Theory and the Extension of the Maximum Likelyhood Principle". In: *2nd International Symposium on Information Theory*, B.N. Petrov and F. Csaki, eds., Budapest.

Alexander, S. (1964). "Price Movements in Speculative Markets: Trends or Random Walks, No. 2" In: *The Random Character of Stock Market Prices*, P.H. Cootner (ed): Cambridge, Mass., MIT Press, 1964, 339-372.

Allais, M. (1953). "Le Comportement de' l Homme Rationnel devant le Risque, Critique des Postulats et Axioms de l'Ecole Americaine," Econometrica, vol. 21, 503-546.

Amemiya, T. (1980). "Selection of Regressors," International Economic Review, vol. 21, 331-354.

Amemiya, T. (1985). *Advanced Econometrics*. Harvard University Press, Cambridge, Mass.

Ammer, J. M. (1991). "Expenses, Yields and Excess Returns: New Evidence on Closed End Fund Discounts from the UK". LSE Discussion Paper 108:

Ariel, R. A. (1987). "A Monthly Effect in Stock Returns." Journal of Financial Economics, vol. 18, no. 1, 161-174.

Arrow, K. and Debreu, G. (1954) , "Existence of an Equilibrium for a Competitive Economy". Econometrica, vol. 22, 256-290.

Arrow, K. (1982). "Risk Perception in Psychology and Economics". Economic. Inquiry, vol. 20, no. 1, 1-9.

Bachelier, L. (1900). "Theorie de la Speculation." In: *The Random Character of Stock Market Prices*, ed., P.H. Cootner, Cambridge, Mass., MIT Press, 1964, 17-78.

Bailey, N. (1957). *The Mathematical Theory of Epidemics*, Griffin, London.

Ball, R. (1992). "What do We Know About Market Efficiency". University of Rochester, Working paper, February.

Ball, R. and J. Bowers. (1986). "Daily Seasonals in Equity and Fixed Interest Returns: Australian Evidence". In: *Stock market Anomalies,* ed: E. Dimson, Cambridge University Press, Cambridge.

Ball, R. and P. Brown. (1968). "An Empirical Investigation of Accounting Income Numbers". Journal of Accounting Research, vol. 6, no. 2 Autumn, 159-178.

Ball, R and S.P. Kothari. (1989). "Nonstationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlations in Returns". Journal of Financial Economics, vol. 25, no. 1, 51-74.

Balvers, R., T.F. Cosimano and B. McDonald. (1990). "Predicting Stock Returns in an Efficient Market." Journal of Finance, vol. 45, no. 4, 1109-1128.

Banz, R. W. (1981). "The Relationship Between Return and Market Value of Common Stocks." Journal of Financial Economics, vol. 9, 3-18.

Basu, S. (1977a). "Investment Performance of Common Stocks in Relation to their Price-Earnings Ratios. A Test of the Efficient Market Hypothesis." Journal of Finance, vol. 32, no. 3, 662-682.

Basu, S. (1977b). "The Relationship between Earnings Yield, Market Value and Returns for NYSE Common Stocks: Further Evidence". Journal of Financial Economics". vol. 12, no. 1, 129-156.

Beaver, W.H. (1981). "Market Efficiency". Accounting Review, vol. 56, January, 23-27.

Belsley, D.A., E. Kuh and R. Welsch. (1980). *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity,* John Wiley and Sons, New York.

Bera, A.K. and M. Higgins. (1993). "ARCH Models, Properties, Estimation and Testing". Journal of Economic Surveys, vol. 7, no. 4, 305 -366.

Berges, A, J.J. McConnell and G.G. Schlarbaum. (1984). " Turn of the Year in Canada". Journal of Finance, vol. 39, 185-192.

Black, Fischer. (1972). "Capital Market Equilibrium with Restricted Borrowing". Journal of Business, July, 444-455.

Black, Fischer. (1986). "Noise". Journal of Finance, vol. 41, no. 3, 529 - 543.

Black, F., M. Jensen and M. Scholes. (1972). "The Capital Asset Pricing Model: Some Empirical Tests." In: *Studies in the Theory Of Capital Markets,* ed. M. Jensen, Praeger, New York.

Blanchard, O. and M. Watson. (1983). "Bubbles, Rational Expectations and Financial Markets". In *Crises in Economic and Financial Structure, ed.,*. Paul Wachtel, Lexington Books: Lexington, Mass. 295-315.

Blanchard, O. (1979). "Speculative Bubbles, Crashes, and Rational Expectations". Economic Letters, vol. 3, 387-389.

Blattberg, R. and N. Gonedes. (1974). "A Comparison of the Stable and Student Distributions as Stochastic Models of Stock Prices". Journal of Business 244-280.

Blume, M. and R. Stambaugh. (1983). "Biases in Computed Returns: An Application to the Size Effect". Journal of Financial Economics. vol. 12, June, 387-404.

Bodie, Zvi. (1976)., "Common Stocks as a Hedge against Inflation". Journal of Finance, vol. 31, no 5, 1575-1616.

Boesky, I.F., J. Madrick. (Eds.). (1986). *Merger Mania.* Bodley Head.

Bollerslev, T. (1986). "Generalised Autoregressive Conditional Heteroscedasticity". Journal of Econometrics, vol. 31, 303-327.

Bollerslev, T. , R. Chow and K. Kroner. (1992). "ARCH Modelling in Finance: a Review of the Theory and Empirical Evidence". Journal of Econometrics, vol. 52, 5-59.

Boudoukh, J. and M. Richardson. (1994). "The Statistics of Long-Horizon Regressions Revisited". Mathematical Finance, vol. 4, no.2, 103-119.

Brealey, R. A. (1970). "The Distribution and Independence of Successive Rates of Return from the British Equity Market". Journal of Business Finance, vol. 2, no. 2, 29-40.

Brealey, R. and S. Myers. (1996). *Principles of Corporate Finance, 5th. ed.* McGraw-Hill Inc., International Edition.

Breusch, T.S. (1978). "Testing for Autocorrelation in Dynamic Linear Models". Australian Economic Papers, vol. 17, 334-355.

Breusch, T.S. and A. R. Pagan (1979). "A Simple Test for Heteroscedasticity and Random Coefficient Variation". Econometrica, vol. 47, 1289-94.

Brown, P. D. Keim, A. Kleidon and T. Marsh. (1983). "Stock Return Seasonalities and the Tax Loss Selling Hypothesis, Analysis of the Arguments and Australian Evidence". Journal of Financial Economics, vol. 12, 105-271.

Bulkley, G. and I. Tonks. (1989). "Are UK Stock Prices Excessively Volatile? Trading Rules and Variance Bounds Tests". Economic Journal, vol. 99, 1083-1098.

Bulkley, G. and I. Tonks. (1992). "Trading Rules and Excess volatility". Journal of Financial and Quantitative Analysis, vol. 27, 365-382.

Campbell, J. Y. and Y. Hamao. (1992). "Predictable Stock Returns in the United States and Japan: A Study of Long Term Capital Market Integration". Journal of Finance. vol. 47, March, 43-69.

Campbell, J. Y. and A. Kyle, (1988). Smart Money, Noise Trading and Stock Price Behaviour, National Bureau of Economic Research, Technical Working Paper 71, Cambridge, Mass.

Campbell, J. Y. and R. J. Shiller. (1987). "Cointegration and Tests of Present Value Models" Journal of Political Economy. vol. 95, 1062-1088.

Campbell, J. Y. and R.J. Shiller, (1988). "Stock Prices, Earnings, and Expected Dividends". Journal of Finance, vol. 43, 661-676.

Campbell, J. Y. and R. J. Shiller. (1989). "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors". Review of Financial Studies, vol. 1, no. 3. 195-228.

Carmerer, C. (1989). "Bubbles and Fads in Asset Prices". Journal of Economic Surveys, vol. 3, no. 1, 3-41.

Cecchetti, S.G., P. Lam and N. C. Mark. (1990). "Mean Reversion in Equilibrium Asset Prices". American Economic Review, vol. 80, no.3, 398-418.

Chan, K.C. (1985). "Can Tax Loss Selling Explain the January Seasonal in Stock Returns". Journal of Finance, vol.45, no.5, 1115-1128.

Charemza, W.W. and D.F. Deadman. (1992). *New Directions in Econometric Practice.* Edward Elgar, Aldershot.

Chopra, N., C. Lee, A. Shleifer, R. Thaler... (1993). "Yes, Discounts on a Closed End Fund are a Confidence Index". Journal of Finance, vol. 48, 801 - 808.

Chopra, N., J. Lakonishok and J.R. Ritter. (1992). "Measuring Abnormal Performance: Do Stocks Overreact". Journal of Financial Economics, vol. 31, 235-268.

Chow, G. "Tests of equalityBetween Sets of Coefficients in Two Linear Regressions". Econometrica, vol 28, 591-605.

Christie, A. and Hertzel, M. (1981). *Capital Asset Pricing Anomalies.* University of Rochester, working paper.

Clare, A., Z. Psaradakis and S. Thomas, (1995). "An Analysis of Seasonality in the UK Equity Market". Economic Journal, vol. 105, March, 398-409.

Clare, A., S. Thomas and M.R. Wickens, (1994). "Is the Gilt-edged Yield Ratio Useful for Predicting UK Stock Returns". Economic Journal vol. 104, 303-315.

Clare, A. and S. Thomas. (1995). "The Overreaction Hypothesis and the UK Stock Market". Journal of Business Finance and Accounting, vol. 22, no.7, 961-973.

Cochrane, J. H. (1991a). "Volatility Tests and Efficient Markets: A Review Essay." Journal of Monetary Economics, vol. 27, no. 3, 463-86.

Cochrane, J. H. (1991b). "A critique of the Use of Unit Root Tests".. Journal of Economic Dynamics and Control, vol. 15, 275-284.

Cochran, S.J. and Robert De Fina. (1995). "New Evidence on Predictability in World Markets". Journal of Business Finance and Accounting, vol. 22, no. 6, 845-853.

Conrad, J, and G. Kaul. (1993) "Long Term Over Reaction or Biases in Expected Returns". Journal of Finance, vol. 48, 39-63.

Cootner, P. H. (1964). *The Random Character of Stock Market Prices.* MIT Press, Cambridge, Mass.

Corhay, A., G. Hawawini and P. Michel. (1988). "The Pricing of Equity on the London Stock Exchange: Seasonality and Size Premium". In: *Stock market Anomalies*: E. Dimson, ed, Cambridge University Press.

Cowles, A. (1933). "Can Stock Market Forecasters, Forecast?" Econometrica, vol. 1, no. 4, 309-324.

Cross, F., (1973). "The Behaviour of Stock Prices on Fridays and Mondays". Financial Analysts Journal, vol. 29, no. 6, 67-69.

Cunningham, S.W. (1973). "The Predictability of British Stock Prices". Applied Statistics, vol. 22, 315-331.

Cutler, D. M., Poterba J.M. and Summers L.H. (1991). "Speculative Dynamics". Review of Economic Studies, vol. 58, 529 - 546.

Davidson, R. and J.G. MacKinnon (1993). *Estimation and Inference in Econometrics.* Oxford University Press, New York.

De Bondt, W. and R. Thaler. (1985). "Does the Stock Market Overreact?" Journal of Finance, vol. 40, no. 3, 793-805.

De Bondt, W and R. Thaler. (1990). "Do Security Analysts Overreact". American Economic Review, vol. 80, no.2, 52-57.

DeJong, D. and C. Whitman. (1991). " The Temporal Stability of Dividends and Stock Prices. Evidence from the Likelyhood Process". American Economic Review, Sept., 600-617.

Diba, B. and H. Grossman. (1988). "Explosive Rational Bubbles in Stock Prices". American Economic Review, vol.78, no.3, 520-530.

Dickey, D. A. and W. Fuller. (1979). "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." Journal of the American Statistical Association. vol. 74, 427-31.

Dickey, D.A. and W. Fuller. (1981). "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root". Econometrica, vol. 49, no.4. 1057-1072.

Dimson, E. (1988) *Stock market Anomalies.* Cambridge University Press, Cambridge.

Dimson, E. and P. Fraletti. (1986). "Brokers Recommendations and the Value of a Telephone Tip". Economic Journal, vol. 96, 139-159.

Dimson, E. and P. Marsh. (1983). "The Stability of Risk Measures and the Problem of Thin Trading". Journal of Finance, vol. 38, 753-783.

Dimson, E. and P. Marsh. (1984). "An Analysis of Brokers' and Analysts' Unpublished Forecasts of UK Stock Returns". Journal of Finance, vol. 39, no. 5, 1257-92.

Dow, C. (1920) "Scientific Stock Speculation". The Magazine of Wall Street, New York.

Dryden, M. M. (1969). "A Source of Bias in Share Price Filter Tests". Journal of Business, vol. 42, no. 3, 49-60.

Dryden, M.M. (1970). "A Statistical Study of UK Share Prices". Scottish Journal of Political Economy, vol. 17, 369-389.

Durbin, J. (1970). "Testing for Serial Correlation in Least Squares Regression When Some of the Regressors Are Lagged Dependent Variables". Econometrica, Vol. 38, 410-421.

Durbin, J and G. Watson. (1950). "Testing for Serial Correlation in Least Squares Regression - I". Biometrica, vol. 37, 409 -29.

Dwass, M. (1957). "Modified Randomisation Tests for Nonparametric Hypotheses". The Annals of Mathematical Statistics, vol. 28, 181-187

Edgington, E.S. (1987). *Randomisation Tests.* Marcel Dekker, New York: .

Efron, B. (1979) "Bootstrap Methods: Another Look at the Jack-knife". The Annals of Statistics, Vol. 7, no. 1, 1-26.

Ellsberg, D. (1961). "Risk Ambiguity and the Savage Axioms". Quarterly Journal of Economics, vol. 75, 670 -690.

Elton, E. and J. Gruber. (1991). *Modern Portfolio Theory and Investment Analysis, 4 ed.* John Wiley and Sons, New York.

Engle, R. F. (1982). "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation". Econometrica, vol. 50, 987 - 1008.

Engle, R. F. and C. W. Granger. (1987). "Co-integration and Error Correction, Representation, Estimation and Testing". Econometrica, vol. 55, no. 2. 251-276.

Fama, E. F. (1965). "The Behaviour of Stock Market Prices". Journal of Business, vol. 38, 34-105.

Fama, E. F. (1970). "Efficient Capital Markets: A Review of the Theory and Empirical Work". Journal of Finance. May 1970, vol. 25 no. 2, 383-417.

Fama, E. F. (1976a). "Efficient Capital Markets: A reply". Journal of Finance, vol. 3, no. 4, 143-145.

Fama, E. F. (1976b). *Foundations of Finance*. Basic Books, New York:.

Fama, E. F. (1991) , "Efficient Capital Markets, II". Journal of Finance, vol. 46, no. 5, 1575-1617.

Fama, E. F. and M. Blume. (1966). "Filter Rules and Stock Market Trading". Journal of Business, vol.39, no.1, 226-241.

Fama, E.F. and K. French. (1988a). "Permanent and Temporary Components of Stock Prices". Journal of Political Economy. vol. 96, 246-273.

Fama, E. F. and K. French. (1988b). "Dividend Yields and Expected Stock Returns." Journal of Financial Economics, vol. 22, 3-25.

Fama, E. F. and K. French. (1989). "Business Conditions and Expected Returns on Stocks and Bonds". Journal of Financial Economics, vol. 25, 23-49.

Fama, E. F. and J. MacBeth. (1973). "Risk, Return, and Equilibrium: Empirical Tests". Journal of Political Economy. vol. 81, no. 3, 607-36.

Fama, E. and G. W. Schwert. (1977). "Asset Returns and Inflation". Journal of Financial Economics, vol. 5, 115-146.

Fama, E., L. Fisher, M. Jensen and R. Roll, (1969). "The Adjustment of Stock Prices to New Information". International Economic Review. vol. 10, no. 1, 1-21.

Fama, E. F.. and J. Macbeth. (1973). "Risk Return, and Equilibrium: Empirical Tests." Journal of Political Economy, vol. 81, no. 3, 607-36.

Ferson, W. E. and C.R. Harvey. (1991). "The Variation of Economic Risk Premiums". Journal of Political Economy , vol. 99, no. 2, 385-415.

Firth, M. (1976). *Share prices and Mergers* Ch. 5 and 6, Saxon House, London.

Fisher, R.A. (1935). *The Design of Experiments* Oliver and Boyd. Edinburgh.

Financial Times. (1989). *A Guide to Financial Times Statistics*, Ed: M. Dickson. Financial Times Business Information, London.

Flavin, M. A., (1983) , "Excess Volatility in Financial Markets: A Reassessment of the Empirical Evidence". Journal of Political Economy, vol. 91, no.6, 929-956.

Flood, R., R. Hodrick and P. Kaplan. (1986). An Evaluation of Recent Evidence on Stock Market Bubbles. (National Bureau of Economic Research. Cambridge Mass.). Working Paper 1971.

Franks, J. and R. Harris. (1989). "Shareholder Wealth Effects of Corporate Take-overs, the UK Experience, 1955-85". Journal of Financial Economics, vol. 23, 224-49

Franks, J., J. Broyles and M. Hecht. (1977). "An Industry Study of the Profitability of Mergers in the United Kingdom". Journal of Finance, vol. 32, no. 5, 1513-1525.

Freedman, D., and D. Lane. (1983). "A Nonstochastic Interpretation of Reported Significance Levels." Journal of Business & Economic Statistics, vol. 1, no 4, 292 -293.

French, K., (1980). "Stock Returns and the Weekend Effect". Journal of Financial Economics, vol. 8, no.1, 55-69.

French, K. and R. Roll. (1986). "Stock return Variances: The Arrival of Information and the reaction of traders". Journal of Financial Economics, vol.17, no.1, 5-26.

French, K. R., G.W. Schwert and R.F. Stambaugh. (1987). "Expected Stock Returns and Volatility". Journal of Financial Economics, vol.19, 3-29.

Friend I, and M. Blume. (1970). "Measurement of Portfolio Performance under Uncertainty" American Economic Review, vol. 60, 561-575.

Friend, I., M. Blume, and J. Crockett. (1970). *Mutual Funds and Other Institutional Investors, A New Perspective*, McGraw-Hill, New York.

Friend, I. and Lang L. (1988). "The Size Effect in Stock Returns: Is it Simply a Risk Effect not Adequately reflected by the Usual measures?". Journal of Business Finance, vol. 12, no 1, 13-30.

Fuller, R., and J. Kling. (1990). "Is the Stock Market Predictable". Journal of Portfolio Management, vol. 16, Summer, 28-36.

Fuller, W. A. (1976) , *Introduction to Statistical Time Series.* John Wiley and Sons, New York.

Gibbons, M. and P. Hess. (1981). "Day of the Week Effects and Asset Returns". Journal of Business, vol. 54, no. 4, 579-596.

Gilles, C. and S.F. Le Roy. (1991). "Econometric Aspects of Variance Bounds Tests: A Survey". The Review of Financial Studies, vol. 4, no.4, 753-791.

Girmes, D.H. and Benjamin A.E. (1975). "Random Walk Process for 543 Stocks Registered on the London Stock Exchange." Journal of Business Finance and Accounting, vol. 2, no 1. 135-145.

Godfrey. L. (1978). "Testing Against General Autoregressive and Moving Average Error Models When Regressors Include Lagged Dependent Variables." Econometrica. Vol. 46, 1293-1302.

Goetzmann, W.N. and P. Jorion. (1993). "Testing the Predictive Power of Dividend Yields" Journal of Finance, vol. 48, no.2, 663-679.

Goetzmann, W.N. and P. Jorion. (1995). "A Longer Look at Dividend Yields ". Journal of Business, vol. 68, no.4, 483-508.

Goodhart, C.A. and R. Smith. (1985). "The Impact of News on Financial Markets in the U.K.". Journal of Money Credit and Banking, vol. 17, no. 4, 507-511.

Graham, B. and D. Dodd .(1938). *Security Analysis*, McGraw Hill, New York

Granger, C. and O. Morgenstern (1964). "Spectral Analysis of New York Stock Market Prices." *In The Random Character of Stock Market Prices*, P. Cootner, ed., 162-88.

Granger, C. and P. Newbold. (1974). "Spurious Regressions in Economics". Journal of Econometrics, vol. 2, 111-120.

Granger, C. and P. Newbold. (1986). *Forecasting Economic Time Series*, 2nd ed. Academic Press, New York.

Greene, W. H. (1993). *Econometric Analysis.* 2nd ed. Macmillan Publishing Company, New York.

Grether, D. M and C.R. Plott. (1979). "Economic Theory of Choice and the Preference Reversal Phenomenon". American Economic Review, vol. 69, 623-638.

Grossman, S. (1976). "On the Efficiency of Competitive Stock Markets Where Trades Have Diverse Information". Journal of Finance, vol. 31, no2, 573-585.

Grossman, S. (1978). "Further Results on the Information Efficiency of Competitive Stock Markets". Journal of Economic Theory, vol.18, no.1, 81-101.

Grossman, S. and J. Stiglitz. (1980). "On the Impossibility of Informationally Efficient Markets". American Economic Review, vol..70, no.3, 393-408.

Guletkin, M. and N. Guletkin. (1983). "Stock Market Seasonality: International Evidence". Journal of Financial Economics, vol.12, no 4, 469-481.

Guletkin, M. and N. Guletkin. (1987). "Stock Return Anomalies and Tests of the APT". Journal of Finance, vol. 42, no.5, 1213-1224.

Hakannson, N.H., J.G. Kunkel and J.A.Ohlson. (1982). "Sufficient and Necessary Conditions for Information to have Social Value in Pure Exchange". Journal of Finance, vol.37, no.5, 1169-1181.

Hansen, L. P. (1982). "Large Sample Properties of Generalized Method of Moments Estimators". Econometrica, vol.50, 1029-1054.

Hansen, L. P., and R. Hodrick. (1980) "Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis". Journal of Political Economy, vol. 88, 829-853.

Harris, L. (1986). "A Transaction Data Study of Weekly and Intra daily Patterns in Stock Returns". Journal of Financial Economics, vol. 16, no.1, 99-117.

Harvey, A.C. (1989) *Forecasting, structural time series models and the Kalman Filter.* Cambridge University Press, Cambridge.

Harvey, A.C. (1990). *Econometric Analysis of Time Series.* 2nd Edition. Philip Allan, London.

Haugen, R. A. (1995) *The New Finance: The Case Against Efficient Markets.* Prentice Hall, Englewood Cliffs, N.J:

Haugen, R. A and J. Lakonishok. (1988), *The Incredible January Effect.* Dow Jones - Irwin, Burridge, Illinois.

Hempel, C. (1965). *Aspects of Scientific Exploration.*, Free Press, New York.

Hendry, N., A. Neale and N. Ericsson (1990). *PC-NAIVE An Interactive Program for Monte Carlo Experimentation in Econometrics.* Institute of Economics and Statistics, University of Oxford.

Henfrey, A. B. Albrecht and P. Richards. (1977). "The UK Stock Market and the Efficient Market Hypothesis". Investment Analyst, September, 5-24.

Hicks, J. (1946). *Value and Capital, 2nd Edition,* Oxford University Press, Oxford.

Hodrick, R. J. (1992). "Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement". Review of Financial Studies, vol. 5, 357-86.

Jaffe, J. and R. Westerfield. (1985). "The Week End Effect in Common Stock Returns: The International Evidence". Journal of Finance, vol. 40, no.2, 433-454.

Jaffe, J. and G. Mandelker. (1976). "The Fisher Effect for Risky Assets: An Empirical Investigation." Journal of Finance, vol. 31, 447-458.

Jain, P. (1988). "Response of Hourly Stock Prices and Trading Volume to Economic News". Journal of Business, vol. 61, no.2, 219-231.

Jegadeesh, N. (1991) "Seasonality in Stock Price Mean Reversion: Evidence from the U.S. and the U.K." Journal of Finance, vol. 46, 1427-1444.

Jegadeesh, N. and S. Titman. (1993). "Returns to Buying Winners and Selling Losers : Implications for Stock Market Efficiency". Journal of Finance, vol..48, no.1, 65-91.

Jensen, M. (1968). "The Performance of Mutual Funds in the Period 1945-1964". Journal of Finance, vol. 23, no.2, 389-416.

Jensen, M. (1978). “Some anomalous evidence regarding market efficiency”. Journal of Financial Economics, vol. 6, 95-101.

Jensen, M. and G. Bennington. (1970). "Random Walks and Technical Theories: Some Additional Evidence". Journal of Finance, vol. 25, no.2, 469-482.

Joy M, R. Litzenberger and R. McEnally. (1977). "The Adjustment of Stock Prices to Announcements of Changes in Quarterly Earnings". Journal of Accounting Research, 205-225.

Kalman, R. (1960) “A New Approach to Linear Filtering and Prediction Problems” Journal of Basic Engineering, Transactions ASME, Series D, 82, 35-45.

Keane, S. M. (1983). *Stock Market Efficiency Theory, Evidence and Implications.* Oxford: Philip Allan.

Keane, S. M. (1991). "Paradox in the Current Crisis in Efficient Market Theory." Journal of Portfolio Management vol. 17 no 2, 30-34. 41

Keim, D. B. (1988). "Stock Market Regularities: A Synthesis of Evidence and Explanations". In: *Stock Market Anomalies*, E. Dimson, ed., Cambridge University Press, Cambridge,16-39.

Keim, D. B. and R. Stambaugh. (1984). "A Further Investigation of the Weekend Effect in Stock Returns". Journal of Finance, vol.39, no.3, 819-837.

Kendall, M. G. (1953). "The Analysis of Economic Time Series - Part 1: Prices”. Journal of Royal Statistical Society, vol. 96 (a), 11-25.

Kendall, M. G. (1973) *Time Series.* Griffin, London.

Kennedy P.E. (1995) "Randomisation Tests in Econometrics". Journal of Business and Economic Statistics, vol. 13 no.1, 85 -94.

Keynes, J. M. (1936) *The General Theory of Employment, Interest and Money.* Macmillan.

Kim, M. J. C. Nelson, and R. Startz. (1991). "Mean Reversion in Stock Prices? A Reappraisal of the Empirical Evidence". Review of Economic Studies, 515 -528.

Kleidon, A. W. (1988). "The Probability of Gross Violations of the Present Value Variance Inequality: A Reply". Journal of Political Economy, vol.96, no.5, 1093-96.

Kleidon, A. W. (1986). “Empirical assessment of Present Value Relations: Comments”. Econometric Reviews, vol.5, no.2, 1261-65.

Klein, B. (1977). "The demand for Quality -Adjusted Cash Balances: Price Uncertainty in the US demand for Money Function". Journal of Political Economy, vol. 85, 692-715.

Klein, R. and V. Bawa. (1977). "The Effect of Limited Information and Estimation Risk on Optimal Portfolio Diversification" Journal of Financial Economics 5, 89.

Koenker, R. (1981) "A Note on Studentising a Test for Heteroscedasticity". Journal of Econometrics, 17, 107-112.

Kotecha M. and S. Yadav. (1995). "Can Dividends Yields Forecast Returns". University of Warwick, Financial Options Research Centre, Working paper 95/59, July.

Kusyszyn, I. (1977). "How Gambling Saved me from a Misspent Sabbatical". Journal of Humanistic Psychology, vol. 17, 19-34.

Lakonishok, J. and M. Levi. (1982) "Weekend Effects on Stock Returns: A Note". Journal of Finance, vol.37, no.3. 883-889.

Lakonishok, J. and S. Smidt. (1984) "Volume and Turn of the Year Behaviour". Journal of Financial Economics, vol. 13, no.3, 435-455.

Lakonishok, J. and S. Smidt. (1988), "Are Seasonal Anomalies Real? A Ninety Day Perspective". Review of Financial Studies vol. 1, no. 4, 403-25.

Lakonishok, J., A. Shleifer, R.Vishny. (1994). "Contrarian Investment, Extrapolation and Risk". Journal of Finance, vol. 49, 1541-1578.

Latham, M. (1986). "Informational Efficiency and Information Subsets". Journal of Finance, vol. 41, no.1, 39-52.

Le Roy, S. F. (1973) "Risk Aversion and the Martingale Property of Stock Prices". International Economic Review , vol.14, no.2, 139-141.

Le Roy, S. F. (1973) "Risk Aversion and the Martingale Property of Stock Prices". International Economic Review, vol. 14, no. 2, 436-446.

Le Roy, S. F. (1976). "Efficient Capital Markets: A Comment". Journal of Finance, vol. 3, no.1, 139-141.

Le Roy, S F. (1989). "Efficient Capital Markets and Martingales". Journal of Economic Literature, vol. 27, December, 1583-1621.

Le Roy, S. F. and R. Porter. (1981). "The Present -Value Relation: Tests Based on Implied Variance Bounds.". Econometrica, vol. 49, no.3, 555-574.

Lease, R.C., W. Lewellen and G. Schlarbaum. (1974) "The Individual Investor: Attributes and Attitudes". Journal of Finance, vol.29, 413-433.

Lee, C., M, A. Shleifer and R. Thaler, (1991). "Investor Sentiment and the Closed End Fund Puzzle". Journal of Finance, vol. 46, 75 -109.

Levis, M. and D. Thomas (1993) "Investor Sentiment and the Investment Trust IPO Market: The UK Evidence". City University Business School, No 3.

Levis, M.. (1989). "Stock Market Anomalies: A Reassessment Based on UK Evidence". Journal of Banking and Finance, vol.13, no.4-5, 675-96.

Lichenstein, S. and P. Slovic. (1971). "Reversals of Preference Between Bids and Choices in Gambling Decisions." Journal of Experimental Psychology vol. 89, January, 46-55.

Lichenstein, S. and P. Slovic. (1973). "Response Induced Reversals and Preference in Gambling: An Extended Replication in Las Vegas." Journal of Experimental Psychology, vol. 101, 16-20.

Lintner, J. (1956) "Distribution of Incomes of Corporations among Dividends, Retained Earnings and Taxes". American Economic Review, vol. 46, 97-113.

Lintner, J. (1965). "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets" Review Economic Statistics. Feb. vol. 47, no.1, 13-37.

Lo, A. and A. C. MacKinlay. (1988). "Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test". Review of Financial Studies, vol. 1, 41-66.

Longman. (1984). *Dictionary of the English Language*, Longman, Harlow.

Ljung, G.M. and G.E. Box. (1978). "On a Measure of Lack of Fit in Time Series Models". Biometrica, vol. 65, 297-303.

McQueen, G. (1992). "Long Horizon Mean Reverting Stock Prices Revisited". Journal of Financial and Quantitative Analysis, vol. 27, no. 1, 1-18.

McWilliams, D.F. (1983). *How the CBI Interprets the Industrial Trends Survey.* In Twenty Five Years of 'ups and 'downs', Confederation of British Industries London, 11 - 22.

Mains, N. E. (1977). "Risk, the Pricing of Capital Assets and the Evaluation of Investment Portfolios: Comment". Journal of Business, 371-384.

Mallows, C.P., (1973). "Some Comments on C_p". Technometrics, vol. 15, 661-675

Mandelbrot, B. (1963). "The Variation of Certain Speculative Prices." Journal of Business, vol. 36, 394-419.

Mandelbrot, B. (1966). " Forecasts of Future Prices, Unbiased markets and 'Martingale' Models". Journal of Business, vol. 39, no. 1, 242-55.

Mankiw, N., D. Romer and M. Shapiro. (1985). "An Unbiased Re-examination of Stock Market Volatility" Journal of Finance, vol. 40, no.3, 677-687.

Mankiw, N., D. Romer and M. Shapiro. (1986). "Do we Reject too Often". Economic Letters, vol. 20, 139-145.

Mankiw, N. D. Romer and M. Shapiro. (1991). "Stock Market Forecastability and Volatility: A Statistical Appraisal". Review of Economic Studies, vol. 58, 455 - 477.

Mantegna, R. and H.E. Stanley. (1995). "Scaling Behaviour in the Dynamics of an Economic Index". Nature, vol. 376, 46-49.

Markowitz, H. (1952) "Portfolio Selection". Journal of Finance, vol. 7, 77-91.

Marsh, T. and R. Merton. (1986). "Dividend Variability and Variance Bounds Tests for the Rationality of Stock Market Prices". American Economic Review, vol.76, no. 3, 483-498.

Marsh, T. and R. Merton. (1987). "Dividend Behaviour for the Aggregate Stock Market". Journal of Business, vol. 60, 1-40.

McNeil, B.J., S.Pauker, H. Sox and A. Tversky. (1981) "On the Elicitation of Preferences for Alternative Therapies". New England Journal of Medicine vol. 306, 1259-1262.

Merton, Robert C. (1973). "An Intertemporal Capital Asset Pricing Model." Econometrica, vol. 41, 867-887.

Merton, Robert C. (1987). "On the Current State of the Stock Market Rationality Hypothesis". In: *Macroeconomics and Finance: Essays in Honor of Franco Modigliani,* eds., Stanley Fischer et Al, MIT Press, Cambridge , 93-124.

Metropolis, N. and S. Ulam. (1949). "The Monte Carlo Method". Journal of the American Statistical Association, vol. 44, 335-41.

Milgrom, P. and N. Stokey. (1982). "Information , Trade and Common Knowledge". Journal of Economic Theory, vol. 26, no.1, 17-27.

Miller, M., and F. Modigliani. (1961). "Dividend Policy, Growth and the Valuation of Shares". Journal of Business, vol. 34, 411 - 433.

Miller, M. and M. Scholes, (1982). "Dividends and Taxes: Some Empirical Evidence". Journal of Political Economy, vol. 90, 1118-1142.

Mills, T. (1992). Predicting the Unpredictable? , Institute of Economic Affairs, London. Occasional Paper 87, October.

Mills, T. (1993). *The Econometric Modelling of Financial Series*, Cambridge University Press , Cambridge.

Moore, A. (1962). A Statistical Analysis of Common Stock Prices. Unpublished Ph.D. thesis, Graduate School of Business, University of Chicago.

Moore, A. B. (1964). "Some Characteristics of Changes in Common Stock Prices". In: *The Random Character of Stock Market Prices,* ed., P Cootner. MIT Press, Cambridge:139-161.

Morgan, E.V. and W.A. Thomas. (1962). *The Stock Exchange. Its History and Functions*. Elek Books, London.

Mossin, J. (1966). "Equilibrium in a Capital Market". Econometrica, vol. 34, no. 4, 768-83.

Mudambi, R., and L. Taylor. (1995). "Some Non-parametric Tests for Duration Dependence: an Application to UK Business Cycle Data." Journal of Applied Statistics, Vol. 22, No.1, 163-177.

Muth, J.F., (1961) "Rational Expectations and the Theory of Price Movements". Econometrica, vol. 29, 315-335.

Nakamura,. and N. Terada. (1984). The Size Effect and Seasonality in Japanese Stock Returns". Nomura Research Institute.

Nelson, C. R. (1976). "Inflation and Rates of Return on Common Stocks." Journal of Finance, vol.31, 471-483.

Nelson, C.R. and H. Kang. (1984). "Pitfalls in the Use of Time as an Explanatory Variable in Regression". Journal of Business and Economic Statistics, vol. 2, 71-82.

Nelson, C. R., and M. Kim. (1993). "Predictable Stock Returns, the Role of Small Sample Bias". Journal of Finance, vol. 48, 641 -661.

Nelson, C. R., and Plossner C.I. (1982) "Trends and Random Walks in Macro Economic Time Series, some Evidence and Implications". Journal of Monetary Economics, vol. 10, 139-162.

Newey, W. and K. West. (1987), "A Simple Positive Definite, Heteroscedastic and Autocorrelation Consistent Covariance Matrix". Econometrica, vol. 55, 703-708

Nicholson, F. (1960). "Price-earnings Ratios". Financial Analysts Journal, July-August, 43-50.

Nicholson, F. (1968). "Price-earnings Ratios in Relation to Investment Results". Financial Analysts Journal, vol.24, no. 1, 105-109.

Niederhoffer, V. and M. Osborne. (1966). "Market Making and Reversal on the Stock Exchange". Journal of American Statistical Association, vol.61, 897-916.

Noreen, E. (1989). *Computer Intensive Methods for Testing Hypotheses: An Introduction*, John Wiley and Sons, New York:

Officer, R.R. (1973). "The Variability of the Market Factor of the New York Stock Exchange". Journal of Business, 46, 434-453.

Osborne, M. (1959). "Brownian Motion in the Stock Market". Operations Research vol. 7 145-173.

Patell, J. and M. Wolfson. (1984). "Intraday Speed of Adjustment of Stock prices to Earnings and Dividend Announcements". Journal of Financial Economics, vol. 13, 223-252.

Pearce, D. K. and V. Rowley. (1985). "Stock Prices and Economic News" Journal of Business, vol. 58, no.1, 49-67.

Pearson, K. and Rayleigh, Lord. (1905). "The Problem of the Random Walk". Nature, vol. 72, 294- 318.

Peasnell, K and L. Skerratt and P. Taylor. (1979). "An Arbitrage Rational for Tests of Mutual Fund Performance". Journal of Business Finance and Accounting, no. 3, 373-400.

Peavy, J. and D. Goodman. (1983). "Industry Relative Price-earnings Ratios as Indicators of Investment Returns". Financial Analysts Journal, Jul-Aug., 60-65.

Pesaran M. H. (1987). *The Limits to Rational Expectations*, Basil Blackwell, Oxford.

Pesaran M.H. and A. Timmermann, (1995) "Predictability of Stock Returns: Robustness and Economic Significance". Journal of Finance, vol. 50, no. 4, 1201-1228.

Phillips P.C B. (1986)., "Understanding Spurious Regressions in Econometrics". Journal of Econometrics, vol.33, 311-340.

Phillips P.C.B. and S. Durlaf. (1986). "Multiple Time Series Regressions with a Unit Root". Review of Economic Studies, vol.53, 473-96.

Price R.H. (1983). The CBI Industrial Trends Survey - An Insight into Answering Practices, Twenty Five Years of 'ups' and 'downs', Confederation of British Industries, London, 23-28.

Poterba, J. and L. Summers. (1988). "Mean Reversion in Stock Prices: Evidence and Implications". Journal of Financial Economics, vol. 22, 27-60.

Power, D., A. Lonie and R. Lonie. (1991). "The Over Reaction Effect - Some UK Evidence." British Accounting Review, vol. 23, 149-170.

Reinganum, M. R. (1981). "Misspecification of Capital Asset Pricing: Empirical Anomalies Based on Earnings' Yields and Market Values". Journal of Financial Economics, vol.9, 19-46.

Reinganum, M.R., (1981). "Abnormal Returns in Small Firms Portfolios.", Financial Analysts Journal, March-April, 52-57.

Reinganum, M. R. (1982). "A Direct Test of Roll's Conjecture on the Firm Size Effect". Journal of Finance, vol. 37, 27-35

Reinganum, M. R. (1983). "Portfolio Strategies Based on Market Capitalization". Journal of Portfolio Management - Summer.

Reinganum, M. R. and A. Shapiro. (1987). "Taxes and Stock Return Seasonality: Evidence from the London Stock Exchange". Journal of Business, vol. 60 no.2. 281-295.

Richards, P. (1979). *UK and European Share Price Behaviour: The Evidence*, Kogan Page, London.

Richardson, M. and J. Stock. (1989). "Drawing Inferences from Statistics Based on Multi-Year Asset Returns". Journal of Financial Economics, vol. 25, 323-348.

Richardson, M. and T. Smith, (1991), "Tests of Financial Models in the Presence of Overlapping Observations". Review of Financial Studies, vol. 4, no. 2, 227-254.

Roberts, H. V. (1959). "Stock Market Patterns and Financial Analysis: Methodological Suggestions." Journal of Finance, vol. 14, 1-10.

Roberts, H. V. (1967). "Statistical versus Clinical Prediction of the Stock Market". University of Chicago.

Rogalski R. and S. Tinic. (1986). "The January Size Effect: Anomaly or Risk Measurement?" Financial Analysts Journal, vol.42, Mar.- April, 63-70.

Roll, R. (1977). "A Critique of the Asset Pricing Theory's Tests". Journal of Financial Economics, March, 129-176.

Roll, R. (1981). "A Possible Explanation of the Small Firm Effect". Journal of Finance, vol. 36, 879-88.

Roll, R. (1983). "On Computing Small Firm Returns and the Small Firm Premium". Journal of Financial Economics, Nov., 371-386.

Roll, R. (1983). "Vas Ist Das? Turn of the year Effect and Risk Premia of Small Firms". Journal of Portfolio Management". vol. 9, no.2, 18-28.

Roll, R. (1984). "Orange Juice and the Weather". American Economic Review, vol. 74, no.5, 861-880.

Romano, J. (1989). "Bootstrap and Randomization Tests of Some Non-parametric Hypotheses". The Annals of Statistics, vol.17, 141-159.

Rose, H. B. (1960). *The Economic Background to Investment.* Cambridge University Press, Cambridge.

Rosenberg, B. K. Reid and R. Lanstein. (1985). "Persuasive Evidence of Market Inefficiency". Journal of Portfolio Management, vol. 11, no.3, 9-16.

Ross, S. A. (1976). "The Arbitrage Theory of Capital Asset Pricing". Journal of Economic Theory, vol.13, 341-360.

Rozeff, M. (1984). "Dividend Yields are Equity Risk Premiums". Journal of Portfolio Management, vol. 16, 28-36.

Rozeff, M. and W. Kinney. (1976). "Capital Market Seasonality: The Case of Stock Returns". Journal of Financial Economics, vol. 3, no.4, 379-402.

Rubinstein, M. (1975). "Securities Market Efficiency in the Arrow-Debreu Economy". American Economic Review, vol. 65, no.5, 812-824.

Said E.S. and D.A. Dickey. (1984). "Testing for Unit Roots in Autoregressive-Moving Average Models of an Unknown Order". Biometrica, vol. 71, 599-607.

Samuelson, P. (1965). "Proof that Properly Anticipated Prices Fluctuate Randomly". Industrial Management Review, vol. 6, Spring, 41-49.

Samuelson, P. (1973). "Proof that Properly Discounted Values of Assets Vibrate Randomly". Bell Journal of Economics, vol.4, no. 2, 369-374.

Schwarz, G. (1978). "Estimating the Dimensions of a Model". Annals of Statistics, Vol.6, 461-464.

Schultz, P. (1985). "Personal Income Taxes and the January Effect: Small Firm Stock Returns Before the War Revenue Act of 1917: A Note." Journal of Finance, vol. 40, March, 333-43.

Sharpe, W. (1964). "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk". Journal of Finance, vol.19, no.4, 425-442.

Sharpe, W. (1966) "Mutual Fund Performance". Journal of Business, January, 119-138.

Shiller, R. J. and P. Perron. (1985). "Testing the Random Walk Hypothesis: Power versus Frequency of Observation". Economic Letters, vol. 18, 381-386.

Shiller, R. J. (1981). "The Use of Volatility Measures in Assessing Market Efficiency". Journal of Finance, May, vol.36, no.2, 291-304.

Shiller, R. J. (1981). "Do Stock Prices Move too Much to be Justified by Subsequent Changes in Dividends". American Economic Review, vol.71, no.3, 421-436.

Shiller, R. J. (1984). "Stock Prices and Social Dynamics". Brookings Papers on Economic Activity, vol. 15, no. 2, 457-498.

Shiller, R. J. (1988). "Fashions, Fads, and Bubbles in Financial Markets". In: *Knights, Raiders and Targets,* eds., Coffee et al. Oxford University Press, Oxford.

Shiller, R. J. (1989a). "Comovements in Stock Prices and Comovements in Dividends". Journal of Finance, vol. 44, 719-729

Shiller, R J. (1989b). *Market Volatility.* The MIT Press, Cambridge, Massachusetts.

Slovic P. and S. Lichenstein. (1968). "The Relative Importance of Probability and Pay-Offs in Risk Taking". Journal of Experimental Psychology, vol. 78, November, part 2, 1-18.

Staumbaugh, R. F. (1986). Bias in Regressions with Lagged Stochastic Regressors, Working paper no. 156, Centre for research in Security Prices, University of Chicago, Chicago IL.

Stigler, G. (1977). "De Gustibus Non Est Disputandum". American Economic Review, vol. 67, no.2, 76-90.

Stock, J. (1987). "Asymptotic Properties of Least Squares Estimates of Cointegrating Vectors". Econometrica, vol. 56, 1035-1036.

Stoll, H. R. and R. Whaley. (1983). "Transaction Costs for the Small Firm Effect". Journal of Financial Economics, vol. 12. no 1. 57-79.

Summers, L. (1986). "Does the Stock Market Rationally Reflect Fundamental Values" Journal of Finance, vol. 41, no 3, 581-601.

Taylor, S. J. (1982) "Tests of the Random walk Hypothesis Against a Price Trend Hypothesis". Journal of Financial and Quantitative Analysis, vol. 17, no.1,. 37-61.

Taylor, S. J. (1986). *Modelling Financial Time Series*, Wiley.

Thaler R. (1992). *The Winner's Curse*. The Free Press, New York.

Theil, H. (1958). *Economic Forecasts and Policy.* North Holland, Amsterdam.

Thomas, D.G. (1995) "Output expectations in Manufacturing Industry". Applied Economics, vol. 27, 403-408.

Timmermann, A. (1993) "How Learning in Financial Markets Generates Excess Volatility and Predictable Stock Prices". Quarterly Journal of Economics, vol. 108, 1135-1145.

Tinic, S., Seha and R. West. (1984). "Risk and Return: January and the Rest of the Year". Journal of Financial Economics, vol.13, no.4, 561-574.

Tinic, S., Seha and R. West. (1986). "Risk, Return and Equilibrium: A Re-visit". Journal of Political Economy, vol. 94, no.1, 126-147.

Tobin, J. (1984). "On the Efficiency of the Financial System". Lloyds Bank Annual Review, vol. 153, July, 52-57.

Tobin, J. (1958) "Liquidity Preference as Behaviour Towards Risk" Review of Economic Studies, vol. 25, 65-85.

Treynor, J. L and R. Ferguson (1985). "In Defense of Technical Analysis". Journal of Finance, vol. 40, no 3, 757-773.

Treynor, J. L. (1965) "How to Rate Management of Investment Funds". Harvard Business Review, vol. 43, no. 1, 63-75.

Tversky, A., and Kahneman D. (1983). "Extensional Versus Intuitive Reasoning: The Conjunction Fallacy in Probability Judgement". Psychological Review, vol. 90, 600-617.

Tversky, A., and Kahneman D. (1986). "Rational Choice and The Framing of Decisions". Journal of Business, October, 251-278.

Van Horne J. and G. Parker. (1968). "Technical Trading Rules: a Comment". Financial Analysts Journal, vol. 24, July-Aug., 128-132.

Von Neumann J. and O. Morgenstern. (1944). *Theory of Games and Economic Behaviour*. Chapters 1 and 2, Princeton University Press, Princeton, N.J.

Wachtel, S.B. (1942). "Certain Observations On Seasonal Movements in Stock Prices" Journal of Business, vol. 15, 184-93.

Ward C. and A. Saunders. (1976). "UK Unit Trust Risk and Return Performance, 1964-1974". Journal of Business Finance and Accounting, vol. 3, no. 4, 83-99.

Watts, R.L. (1978). "Systematic Abnormal Returns after Quarterly Earnings Announcements". Journal of Financial Economics, vol. 6, 127-150.

West, K. D. (1987). "A Specification Test for Rational Bubbles". Quarterly Journal of Economics. vol. 102, 553-580.

West, K. D. (1988a) "Dividend Innovations and Stock Price Volatility". Econometrica, vol. 56, no.1, 37-61.

West, K D. (1988b) "Bubbles, Fads and Stock Price Volatility Tests: A Partial Evaluation". Journal of Finance, vol. 43, no. 3, 639-60.

White, H. (1980). "A Heteroskedastic-Consistent Covariance Matrix Estimator and Direct Test of Hetroskedasticity". Econometrica, vol. 48, 817-838.

Williamson, P. (1972). "Measurement and Forecasting of Mutual Fund Performance: Choosing an Investment Strategy" Financial Analysts Journal. vol.28, no.5, 78-84.

Wood, J. (1992). Full Industrial Trends Survey. Confederation of British Industries. April

Working, H. (1934) "A Random Difference Series for Use In Analysis of Time Series" Journal of the American Statistical Association, vol. 29, 11-24.

Zarowin, P. (1989). "Does the Stock Market Overreact to Corporate Earnings Information" Journal of Finance, vol. 44, no.5, 1385-1399.

Appendices

APPENDIX 1

Data

Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation 3.8* Business Optimism	Investment in Buildings	Investment in Plant	Future Orders
10-Feb-65	105.46	101.77	22	-10	-2	11	13
19-Mar-65	99.92	95.91					
30-Apr-65	103.56	98.79					
9-Jun-65	102.80	97.50	23	-27	-5	4	5
23-Jul-65	99.80	94.00					
3-Sep-65	100.78	94.31					
20-Oct-65	111.01	103.16	24	-20	-15	3	3
26-Nov-65	114.20	105.56					
7-Jan-66	112.32	103.20					
16-Feb-66	118.97	108.71	25	-9	-18	5	14
25-Mar-66	116.96	106.30					
6-May-66	117.55	106.20					
15-Jun-66	121.97	109.59	26	-12	-20	-4	12
27-Jul-66	111.98	100.02					
7-Sep-66	104.51	92.72					
19-Oct-66	104.04	91.68	27	-64	-49	-39	-33
25-Nov-66	104.03	91.09					
2-Jan-67	107.93	93.95					
7-Feb-67	110.69	95.81	28	13	-36	-25	0
22-Mar-67	114.03	98.04					
4-May-67	122.01	104.24					
16-Jun-67	123.23	104.63	29	-4	-30	-8	11
27-Jul-67	126.23	106.58					
6-Sep-67	133.44	112.05					
18-Oct-67	139.51	116.53	30	5	-27	0	17
29-Nov-67	150.90	125.41					
10-Jan-68	148.36	122.69					
21-Feb-68	151.80	124.92	31	7	-17	2	25
29-Mar-68	167.38	137.15					
10-May-68	186.01	151.76					
19-Jun-68	188.58	153.26	32	21	-10	14	26
26-Jul-68	200.31	162.22					
6-Sep-68	208.57	168.27					
16-Oct-68	202.52	162.81	33	27	1	17	32
27-Nov-68	201.80	161.60					
8-Jan-69	215.52	171.94					
19-Feb-69	212.67	169.05	34	16	6	21	32
28-Mar-69	207.04	163.99					
9-May-69	196.50	155.01					
18-Jun-69	171.87	135.01	35	-4	-4	12	17
25-Jul-69	167.21	130.79					
5-Sep-69	177.87	138.45					

APPENDIX 1

Data - 2

Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation 3.8* Business Optimism	Investment in Buildings	Investment in Plant	Future Orders
15-Oct-69	178.41	138.26	36	8	-14	10	35
26-Nov-69	181.18	139.73					
07-Jan-70	192.92	148.11					
18-Feb-70	191.59	146.45	37	9	-18	-5	33
01-Apr-70	188.23	143.21					
13-May-70	167.71	126.96					
24-Jun-70	164.82	124.07	38	-6	-20	-3	26
31-Jul-70	174.26	130.54					
11-Sep-70	174.05	129.69					
21-Oct-70	191.60	142.10	39	-1	-21	-8	29
02-Dec-70	177.27	130.80					
14-Jan-71	187.52	137.64					
26-Feb-71	183.08	133.68	40	-1	-21	-8	29
02-Apr-71	196.83	143.11					
10-May-71	225.69	163.43					
16-Jun-71	225.92	162.97	41	-10	-25	-31	15
23-Jul-71	250.25	179.85					
27-Aug-71	254.58	182.36					
05-Oct-71	254.13	181.41	42	16	-25	-13	29
12-Nov-71	243.90	173.46					
23-Dec-71	268.24	190.05					
01-Feb-72	284.61	200.96	43	37	-17	3	39
02-Mar-72	302.51	213.04					
31-Mar-72	309.86	217.69					
02-May-72	325.39	228.04	44	38	-11	9	51
01-Jun-72	307.77	215.16					
30-Jun-72	296.02	206.42					
02-Aug-72	321.42	223.53	45	22	-4	16	44
01-Sep-72	319.07	221.33					
29-Sep-72	287.59	199.00					
01-Nov-72	301.13	207.76	46	29	-2	17	46
01-Dec-72	322.13	221.65					
05-Jan-73	319.14	218.94					
07-Feb-73	287.25	196.48	47	31	4	30	50
07-Mar-73	270.55	184.54					
04-Apr-73	282.34	192.03					
02-May-73	282.26	191.44	48	41	11	35	50
01-Jun-73	288.79	195.26					
29-Jun-73	284.68	191.95					
01-Aug-73	269.26	180.94	49	26	18	39	44
31-Aug-73	262.15	175.57					

APPENDIX 1

Data - 3

Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation. 3.8* Business Optimism	Investment in Buildings	Investment in Plant	Future Orders
02-Oct-73	273.54	182.58					
02-Nov-73	280.89	186.85	50	12	16	38	43
04-Dec-73	235.70	156.24					
04-Jan-74	222.82	147.05					
06-Feb-74	210.53	138.33	51	-75	-15	-3	-25
08-Mar-74	199.96	130.82					
05-Apr-74	189.90	123.69					
08-May-74	198.77	128.80	52	-9	-10	2	11
05-Jun-74	186.29	120.14					
04-Jul-74	162.84	104.42					
02-Aug-74	151.11	96.33	53	-43	-22	-6	-11
03-Sep-74	138.95	87.95					
04-Oct-74	122.12	76.65					
08-Nov-74	123.12	76.54	54	-56	-39	-33	-9
06-Dec-74	106.43	65.59					
03-Jan-75	103.71	63.32					
03-Feb-75	168.32	101.94	55	-63	-47	-41	-28
07-Mar-75	224.29	134.99					
09-Apr-75	202.86	121.39					
12-May-75	243.28	144.81	56	-44	-42	-27	-13
09-Jun-75	252.70	149.77					
08-Jul-75	236.54	139.52					
06-Aug-75	212.72	124.82	57	-35	-39	-24	-6
05-Sep-75	243.68	142.22					
03-Oct-75	248.25	144.23					
05-Nov-75	267.53	154.64	58	-18	-31	-15	3
04-Dec-75	267.55	153.97					
02-Jan-76	280.19	160.52					
02-Feb-76	301.52	172.02	59	10	-12	10	23
03-Mar-76	290.84	165.20					
02-Apr-76	286.61	162.07					
03-May-76	304.87	171.66	60	24	-9	15	41
02-Jun-76	268.68	150.59					
02-Jul-76	285.29	159.11					
02-Aug-76	270.99	150.42	61	31	-3	25	45
01-Sep-76	261.51	144.39					
01-Oct-76	243.66	133.77					
01-Nov-76	224.19	122.31	62	-9	1	26	34
03-Dec-76	245.52	133.03					
05-Jan-77	289.47	155.91					
07-Feb-77	317.93	170.34	63	6	4	29	32

Data - 4

Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation 3.8* Business Optimism	Investment in Buildings	Investment in plant	Future Orders
07-Mar-77	320.95	171.18					
04-Apr-77	321.85	170.91					
02-May-77	342.05	180.83	64	7	0	31	38
30-May-77	354.61	186.69					
28-Jun-77	364.66	191.12					
27-Jul-77	352.49	183.90	65	-7	-4	23	14
26-Aug-77	388.45	201.73					
29-Sep-77	429.19	221.85					
31-Oct-77	426.80	219.70	66	0	-3	21	22
30-Nov-77	406.78	208.45					
30-Dec-77	420.53	214.53					
30-Jan-78	404.96	205.70	67	1	-4	21	19
03-Mar-78	378.98	191.49					
05-Apr-78	410.06	206.15					
08-May-78	433.86	217.03	68	-3	-7	18	13
05-Jun-78	432.70	215.54					
03-Jul-78	423.27	209.94					
31-Jul-78	453.89	224.17	69	0	-15	13	15
30-Aug-78	471.97	232.07					
29-Sep-78	466.47	228.35					
30-Oct-78	455.56	222.03	70	6	-11	10	16
29-Nov-78	463.03	224.58					
29-Dec-78	456.22	220.22					
29-Jan-79	459.46	220.77	71	-5	-7	12	10
02-Mar-79	502.55	240.21					
05-Apr-79	560.54	266.68					
09-May-79	586.11	277.60	72	6	-6	12	14
05-Jun-79	554.43	261.62					
02-Jul-79	528.21	248.29					
30-Jul-79	504.48	236.10	73	-22	-9	8	-10
29-Aug-79	528.55	246.14					
28-Sep-79	549.78	254.73					
29-Oct-79	520.80	240.13	74	-40	-20	-9	-18
29-Nov-79	499.89	229.10					
31-Dec-79	504.29	229.79					
01-Feb-80	549.58	248.91	75	-45	-30	-18	-24
29-Feb-80	585.26	263.81					
28-Mar-80	531.84	238.52					
25-Apr-80	544.14	242.76	76	-41	-31	-18	-21

Data - 5

Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation 3.8* Business Optimism	Investment in Buildings	Investment in plant	Future Orders
26-May-80	556.86	247.08					
27-Jun-80	610.79	269.35					
29-Jul-80	642.29	281.76	77	-70	-47	-43	-47
27-Aug-80	659.78	287.99					
25-Sep-80	676.36	293.79					
24-Oct-80	705.62	305.01	78	-54	-49	-46	-32
21-Nov-80	727.52	313.07					
23-Dec-80	675.38	289.16					
23-Jan-81	661.95	281.85	79	-27	-46	-38	-17
20-Feb-81	696.73	295.27					
24-Mar-81	728.12	307.02					
24-Apr-81	790.99	331.87	80	-6	-40	-30	-2
26-May-81	759.48	317.16					
26-Jun-81	764.78	317.77					
29-Jul-81	767.57	317.31	81	2	-35	-23	4
28-Aug-81	813.26	334.63					
25-Sep-81	680.77	278.87					
27-Oct-81	695.36	283.30	82	-9	-33	-13	2
27-Nov-81	772.77	313.15					
29-Dec-81	769.22	310.15					
29-Jan-82	825.03	330.93	83	8	-25	-5	4
26-Feb-82	793.49	316.89					
26-Mar-82	812.43	323.00					
27-Apr-82	828.84	327.88	84	10	-25	-2	8
28-May-82	857.44	337.46					
28-Jun-82	816.40	319.78					
30-Jul-82	857.16	333.89	85	-22	-26	-11	-3
27-Aug-82	884.68	343.05					
28-Sep-82	944.13	364.37					
26-Oct-82	969.88	372.77	86	-28	-33	-20	-4
26-Nov-82	969.02	370.72					
27-Dec-82	995.94	379.39					
28-Jan-83	1037.76	393.44	87	-5	-26	-5	5
25-Feb-83	1062.48	401.27					
25-Mar-83	1099.56	413.71					
22-Apr-83	1163.21	436.04	88	31	-15	6	23
24-May-83	1143.84	427.04					
23-Jun-83	1230.35	457.52					
29-Jul-83	1204.95	445.97	89	24	-5	18	16

APPENDIX 1

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Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation 3.8* Business Optimism	Investment in Buildings	Investment in plant	Future Orders
26-Aug-83	1239.96	457.30					
27-Sep-83	1212.03	445.21					
28-Oct-83	1178.70	431.09	90	7	-8	12	12
25-Nov-83	1253.13	456.63					
27-Dec-83	1292.83	469.24					
27-Jan-84	1396.12	504.73	91	27	-5	20	23
28-Feb-84	1369.98	493.42					
27-Mar-84	1452.53	521.40					
27-Apr-84	1495.75	534.83	92	26	-3	21	20
25-May-84	1389.97	495.29					
26-Jun-84	1356.63	481.45					
27-Jul-84	1327.24	468.94	93	-3	-5	14	10
24-Aug-84	1457.69	513.11					
25-Sep-84	1508.81	528.97					
26-Oct-84	1530.13	534.21	94	-5	-5	18	15
23-Nov-84	1579.81	549.62					
25-Dec-84	1676.01	580.86					
25-Jan-85	1791.48	620.20	95	4	-8	11	19
22-Feb-85	1768.58	611.11					
26-Mar-85	1818.77	622.16					
26-Apr-85	1826.11	623.22	96	18	-3	14	23
24-May-85	1869.34	634.53					
25-Jun-85	1786.24	604.08					
26-Jul-85	1770.95	597.12	97	0	-21	0	15
23-Aug-85	1892.64	635.04					
24-Sep-85	1865.16	623.82					
25-Oct-85	1966.86	656.66	98	-6	-21	4	13
22-Nov-85	2099.59	699.64					
24-Dec-85	2027.64	673.30					
24-Jan-86	2028.55	673.39	99	-1	-16	2	9
21-Feb-86	2225.22	737.54					
25-Mar-86	2418.60	796.71					
25-Apr-86	2433.23	797.32	100	8	-15	10	16
23-May-86	2432.96	793.73					
24-Jun-86	2465.83	801.84					
25-Jul-86	2362.22	767.00	101	-9	-15	5	4
25-Aug-86	2457.99	794.23					
23-Sep-86	2469.25	794.39					
24-Oct-86	2440.80	783.44	102	0	-13	8	18

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Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation 3.8* Business Optimism	Investment in Buildings	Investment in plant	Future Orders
21-Nov-86	2521.58	807.63					
23-Dec-86	2595.39	827.01					
23-Jan-87	2812.84	896.04	103	12	-10	10	20
20-Feb-87	3062.44	974.35					
24-Mar-87	3249.38	1026.50					
24-Apr-87	3178.52	1001.30	104	29	-3	13	25
22-May-87	3455.60	1084.40					
23-Jun-87	3630.62	1136.10					
24-Jul-87	3816.09	1192.60	105	25	1	20	25
21-Aug-87	3613.97	1125.30					
22-Sep-87	3837.26	1190.50					
23-Oct-87	3003.81	930.33	106	23	-3	17	25
20-Nov-87	2648.58	818.26					
22-Dec-87	2879.91	884.84					
22-Jan-88	2947.95	905.54	107	11	1	20	16
19-Feb-88	2898.88	889.24					
22-Mar-88	3099.44	944.07					
22-Apr-88	3017.73	914.55	108	19	6	32	23
23-May-88	3026.19	911.92					
21-Jun-88	3196.99	960.57					
22-Jul-88	3212.23	962.01	109	8	-6	19	23
19-Aug-88	3228.64	961.62					
20-Sep-88	3098.38	918.57					
21-Oct-88	3271.10	968.02	110	6	-4	21	24
18-Nov-88	3224.36	951.59					
20-Dec-88	3119.07	916.64					
20-Jan-89	3373.66	988.99	111	-6	-9	21	21
17-Feb-89	3616.62	1058.89					
21-Mar-89	3698.14	1075.12					
21-Apr-89	3679.41	1063.01	112	-5	-1	18	9
19-May-89	3922.37	1131.41					
20-Jun-89	3866.69	1108.39					
21-Jul-89	4083.75	1166.44	113	-19	-7	3	9
18-Aug-89	4237.26	1204.75					
19-Sep-89	4229.38	1198.20					
20-Oct-89	3885.58	1097.64	114	-26	-10	-3	-8
21-Nov-89	3897.69	1098.59					
22-Dec-89	4198.39	1177.11					
26-Jan-90	4135.93	1158.48	115	-29	-23	-8	-5

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Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation 3.8* Business Optimism	Investment in Buildings	Investment in plant	Future Orders
23-Feb-90	3988.38	1114.95					
27-Mar-90	4048.92	1120.83					
27-Apr-90	3795.00	1047.08	116	-22	-23	-8	4
25-May-90	4076.11	1120.03					
26-Jun-90	4324.16	1181.10					
27-Jul-90	4228.42	1148.93	117	-27	-22	-7	-8
24-Aug-90	3765.17	1018.83					
25-Sep-90	3589.08	965.39					
26-Oct-90	3717.88	997.77	118	-47	-26	-15	-22
26-Nov-90	3871.92	1035.23					
25-Dec-90	3885.21	1036.52					
25-Jan-91	3789.25	1006.76	119	-51	-33	-31	-35
22-Feb-91	4211.21	1117.02					
26-Mar-91	4499.02	1185.32					
26-Apr-91	4574.85	1197.40	120	-17	-35	-34	-8
27-May-91	4577.36	1192.72					
26-Jun-91	4509.53	1170.72					
26-Jul-91	4777.58	1235.92	121	-26	-35	-30	-15
26-Aug-91	4918.43	1264.73					
24-Sep-91	4880.79	1249.20					
25-Oct-91	4761.66	1216.20	122	2	-24	-7	2
25-Nov-91	4658.32	1185.34					
24-Dec-91	4499.26	1142.61					
24-Jan-92	4745.36	1200.51	123	-24	-34	-16	2
21-Feb-92	4826.34	1219.36					
24-Mar-92	4714.14	1180.40					
24-Apr-92	5114.05	1275.75	124	8	-30	-10	7
25-May-92	5310.80	1319.18					
23-Jun-92	5000.06	1236.62					
24-Jul-92	4614.57	1138.01	125	-9	-30	-9	1
24-Aug-92	4486.41	1098.98					
23-Sep-92	4992.87	1216.92					
23-Oct-92	5181.69	1259.33	126	-23	-35	-18	-1
20-Nov-92	5338.14	1294.43					
22-Dec-92	5627.75	1359.55					
22-Jan-93	5592.13	1348.55	127	11	-23	-7	13
19-Feb-93	5759.85	1387.47					
23-Mar-93	5868.85	1406.06					
23-Apr-93	5888.00	1399.80	128	31	-20	-8	20

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Date	FT-Actuaries All Share Return Index	FT-Actuaries All Share Price Index	CBI NO	Confederation of British Industries Balance *-see equation 3.8* Business Optimism	Investment in Buildings	Investment in plant	Future Orders
24-May-93	5901.79	1397.91					
22-Jun-93	6063.64	1433.01					
23-Jul-93	5949.15	1402.39	129	11	-20	-3	4
20-Aug-93	6465.86	1518.01					
21-Sep-93	6389.82	1492.99					
22-Oct-93	6766.46	1577.12	130	1	-18	-1	5
22-Nov-93	6519.28	1517.41					
22-Dec-93	7117.11	1651.09					
21-Jan-94	7525.13	1743.65					
22-Feb-94	7255.02	1679.41					
22-Mar-94	7023.57	1617.05					
22-Apr-94	6908.12	1583.61					
20-May-94	6886.76	1573.88					
22-Jun-94	6527.84	1485.05					
22-Jul-94	6851.54	1555.53					
22-Aug-94	7037.32	1590.67					
22-Sep-94	6737.07	1517.35					

Basic Statistics for Data Series - 1
1966 -1993

Variable	Period	No. of obs.	Mean %	Std. deviation %	Minimum %	Maximum %	Coefficient of variation	Skewness	Kurtosis
Return - 3 months	Jun 66 - Oct 93	105	4.77	12.80	-25.0	44.5	2.68	0.26	0.84
Return - 6 months (1)	Oct 66 - July 93	52	9.67	15.16	-28.2	41.7	1.57	-0.37	0.10
Return - 6 months (2)	Jun 66 - Oct 93	53	9.81	21.16	-38.0	97.6	2.16	1.17	4.94
Return - 12 months (1)	Jun 66 - Oct 92	26	21.46	33.91	-56.2	117.3	1.58	0.68	2.47
Return - 12 months (2)	Oct 66 - Jan 93	26	19.81	21.55	-26.7	79.1	1.09	0.27	1.75
Return - 12 months (3)	Feb 67 - Apr 93	26	19.50	23.79	-29.6	77.7	1.22	0.47	0.94
Return - 12 months (4)	Jun 67 - Jul 93	26	19.36	23.89	-43.9	64.3	1.23	-0.53	0.96
Dividend Yield - 3 months *	Jun 66 - Oct 93	105	4.73	1.13	2.67	10.17	0.22	1.04	2.94
Dividend Yield - 6 months (1) *	Oct 66 - July 93	52	4.74	1.07	2.81	7.84	0.22	0.44	0.17
Dividend Yield - 6 months (2) *	Jun 66 - Oct 93	53	4.71	1.18	2.67	10.17	0.23	1.55	5.41
Dividend Yield - 12 months(1)	Jun 66 - Oct 92	26	4.91	1.44	3.11	10.17	0.27	1.73	4.76
Dividend Yield - 12 months (2)	Oct 66 - Jan 93	26	4.76	1.02	3.00	7.64	0.21	0.59	0.54
Dividend Yield - 12 months (3)	Feb 67 - Apr 93	26	4.56	0.87	2.67	6.30	0.18	-0.14	-0.43
Dividend Yield - 12 months (4)	Jun 67 - Jul 93	26	4.71	1.03	2.81	7.84	0.23	0.37	0.11
Confederation of British Industries									
Business Optimism - 3 months	Jun 66 - Oct 93	105	-3.64	25.26	-75.00	41.00	6.93	-0.74	0.24
Business Optimism - 6 months (1)	Oct 66 - July 93	52	-6.85	27.00	-75.00	37.00	3.94	-0.78	0.22
Business Optimism - 6 months (2)	Jun 66 - Oct 93	53	-0.49	23.24	-56.00	41.00	48.89	-0.60	-0.04
Business Optimism - 12 months (1)	Jun 66 - Oct 92	26	-16.88	15.40	-49.00	16.00	1.84	-0.65	-0.17
Business Optimism - 12 months (2)	Oct 66 - Jan 93	26	-9.04	29.77	-75.00	37.00	3.29	-0.80	-0.08
Business Optimism - 12 months (3)	Feb 67 - Apr 93	26	-7.31	21.88	-44.00	41.00	2.91	-0.77	-0.32
Business Optimism - 12 months (4)	Jun 67 - Jul 93	26	-4.65	24.33	-70.00	31.00	5.23	-0.65	0.59

( ) Indicates the number of the series - see Table 3.3

* Based on annual dividends

Basic Statistics for Data Series - 2

1966 -1993

Variable	Period	No. of obs.	Mean %	Std. deviation %	Minimum %	Maximum %	Coefficient of variation	Skewness	Kurtosis
Confederation of British Industries									
Investment in Buildings - 3 months	Jun 66 - Oct 93	105	-16.62	14.68	-49.00	18.00	0.89	-0.20	-0.44
Investment in Buildings - 6 months (1)	Oct 66 - July 93	52	-17.21	14.88	-49.00	18.00	0.86	-0.27	-0.26
Investment in Buildings - 6 months (2)	Jun 66 - Oct 93	53	-16.04	14.61	-49.00	16.00	1.08	-0.13	-0.60
Investment in Buildings - 12 months (1)	Jun 66 - Oct 92	26	-16.88	15.40	-49.00	16.00	1.10	0.04	-0.38
Investment in Buildings - 12 months (2)	Oct 66 - Jan 93	26	-18.15	15.09	-49.00	4.00	1.20	-0.56	-0.34
Investment in Buildings - 12 months (3)	Feb 67 - Apr 93	26	-15.15	14.31	-42.00	11.00	1.02	-0.35	--0.75
Investment in Buildings - 12 months (4)	Jun 67 - Jul 93	26	-16.27	14.92	-47.00	18.00	1.09	0.01	-0.13
Investment in Plant- 3 months	Jun 66 - Oct 93	105	1.11	19.48	-46.00	39.00	0.51	-0.41	-0.42
Investment in Plant - 6 months (1)	Oct 66 - July 93	52	0.08	20.02	-43.00	39.00	250.00	-0.46	-0.43
Investment in Plant - 6 months (2)	Jun 66 - Oct 93	53	1.94	19.08	-46.00	38.00	9.02	0.37	-0.37
Investment in Plant - 12 months (1)	Jun 66 - Oct 92	26	0.54	19.54	-46.00	38.00	36.18	-0.32	-0.03
Investment in Plant - 12 months (2)	Oct 66 - Jan 93	26	-0.62	20.46	-41.00	30.00	33.00	-0.57	-0.39
Investment in Plant - 12 months (3)	Feb 67 - Apr 93	26	3.46	19.25	-34.00	35.00	4.92	-0.47	-0.59
Investment in Plant - 12 months (4)	Jun 67 - Jul 93	26	0.77	19.95	-43.00	39.00	25.91	-0.36	-0.33
Future Orders- 3 months	Jun 66 - Oct 93	105	11.59	20.22	-47.00	51.00	1.77	-0.39	0.10
Future Orders - 6 months (1)	Oct 66 - July 93	52	9.10	21.60	-47.00	50.00	2.37	-0.47	0.07
Future Orders - 6 months (2)	Jun 66 - Oct 93	53	14.04	18.68	-32.00	51.00	1.36	-0.18	-0.12
Future Orders - 12 months (1)	Jun 66 - Oct 92	26	11.42	19.51	-32.00	46.00	1.70	-0.35	-0.22
Future Orders - 12 months (2)	Oct 66 - Jan 93	26	8.04	22.81	-35.00	50.00	2.84	-0.50	-0.50
Future Orders - 12 months (3)	Feb 67 - Apr 93	26	17.00	18.00	-21.00	51.00	1.10	0.03	-0.14
Future Orders - 12 months (4)	Jun 67 - Jul 93	26	10.15	20.71	-47.00	45.00	2.84	-0.42	1.12

( ) Indicates the number of the series - see Table 3.3

Dates of Publication of Confederation of British Industries Industrial Trends Surveys

Survey Number	Date				Survey Number	Date				Survey Number	Date			
13	Fri.	16	Feb.	1962	**53**	Fri.	2	Aug.	1974	**93**	Tue	31	July	1984
14	Fri.	15	June	1962	**54**	Tue.	12	Nov.	1974	**94**	Tue	30	Oct	1984
15	Fri.	12	Oct.	1962	**55**	Wed.	5	Feb.	1975	**95**	Tue.	29	Jan.	1985
16	Fri.	15	Feb.	1963	**56**	Wed.	14	May	1975	**96**	Tue	30	Apr.	1985
17	Fri.	14	June	1963	**57**	Fri.	8	Aug.	1975	**97**	Tue	30	July	1985
18	Fri.	11	Oct.	1963	**58**	Fri.	7	Nov.	1975	**98**	Tue.	29	Oct	1985
19	Fri.	14	Feb.	1964 (1)	**59**	Wed.	4	Feb.	1976	**99**	Tue	28	Jan	1986
20	Fri.	12	June	1964	**60**	Mon.	5	Apr.	1976	**100**	Fri.	28	Apr	1986
21	Fri.	13	Nov.	1964	**61**	Wed.	4	Aug.	1976	**101**	Tue	29	July	1986
22	Fri.	12	Feb.	1965	**62**	Wed.	3	Nov.	1976	**102**	Tue	28	Oct	1986
23	Wed.	11	June	1965	**63**	Wed.	9	Feb.	1977	**103**	Tue	27	Jan	1987
24	Fri.	22	Oct.	1965	**64**	Wed.	4	May	1977	**104**	Tue	28	Apr	1987
25	Fri.	18	Feb.	1966	**65**	Fri.	29	July	1977	**105**	Tue	28	Jul	1987
26	Fri.	17	June	1966	**66**	Wed.	2	Nov.	1977	**106**	Tue	27	Oct	1987
27	Fri.	21	Oct.	1966	**67**	Wed.	1	Feb.	1978	**107**	Tue	26	Jan	1988
28	Thurs.	9	Feb.	1967	**68**	Wed.	10	May	1978	**108**	Tue	26	Apr	1988
29	Fri.	20	June	1967	**69**	Wed.	2	Aug.	1978	**109**	Tue	25	Jul	1988
30	Fri.	20	Oct.	1967	**70**	Wed.	1	Nov.	1978	**110**	Tue	25	Oct	1988
31	Fri.	23	Feb.	1968	**71**	Wed.	31	Jan.	1979	**111**	Tue	24	Jan	1989
32	Fri.	21	June	1968	**72**	Fri.	11	May	1979	**112**	Tue	24	Apr.	1989
33	Fri.	18	Oct.	1968	**73**	Wed.	1	Aug.	1979	**113**	Tue.	26	July	1989
34	Fri.	21	Feb.	1969	**74**	Wed.	31	Oct.	1979	**114**	Tue	25	Oct	1989
35	Fri.	20	June	1969	**75**	Tue.	5	Feb.	1980	**115**	Tue	30	Jan	1990
36	Fri.	17	Oct.	1969	**76**	Tue.	29	Apr.	1980	**116**	Tue	1	May	1990
37	Fri.	20	Feb.	1970	**77**	Thurs.	31	July	1980	**117**	Tue	31	July	1990
38	Fri.	26	June	1970	**78**	Tue.	28	Oct.	1980	**118**	Tue	30	Oct	1990
39	Fri.	23	Oct.	1970	**79**	Tue.	27	Jan.	1981	**119**	Tue	29	Jan	1991
40				1971 (2)	**80**	Tue.	28	Apr.	1981	**120**	Tue	30	Apr.	1991
41	Fri.	18	June	1971	**81**	Fri.	31	July	1981	**121**	Tue	30	Jul	1991
42	Thur.	7	Oct.	1971	**82**	Thurs.	29	Oct.	1981	**122**	Tue	29	Oct	1991
43	Thur.	3	Feb.	1972	**83**	Tue.	2	Feb.	1982	**123**	Tue	28	Jan	1992
44	Thur.	4	May	1972	**84**	Tue.	29	Apr.	1982	**124**	Tue	28	Apr	1992
45	Fri.	4	Aug.	1972	**85**	Tue.	3	Aug.	1982	**125**	Tue	28	Jul	1992
46	Fri.	3	Nov.	1972	**86**	Thurs.	28	Oct.	1982	**126**	Tue	27	Oct	1992
47	Fri.	9	Feb.	1973	**87**	Tue.	1	Feb.	1983	**127**	Tue.	26	Jan.	1993
48	Fri.	4	May	1973	**88**	Tue.	26	Apr.	1983	**128**	Tue.	27	Apr	1993
49	Fri.	3	Aug.	1973	**89**	Tue.	2	Aug.	1983	**129**	Tue	27	Jul	1993
50	Fri.	2	Nov.	1973	**90**	Tue.	1	Nov.	1983	**130**	Tue	26	Oct	1994
51	Fri.	8	Feb.	1974	**91**	Tue	31	Jan	1984					
52	Fri.	10	May	1974	**92**	Tue	1	May	1984					

Notes 1. Postponed due to General Election
2 Survey abandoned due to postal strike

APPENDIX 4.1

Autocorrelation Statistics - 1
1966 -1993

	Auto Correlation Coefficients Lags					Ljung Box Q - Significance (p) Lags				
	1	2	3	4	5	1	2	3	4	5
Return										
3 months	-0.064	-0.091	0.086	-0.142	-0.074	0.50	0.51	0.54	0.36	0.42
6 months (1)	-0.024	0.054	-0.238	-0.070	0.037	0.86	0.91	0.33	0.44	0.58
6 months (2)	-0.147	-0.235	-0.217	0.274	-0.172	0.27	0.11	0.07	0.02	0.02
12 months (1)	-0.571	0.303	-0.231	0.066	-0.131	0.00	0.00	0.00	0.01	0.01
12 months (2)	-0.169	-0.175	-0.070	0.107	-0.138	0.36	0.41	0.59	0.68	0.71
12 months (3)	-0.282	-0.257	0.356	-0.051	-0.283	0.13	0.12	0.04	0.08	0.05
12 months (4)	-0.169	-0.105	0.045	0.027	-0.369	0.36	0.56	0.75	0.87	0.31
24 months (1)	0.224	-0.168	-0.157	-0.115	-0.120	0.23	0.33	0.40	0.50	0.57
24 months (2)	0.321	-0.241	-0.147	-0.034	-0.086	0.09	0.10	0.15	0.26	0.35
24 months (3)	0.134	-0.172	0.145	-0.114	-0.178	0.48	0.50	0.57	0.65	0.62
24 months (4)	0.347	-0.157	-0.096	-0.080	-0.192	0.07	0.13	0.22	0.33	0.32
36 months (1)	0.071	0.203	-0.351	-0.065	-0.086	0.71	0.52	0.17	0.28	0.37
36 months (2)	0.514	0.152	-0.230	-0.183	-0.063	0.01	0.02	0.02	0.03	0.06
36 months (3)	0.589	0.348	-0.121	0.090	-0.186	0.00	0.00	0.00	0.01	0.01
36 months (4)	0.515	0.220	-0.230	-0.167	-0.219	0.01	0.01	0.02	0.03	0.03
Dividend Yield										
3 months	0.791	0.598	0.487	0.322	0.238	0.00	0.00	0.00	0.00	0.00
6 months (1)	0.737	0.472	0.258	0.151	0.055	0.00	0.00	0.00	0.00	0.00
6 months (2)	0.487	0.202	0.132	0.224	-0.014	0.00	0.00	0.00	0.00	0.00
12 months (1)	0.122	0.236	-0.146	-0.028	-0.149	0.51	0.34	0.42	0.59	0.61
12 months (2)	0.448	0.130	-0.041	-0.149	-0.199	0.01	0.04	0.09	0.13	0.13
12 months (3)	0.363	0.135	0.132	-0.208	-0.287	0.05	0.11	0.18	0.17	0.10
12 months (4)	0.490	0.168	0.020	-0.092	-0.209	0.00	0.01	0.05	0.09	0.09
CBI - Balance of Business Optimism										
3 months	0.645	0.478	0.328	0.225	0.008	0.00	0.00	0.00	0.00	0.00
6 months (1)	0.494	0.147	-0.139	-0.264	-0.222	0.00	0.00	0.00	0.00	0.00
6 months (2)	0.441	0.306	-0.154	-0.076	-0.313	0.00	0.00	0.00	0.00	0.00
12 months (1)	0.237	0.112	0.153	-0.035	0.032	0.20	0.36	0.43	0.59	0.72
12 months (2)	0.206	-0.331	-0.228	-0.209	-0.089	0.27	0.10	0.10	0.10	0.17
12 months (3)	0.241	-0.276	-0.190	-0.029	0.083	0.19	0.13	0.16	0.27	0.37
12 months (4)	0.054	-0.173	-0.105	-0.073	0.058	0.77	0.61	0.72	0.82	0.90

( ) Indicates the number of the series - see Table 3.3

Autocorrelation Statistics - 2
1966 -1993

	Auto Correlation Coefficients Lags					Ljung Box Q - Significance (p) Lags				
	1	2	3	4	5	1	2	3	4	5
CBI - Balance of Investment in Buildings										
3 months	0.856	0.672	0.465	0.241	0.028	0.00	0.00	0.00	0.00	0.00
6 months (1)	0.654	0.231	-0.164	-0.299	-0.215	0.00	0.00	0.00	0.00	0.00
6 months (2)	0.692	0.251	-0.134	-0.267	0.250	0.00	0.00	0.00	0.00	0.00
12 months (1)	0.167	-0.290	-0.106	0.004	-0.128	0.37	0.19	0.29	0.44	0.51
12 months (2)	0.273	-0.283	-0.174	-0.209	-0.219	0.14	0.10	0.14	0.14	0.12
12 months (3)	0.334	-0.254	-0.221	-0.160	-0.108	0.07	0.07	0.08	0.11	0.16
12 months (4)	0.185	-0.319	-0.128	-0.006	-0.030	0.32	0.13	0.20	0.33	0.46
CBI - Balance of Investment in Plant										
3 months	0.849	0.668	0.474	0.262	0.048	0.00	0.00	0.00	0.00	0.00
6 months (1)	0.654	0.253	-0.141	-0.245	-0.279	0.00	0.00	0.00	0.00	0.00
6 months (2)	0.684	0.270	-0.109	-0.266	-0.278	0.00	0.00	0.00	0.00	0.00
12 months (1)	0.205	-0.288	-0.141	-0.073	-0.105	0.27	0.15	0.22	0.34	0.42
12 months (2)	0.273	-0.319	-0.243	-0.174	-0.109	0.14	0.07	0.06	0.09	0.13
12 months (3)	0.320	-0.263	-0.223	-0.122	-0.144	0.08	0.08	0.08	0.13	0.16
12 months (4)	0.231	-0.372	-0.201	-0.019	-0.009	0.21	0.06	0.07	0.13	0.22
CBI - Balance of Future Orders										
3 months	0.767	0.655	0.495	0.369	0.190	0.00	0.00	0.00	0.00	0.00
6 months (1)	0.612	0.282	-0.003	-0.148	-0.179	0.00	0.00	0.00	0.00	0.00
6 months (2)	0.705	0.465	0.146	0.016	-0.066	0.00	0.00	0.00	0.00	0.00
12 months (1)	0.504	0.054	-0.010	-0.026	0.038	0.00	0.02	0.06	0.11	0.18
12 months (2)	0.254	-0.255	-0.310	-0.211	-0.073	0.17	0.15	0.07	0.08	0.13
12 months (3)	0.380	-0.089	-0.107	-0.110	-0.023	0.04	0.11	0.19	0.27	0.39
12 months (4)	0.315	-0.207	0.033	-0.064	0.025	0.09	0.23	0.40	0.54	0.68

( ) Indicates the number of the series - see Table 3.3

APPENDIX 4.2

Unit Root tests
1966 -1993

Variable	No of obs.	DF	ADF(1)	ADF(2)	ADF(3)	ADF(4)	5% Critical
Return							
3 months	105	-10.82	-8.09	-5.83	-5.83	-5.34	-2.89
6 months (1)	52	-7.44	-4.89	-5.15	-4.10	-3.53	-2.92
6 months (2)	52	-8.18	-6.91	-6.73	-4.20	-4.67	-2.92
12 months (1)	26	-9.37	-4.35	-3.37	-2.98	-2.89	-2.98
24 months (1)	25	-3.87	-3.62	-2.85	-2.55	-2.31	-2.98
36 months (1)	24	-4.46	-2.47	-3.18	-2.50	-1.90	-2.99
Dividend yield							
3 months	105	-3.29	-3.42	-2.87	-3.40	-2.71	-2.92
6 months (1)	52	-2.64	-2.79	-2.79	-2.34	-2.22	-2.92
6 months (2)	52	-4.07	-3.65	-2.92	-2.14	-2.74	-2.92
12 months (1)	26	-4.25	-2.41	-2.67	-2.24	-2.08	-2.98
CBI - Balance of business optimism							
3 months	105	-4.63	-3.68	-3.46	-3.29	-4.50	-2.92
6 months (1)	52	-4.12	-3.77	-4.57	-3.98	-3.32	-2.92
6 months (2)	52	-4.25	-3.21	-4.55	-3.02	-3.70	-2.92
12 months (1)	26	-3.79	-3.48	-2.75	-2.18	-1.80	-2.98
CBI - Investment in buildings							
3 months	105	-2.90	-3.37	-3.92	-4.62	-4.87	-2.92
6 months (1)	52	-3.29	-4.41	-5.04	-3.35	-2.51	-2.92
6 months (2)	52	-3.01	-4.44	-4.65	-3.23	-3.13	-2.92
12 months (1)	26	-4.10	-4.25	-2.58	-2.56	-2.35	-2.98
CBI - Investment in Plant							
3 months	105	-2.89	-3.37	-3.62	-4.12	-4.83	-2.92
6 months (1)	52	-3.28	-3.95	-4.97	-3.87	-2.54	-2.92
6 months (2)	52	-3.04	-4.06	-4.58	-3.31	-3.02	-2.92
12 months (1)	26	-3.92	-4.16	-2.72	-2.72	-2.42	-2.98
CBI - Future Orders							
3 months	105	-3.66	-2.92	-3.09	-3.13	-3.96	-2.92
6 months (1)	52	-3.52	-3.48	-4.00	-3.37	-2.99	-2.92
6 months (2)	52	-2.93	-2.87	-3.71	-2.77	-2.55	-2.92
12 months (1)	26	-2.75	-3.02	-1.81	-1.82	-1.32	-2.98

DF is the Dickey Fuller test - see equation 3.30
ADF is the Augumented Dickey Fuller test - see equation 3.31. Numbers in ADF( ) indicate lags.

Correlation Matrices - 1
1966 -1993

3 months

	Returns	Dividend Yield	CBIA	CBIB	CBIC	CBID
Returns	1.000	0.346	-0.230	-0.260	-0.231	-0.201
Dividend Yield		1.000	-0.650	-0.505	-0.467	-0.574
CBIA			1.000	0.658	0.697	0.882
CBIB				1.000	0.962	0.751
CBIC					1.000	0.782
CBID						1.000

6 months - series 1

	Returns	Dividend Yield	CBIA	CBIB	CBIC	CBID
Returns	1.000	0.332	-0.151	-0.375	-0.315	-0.202
Dividend Yield		1.000	-0.658	-0.552	-0.480	-0.637
CBIA			1.00	0.693	0.730	0.906
CBIB				1.000	0.960	0.765
CBIC					1.000	0.787
CBID						1.000

6 months - series 2

	Returns	Dividend Yield	CBIA	CBIB	CBIC	CBID
Returns	1.000	0.586	-0.371	-0.352	-0.297	-0.261
Dividend Yield		1.000	-0.660	-0.464	-0.478	-0.524
CBIA			1.000	0.622	0.659	0.833
CBIB				1.000	0.963	0.740
CBIC					1.000	0.780
CBID						1.000

CBIA is the CBI, Balance of Business Optimism Series
CBIB is the CBI, Balance of Investment in Buildings Series
CBIC is the CBI, Balance of Business Optimism Series
CBID is the CBI, Balance of Future Orders Series

APPENDIX 5

Correlation Matrices - 2

1966 -1993

12 months - series 1

	Returns	Dividend Yield	CBIA	CBIB	CBIC	CBID
Returns	1.000	0.751	-0.387	-0.376	-0.301	-0.210
Dividend Yield		1.000	-0.681	-0.447	-0.453	-0.466
CBIA			1.000	0.680	0.755	0.882
CBIB				1.000	0.962	0.758
CBIC					1.000	0.815
CBID						1.000

12 months - series 2

	Returns	Dividend Yield	CBIA	CBIB	CBIC	CBID
Returns	1.000	0.547	-0.263	-0.531	-0.505	-0.343
Dividend Yield		1.000	-0.733	-0.634	-0.643	-0.752
CBIA			1.000	0.671	0.732	0.922
CBIB				1.000	0.977	0.771
CBIC					1.000	0.826
CBID						1.000

12 months - series 3

	Returns	Dividend Yield	CBIA	CBIB	CBIC	CBID
Returns	1.000	0.553	-0.352	-0.407	-0.368	-0.394
Dividend Yield		1.000	-0.669	-0.531	-0.503	-0.667
CBIA			1.000	0.595	0.591	0.802
CBIB				1.000	0.965	0.722
CBIC					1.000	0.742
CBID						1.000

12 months - series 4

	Returns	Dividend Yield	CBIA	CBIB	CBIC	CBID
Returns	1.000	0.459	-0.389	-0.471	-0.350	-0.356
Dividend Yield		1.000	-0.592	-0.479	-0.331	-0.529
CBIA			1.000	0.725	0.734	0.910
CBIB				1.000	0.943	0.757
CBIC					1.000	0.743
CBID						1.000

Classical Regression Results
Regressions of returns on dividend yields and CBI data
1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta	Beta t	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	Durbin Watson	L.M. p	L.B.Q. p	B.P p
					Dividend Yields - *See equation 3.1.*							
3		3.927	3.738	0.000	0.008		0.1195	0.111	1.94	0.794	0.198	0.002
6	Jan & July	4.710	2.496	0.016	0.006		0.1108	0.093	1.85	0.644	0.352	0.313
6	Apr & Oct	10.665	5.199	0.000	0.000		0.3590	0.346	1.75	0.266	0.419	0.236
12	October	17.634	5.556	0.000	0.000		0.5625	0.544	2.10	0.489	0.458	0.534
12	January	11.544	3.588	0.004	0.003		0.3013	0.272	1.81	0.694	0.911	0.964
12	April	15.303	3.290	0.003	0.000		0.3109	0.282	1.80	0.805	0.619	0.790
12	July	9.553	2.497	0.020	0.004		0.2062	0.173	1.81	0.982	0.600	0.127
24	October	14.634	4.027	0.000	0.002	0.002	0.4135	0.388	1.34	0.118	0.451	0.662
24	January	18.039	4.130	0.000	0.000	0.003	0.4258	0.401	1.11	0.018	0.378	0.012
24	April	19.933	3.686	0.001	0.000	0.003	0.3720	0.344	1.37	0.126	0.510	0.061
24	July	18.186	3.683	0.001	0.000	0.000	0.3710	0.344	1.00	0.010	0.074	0.207
36	October	33.505	8.256	0.000	0.000	0.000	0.7560	0.745	1.19	0.044	0.341	0.050
36	January	28.544	5.439	0.000	0.000	0.000	0.5735	0.554	0.79	0.002	0.045	0.026
36	April	25.251	3.819	0.001	0.000	0.000	0.3986	0.371	1.02	0.027	0.161	0.173
36	July	28.750	4.273	0.000	0.000	0.000	0.4535	0.429	1.00	0.012	0.045	0.474
Number of series significant at 1%				**13**	**15**							
Number of series significant at 5%				**15**	**15**							

See explanatory notes at the end of this appendix.

Regressions of returns on dividend yields and CBI data
1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta x 10	Beta t	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	Durbin Watson	L.M. p	L.B.Q. p	B.P p
Confederation of British Industries - Business Optimism - *See equation 3.9.*												
3		-1.163	-2.394	0.018	0.043		0.0527	0.044	2.04	0.704	0.128	0.016
6	Jan & July	-0.845	-1.077	0.287	0.422		0.0227	0.003	2.00	0.854	0.182	0.359
6	Apr & Oct	-3.374	-2.851	0.006	0.290		0.1374	0.121	2.18	0.386	0.402	0.028
12	October	-5.771	-2.057	0.051	0.091		0.1499	0.114	3.08	0.003	0.019	0.124
12	January	-1.900	-1.333	0.195	0.385		0.0659	0.030	2.22	0.045	0.809	0.167
12	April	-3.829	-1.843	0.078	0.018		0.1240	0.087	2.08	0.296	0.329	0.539
12	July	-3.816	-2.066	0.050	0.044		0.1511	0.116	1.85	0.869	0.379	0.441
24	October	-6.508	-2.401	0.025	0.026	0.093	0.2000	0.165	1.65	0.424	0.370	0.025
24	January	-4.954	-2.903	0.008	0.011	0.005	0.2682	0.236	0.97	0.001	0.190	0.091
24	April	-3.827	-1.444	0.162	0.147	0.298	0.0831	0.043	1.64	0.298	0.019	0.019
24	July	-3.527	-1.250	0.224	0.205	0.212	0.0636	0.023	1.30	0.159	0.184	0.205
36	October	-15.117	-3.626	0.001	0.006	0.039	0.3740	0.346	2.01	0.792	0.248	0.063
36	January	-6.031	-2.431	0.024	0.043	0.000	0.2117	0.176	1.04	0.161	0.107	0.267
36	April	-4.814	-1.456	0.159	0.151	0.250	0.0880	0.046	0.77	0.002	0.012	0.025
36	July	-6.282	-1.556	0.134	0.115	0.099	0.0582	0.058	0.83	0.004	0.005	0.677
Number of series significant at 1%				**3**	**1**							
Number of series significant at 5%				**7**	**7**							

See explanatory notes at the end of this appendix.

Regressions of returns on dividend yields and CBI data

1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta x 10	Beta t	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	Durbin Watson	L.M. p	L.B.Q. p	B.P p
Confederation of British Industries - Investment in Buildings - *See equation 3.10*												
3		-2.268	-2.736	0.007	0.006		0.0678	0.059	2.17	0.289	0.027	0.871
6	Jan & July	-3.817	-2.856	0.006	0.002		0.1406	0.123	2.16	0.496	0.040	0.431
6	Apr & Oct	-5.103	-2.688	0.009	0.024		0.1241	0.107	2.34	0.152	0.056	0.368
12	October	-8.290	-1.991	0.057	0.148		0.1418	0.106	3.12	0.004	0.011	0.856
12	January	-7.578	-3.065	0.005	0.005		0.2814	0.252	2.17	0.251	0.587	0.997
12	April	-6.772	-2.180	0.040	0.044		0.1659	0.131	2.38	0.166	0.151	0.469
12	July	-7.544	-2.617	0.015	0.028		0.2220	0.190	2.08	0.579	0.262	0.693
24	October	-7.749	-1.810	0.083	0.065	0.080	0.1247	0.087	1.66	0.421	0.426	0.199
24	January	-9.140	-2.679	0.013	0.006	0.004	0.2379	0.205	1.35	0.088	0.468	0.187
24	April	-5.117	-1.280	0.213	0.099	0.166	0.0665	0.026	1.80	0.558	0.538	0.231
24	July	-8.560	-1.959	0.062	0.027	0.062	0.1430	0.106	1.26	0.163	0.164	0.526
36	October	-15.799	-2.189	0.039	0.056	0.039	0.1789	0.142	1.90	0.813	0.461	0.227
36	January	-12.830	-2.637	0.015	0.000	0.001	0.2402	0.206	1.09	0.027	0.306	0.975
36	April	-8.139	-1.626	0.118	0.020	0.015	0.1073	0.067	0.95	0.009	0.109	0.820
36	July	-8.304	-1.224	0.233	0.112	0.140	0.0638	0.021	0.96	0.007	0.041	0.483
Number of series significant at 1%				4	5							
Number of series significant at 5%				9	10							

See explanatory notes at the end of this appendix.

Regressions of returns on dividend yields and CBI data

1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta x 10	Beta t	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	Durbin Watson	L.M. p	L.B.Q. p	B.P p
Confederation of British Industries - Investment in Plant - *see equation 3.11*												
3		-1.520	-2.413	0.017	0.039		0.0535	0.044	2.14	0.369	0.046	0.706
6	Jan & July	-2.382	-2.34	0.023	0.011		0.0990	0.081	2.12	0.467	0.042	0.603
6	Apr & Oct	-3.291	-2.220	0.030	0.084		0.0861	0.070	2.30	0.200	0.083	0.292
12	October	-5.233	-1.549	0.134	0.289		0.0909	0.053	3.12	0.004	0.010	0.909
12	January	-5.316	-2.864	0.009	0.009		0.2547	0.224	2.16	0.222	0.732	0.605
12	April	-4.545	-1.939	0.064	0.028		0.1354	0.099	2.35	0.189	0.236	0.405
12	July	-4.189	-1.829	0.080	0.108		0.1224	0.086	2.06	0.564	0.181	0.261
24	October	-4.972	-1.456	0.159	0.147	0.181	0.0844	0.044	1.57	0.316	0.357	0.183
24	January	-7.032	-2.835	0.009	0.002	0.002	0.2590	0.227	1.22	0.043	0.393	0.174
24	April	-3.074	-1.017	0.320	0.205	0.281	0.0430	0.001	1.73	0.457	0.642	0.168
24	July	-3.877	-1.129	0.270	0.213	0.277	0.0530	0.011	1.23	0.117	0.177	0.525
36	October	-1.087	-1.892	0.072	0.138	0.098	0.1399	0.101	1.87	0.757	0.327	0.152
36	January	-9.102	-2.547	0.018	0.000	0.000	0.2277	0.193	1.02	0.161	0.179	0.867
36	April	-4.059	-1.016	0.298	0.142	0.151	0.0491	0.005	0.89	0.006	0.053	0.758
36	July	-1.754	-0.340	0.737	0.730	0.667	0.0052	-0.040	0.94	0.008	0.036	0.881
Number of series significant at 1%				**2**	**3**							
Number of series significant at 5%				**6**	**6**							

See explanatory notes at the end of this appendix.

APPENDIX 6.4

Regressions of returns on dividend yields and CBI data
1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta x 10	Beta t	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	Durbin Watson	L.M. p	L.B.Q. p	B.P p
Confederation of British Industries - Future Orders - *See equation 3.12*												
3		-1.274	-2.086	0.039	0.053		0.0405	0.031	2.08	0.567	0.076	0.640
6	Jan & July	-1.418	-1.459	0.151	1.348		0.0408	0.022	2.04	0.793	0.144	0.816
6	Apr & Oct	-2.961	-1.932	0.058	0.058		0.0682	0.049	2.26	0.257	0.151	0.695
12	October	-3.648	-1.052	0.303	0.375		0.0441	0.004	3.14	0.003	0.012	0.676
12	January	-3.245	-1.811	0.086	0.164		0.1180	0.081	2.28	0.058	0.686	0.167
12	April	-5.205	-2.098	0.047	0.023		0.1550	0.120	2.18	0.300	0.353	0.515
12	July	-4.110	-1.868	0.074	0.100		0.1270	0.091	2.00	0.600	0.356	0.300
24	October	-5.675	-1.703	0.102	0.173	0.274	0.1119	0.073	1.66	0.441	0.429	0.035
24	January	-7.371	-3.553	0.002	0.003	0.004	0.3544	0.326	1.14	0.013	0.147	0.059
24	April	-4.844	-1.550	0.135	0.184	0.296	0.0946	0.055	1.78	0.519	0.475	0.002
24	July	-4.677	-1.435	0.165	0.233	0.334	0.0822	0.043	1.37	0.214	0.172	0.086
36	October	-13.504	-2.483	0.021	0.024	0.060	0.2189	0.183	2.05	0.815	0.175	0.462
36	January	-10.151	-3.523	0.002	0.001	0.000	0.3607	0.332	1.30	0.094	0.296	0.434
36	April	-9.672	-2.702	0.013	0.006	0.046	0.2491	0.215	0.96	0.013	0.076	0.062
36	July	-9.274	-2.029	0.055	0.016	0.070	0.1576	0.119	0.96	0.008	0.003	0.724
Number of series significant at 1%				**2**	**3**							
Number of series significant at 5%				**6**	**6**							

See explanatory notes at the end of this appendix.

Explanatory Notes to Appendix 6

p is the marginal significance of the test statistic.

The **HCSE** column gives *p* values for the heteroscedasticity adjusted standard errors, see White (1980).

The **HHNW** column gives the *p* values for the heteroscedasticity and serial correlation corrected standard errors using the method of Hansen (1982) and Newey West (1987).

L.M. is the *p* value for Lagrange Multiplier test for 1st order serial correlation.

The **L.B.Q**. column shows the *p* value for the Lung Box *Q* test for serial correlation.

The **BP** column gives the *p* value for the Breusch Pagan (1979) test, as adapted by Koenker (1981), for heteroscedasticity.

Weighted Least Squares
Regressions of Returns on Dividend Yields and CBI data
1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta	Beta t	Beta p	R^2	$\bar{R}^2$	D.W. p
			Dividend Yields				
3		1.696	2.962	0.0038	0.0785	0.0695	2.19
6	Jan & July	4.159	3.435	0.0012	0.1909	0.1747	2.07
6	Apr & Oct	5.345	4.296	0.0001	0.2657	0.2513	1.99
12	October	9.999	3.981	0.0006	0.3977	0.3726	2.64
12	January	8.385	4.199	0.0003	0.4235	0.3995	1.90
12	April	10.979	3.955	0.0006	0.3946	0.3694	1.96
12	July	9.498	3.100	0.0049	0.2860	0.2562	1.73
24	October	16.280	5.424	0.0000	0.5612	0.5421	1.38
24	January	14.628	5.150	0.0000	0.5357	0.5155	1.18
24	April	14.952	4.730	0.0000	0.4932	0.4712	1.46
24	July	15.530	3.849	0.0005	0.4145	0.3890	1.08
36	October	24.674	6.968	0.0000	0.6881	0.6740	1.27
36	January	22.764	6.705	0.0000	0.6715	0.6565	1.01
36	April	21.592	5.548	0.0000	0.5832	0.5642	1.00
36	July	24.961	4.427	0.0002	0.4711	0.4470	1.08
		Confederation of British Industries - Business Optimism					
		x 10					
3		-0.413	-1.120	0.2652	0.0120	0.0024	2.10
6	Jan & July	-0.842	-1.125	0.2661	0.0247	0.0052	1.98
6	Apr & Oct	-1.068	-1.196	0.2371	0.0273	0.0082	2.06
12	October	-2.948	-1.401	0.1739	0.0756	0.0371	2.87
12	January	-1.868	-1.356	0.1879	0.0711	0.0324	1.73
12	April	-1.621	-7.200	0.4786	0.0211	-0.0197	2.15
12	July	-2.564	-1.262	0.2191	0.0622	0.0232	1.80
24	October	-4.332	-1.474	0.1540	0.0863	0.0466	1.52
24	January	-3.525	-1.689	0.1058	0.1103	0.0716	0.95
24	April	-1.219	-0.038	0.9701	0.0000	-0.0434	1.50
24	July	-1.047	-0.330	0.7440	0.0047	-0.0386	1.18
36	October	-9.923	-2.554	0.0182	0.2287	0.1936	1.62
36	January	-4.871	-1.513	0.1443	0.0943	0.0531	0.72
36	April	-0.537	-0.125	0.9024	0.0007	-0.0447	0.70
36	July	-3.437	-0.737	0.4685	0.0242	-0.0202	0.94

Weighted Least Squares
Regressions of Returns on Dividend Yields and CBI data
1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta x 10	Beta t	Beta p	R^2	$\bar{R}^2$	D.W. p
	Confederation of British Industries - Investment in Buildings						
3		1.100	-1.948	0.0541	0.0355	0.0262	2.22
6	Jan & July	-3.099	-2.719	0.0090	0.1288	0.1114	2.17
6	Apr & Oct	-3.433	-2.650	0.0107	0.1210	0.1038	2.18
12	October	-5.589	-1.987	0.0584	0.1413	0.1055	2.99
12	January	-6.797	-3.417	0.0021	0.3272	0.2992	1.95
12	April	-6.560	-2.146	0.0423	0.1610	0.1261	2.26
12	July	-6.073	-2.106	0.0459	0.1559	0.1208	1.92
24	October	-7.119	-1.645	0.1336	0.1053	0.0664	1.59
24	January	-8.393	-2.574	0.0170	0.2237	0.0190	1.30
24	April	-5.419	-1.330	0.1965	0.0714	0.0311	1.59
24	July	-7.233	-1.602	0.1228	0.1003	0.0613	1.14
36	October	-13.067	-2.178	0.0404	0.1774	0.1400	1.64
36	January	-1.479	-3.119	0.0050	0.3066	0.2751	1.05
36	April	-10.498	-1.966	0.0620	0.1495	0.1108	0.89
36	July	-6.921	-0.950	0.3524	0.0394	-0.0043	1.03
	Confederation of British Industries - Investment in Plant						
3		-0.518	-1.108	0.2703	0.0118	0.0022	2.17
6	Jan & July	-1.712	-1.778	0.0815	0.0595	0.0407	2.07
6	Apr & Oct	-1.438	-1.317	0.1937	0.0329	0.0139	2.15
12	October	-2.199	-0.802	0.4302	0.0261	-0.0144	2.89
12	January	-4.019	-2.292	0.0310	0.1796	0.1454	1.80
12	April	-3.155	-1.288	0.2100	0.0647	0.0257	2.27
12	July	-2.281	-0.927	0.3653	0.0343	-0.0060	1.95
24	October	-2.251	-0.929	0.3626	0.0362	-0.0057	1.45
24	January	-4.609	-1.822	0.0778	0.1290	0.0911	1.16
24	April	-0.929	-0.539	0.5953	0.0125	-0.0300	1.51
24	July	-0.971	-0.458	0.6512	0.0090	-0.0340	1.16
36	October	-6.264	-1.184	0.2490	0.0599	0.0172	1.50
36	January	-7.601	-2.074	0.0500	0.1635	0.1255	0.78
36	April	-2.158	-0.680	0.5035	0.0206	-0.0240	0.76
36	July	1.506	0.265	0.7931	0.0032	-0.0421	1.01

Regressions of Returns on Dividend Yields and CBI data 1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta x 10	Beta t	Beta p	R^2	$\bar{R}^2$	D.W.
	Confederation of British Industries - Future Orders						
3		-0.438	-0.940	0.3492	0.0085	-0.0011	2.13
6	Jan & July	-1.222	-1.333	0.1884	0.0343	0.0150	2.00
6	Apr & Oct	-1.111	-0.952	0.3458	0.0174	-0.0020	2.11
12	October	-1.424	-0.539	0.5952	0.0119	-0.0292	2.87
12	January	-2.533	-1.490	0.1493	0.0847	0.0465	1.77
12	April	-3.322	-1.151	0.2609	0.0523	0.0129	2.19
12	July	-2.394	-0.969	0.3421	0.0377	-0.0024	1.93
24	October	-2.656	-0.726	0.4751	0.0224	-0.0201	1.47
24	January	-4.816	-1.859	0.0758	0.1306	0.0928	1.08
24	April	-0.961	-0.239	0.8132	0.0020	-0.0409	1.51
24	July	-1.225	-0.317	0.7543	0.0043	-0.0289	1.21
36	October	-9.506	-1.869	0.0750	0.1370	0.0978	1.65
36	January	-8.840	-2.355	0.0279	0.2013	0.1650	0.81
36	April	-6.243	-1.138	0.2672	0.0556	0.0127	0.73
36	July	-5.855	-1.021	0.3187	0.0452	0.0018	1.01

Classical Regression Results
Multiple regressions of returns on dividend yields and CBI data
1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta	Beta p	HCSE p	HHNW p	Beta x 10	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	F p	Durbin Watson
See equation 8.3.			**Dividend Yields**			**CBI - Business Optimism**							
3		3.863	0.006	0.039		-0.044	0.943	0.944		0.120	0.102	0.002	1.94
6	Jan & July	5.833	0.025	0.020		0.676	0.501	0.576		0.119	0.083	0.045	1.85
6	Apr & Oct	11.177	0.000	0.001		0.397	0.773	0.694		0.360	0.335	0.000	1.76
12	October	21.291	0.000	0.000		3.409	0.221	0.068		0.591	0.555	0.000	2.06
12	January	16.241	0.005	0.004		2.202	0.234	0.304		0.344	0.287	0.008	1.69
12	April	15.996	0.020	0.007		0.410	0.873	0.849		0.312	0.252	0.014	1.82
12	July	7.254	0.142	0.103		-1.813	0.425	0.396		0.228	0.161	0.051	1.71
24	October	14.526	0.010	0.004	0.004	-0.100	0.976	0.970	0.974	0.414	0.360	0.003	1.34
24	January	16.276	0.021	0.001	0.010	-0.834	0.716	0.586	0.614	0.429	0.378	0.002	1.04
24	April	24.982	0.003	0.000	0.000	3.030	0.318	0.116	0.155	0.400	0.345	0.004	1.38
24	July	20.985	0.003	0.000	0.000	2.236	0.446	0.132	0.132	0.388	0.332	0.005	0.98
36	October	32.921	0.000	0.000	0.000	-0.542	0.884	0.826	0.791	0.756	0.733	0.000	1.19
36	January	34.295	0.000	0.000	0.000	2.724	0.322	0.169	0.208	0.593	0.554	0.000	0.71
36	April	31.749	0.002	0.000	0.003	3.900	0.295	0.214	0.326	0.430	0.376	0.003	1.18
36	July	31.783	0.001	0.000	0.000	2.419	0.545	0.342	0.342	0.463	0.412	0.001	1.10
Number of series significant at 1%			**10**	**12**			**0**	**0**					
Number of series significant at 5%			**13**	**15**			**0**	**0**					

For explanatory notes see appendix 6.6

APPENDIX 8.1

Multiple regressions of returns on dividend yields and CBI data
1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta	Beta p	HCSE p	HHNW p	Beta x 10	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	F p	Durbin Watson
See equation 8.4			**Dividend Yields**			**CBI - Investment in Buildings**							
3		3.267	0.008	0.079		-1.003	0.285	0.377		0.129	0.112	0.000	1.99
6	Jan & July	2.562	0.254	0.166		-2.800	0.086	0.045		0.164	0.129	0.014	2.02
6	Apr & Oct	9.884	0.000	0.002		-1.369	0.461	0.463		0.366	0.341	0.000	1.79
12	October	17.096	0.000	0.000		-1.125	0.743	0.810		0.565	0.527	0.000	2.12
12	January	7.474	0.114	0.082		-4.357	0.172	0.062		0.357	0.310	0.006	1.91
12	April	13.043	0.027	0.000		--2.580	0.449	0.402		0.328	0.370	0.010	1.85
12	July	6.237	0.152	0.073		-5.272	0.114	0.168		0.280	0.228	0.020	1.84
24	October	13.924	0.003	0.005	0.007	-1.464	0.721	0.655	0.639	0.417	0.364	0.003	1.38
24	January	15.990	0.027	0.003	0.000	-2.156	0.589	0.473	0.000	0.434	0.382	0.002	1.16
24	April	21.614	0.003	0.001	0.000	1.905	0.634	0.534	0.345	0.378	0.321	0.005	1.32
24	July	16.633	0.008	0.004	0.000	-2.417	0.584	0.519	0.538	0.380	0.323	0.005	1.02
36	October	33.263	0.000	0.000	0.000	-0.495	0.915	0.919	0.698	0.756	0.733	0.000	1.19
36	January	28.900	0.001	0.000	0.003	0.373	0.941	0.890	0.900	0.574	0.533	0.000	0.77
36	April	25.883	0.004	0.000	0.000	0.713	0.888	0.847	0.392	0.399	0.342	0.005	1.02
36	July	30.703	0.001	0.000	0.000	3.114	0.610	0.570	0.488	0.460	0.409	0.002	0.99
Number of series significant at 1%			**10**	**11**			**0**	**0**					
Number of series significant at 5%			**12**	**11**			**0**	**0**					

For explanatory notes see appendix 6.6

APPENDIX 8.3

Multiple regressions of returns on dividend yields and CBI data

1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta	Beta p	HCSE p	HHNW p		Beta x 10	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	F p	Durbin Watson
See equation 8.5			**Dividend Yields**				**CBI - Investment in Plant**							
3		3.453	0.004	0.051		1	-0.587	0.396	0.459		0.126	0.109	0.001	1.97
6	Jan & July	3.343	0.124	0.066		2	-1.523	0.188	0.107		0.142	0.107	0.023	1.96
6	Apr & Oct	10.431	0.000	0.000		3	-0.318	0.822	0.805		0.360	0.334	0.000	1.76
12	October	18.149	0.000	0.000		4	0.840	0.757	0.807		0.564	0.527	0.000	2.08
12	January	8.045	0.097	0.054		5	-2.724	0.254	0.110		0.341	0.283	0.008	1.89
12	April	13.685	0.020	0.000		6	-1.447	0.561	0.520		0.321	0.262	0.012	1.83
12	July	7.993	0.059	0.011		7	-2.684	0.253	0.290		0.251	0.186	0.036	1.78
24	October	14.774	0.002	0.002	0.003	8	0.225	0.943	0.923	0.912	0.414	0.361	0.003	1.33
24	January	15.432	0.015	0.005	0.011	9	-1.995	0.501	0.358	0.000	0.438	0.387	0.002	1.13
24	April	22.327	0.002	0.000	0.000	10	2.116	0.471	0.294	0.029	0.386	0.331	0.005	1.32
24	July	17.914	0.003	0.000	0.000	11	-0.459	0.881	0.837	0.856	0.372	0.315	0.006	1.00
36	October	34.373	0.000	0.000	0.000	12	1.386	0.700	0.713	0.306	0.758	0.735	0.000	1.19
36	January	29.526	0.000	0.000	0.003	13	0.754	0.837	0.801	0.824	0.574	0.534	0.000	0.76
36	April	28.298	0.002	0.000	0.000	14	2.684	0.462	0.342	0.196	0.414	0.359	0.004	1.00
36	July	31.155	0.000	0.000	0.000	15	4.117	0.321	0.263	0.185	0.479	0.430	0.001	1.01
Number of series significant at 1%			**10**	**11**				**0**	**0**					
Number of series significant at 5%			**12**	**12**				**0**	**0**					

For explanatory notes see appendix 6.6

Multiple regressions of returns on dividend yields and CBI data
1966 - 1993

Return Horizon Months	Returns following CBI survey	Beta	Beta p	HCSE p	HHNW p		Beta x10	Beta p	HCSE p	HHNW p	R^2	$\bar{R}^2$	F p	Durbin Watson
See equation 8.6			**Dividend Yields**				**CBI - Future Orders**							
3		3.898	0.003	0.042		1	-0.029	0.968	0.972		0.120	0.102	0.002	1.94
6	Jan & July	4.864	0.055	0.032		2	0.119	0.923	0.921		0.111	0.075	0.056	1.85
6	Apr & Oct	11.343	0.000	0.000		3	0.824	0.586	0.545		0.363	0.337	0.000	1.74
12	October	19.585	0.000	0.000		4	3.097	0.252	0.251		0.587	0.552	0.000	2.01
12	January	14.079	0.018	0.009		5	1.513	0.548	0.579		0.313	0.253	0.014	1.70
12	April	14.591	0.032	0.002		6	-0.513	0.869	0.846		0.312	0.252	0.014	1.80
12	July	7.759	0.102	0.056		7	-1.858	0.464	0.477		0.225	0.158	0.053	1.78
24	October	14.217	0.003	0.004	0.004	8	-0.656	0.837	0.875	0.874	0.415	0.361	0.003	1.36
24	January	13.035	0.062	0.004	0.013	9	-2.980	0.326	0.224	0.185	0.451	0.401	0.001	1.06
24	April	23.827	0.004	0.000	0.000	10	2.811	0.433	0.306	0.371	0.389	0.334	0.004	1.25
24	July	19.137	0.004	0.000	0.000	11	0.964	0.771	0.708	0.770	0.374	0.317	0.006	0.96
36	October	32.293	0.000	0.000	0.000	12	-1.892	0.597	0.516	0.516	0.759	0.736	0.000	1.22
36	January	26.542	0.004	0.000	0.001	13	-1.193	0.747	0.612	0.573	0.576	0.535	0.000	0.85
36	April	21.590	0.027	0.005	0.001	14	-2.637	0.555	0.422	0.470	0.409	0.353	0.004	1.03
36	July	27.597	0.003	0.000	0.000	15	-1.176	0.795	0.590	0.667	0.455	0.403	0.002	0.99
Number of series significant at 1%			**9**	**12**				**0**	**0**					
Number of series significant at 5%			**12**	**14**				**0**	**0**					

For explanatory notes see appendix 6.6

Multiple Regressions
Model Selection Criteria 1966 - 1993

Return Horizon Months	Returns following CBI surveys	R-bar Sq Univariate Div. yield	R-bar Sq Multivariate Div. yield & CBI		Akaike Inf. Criteria Univariate Div. yield	Akaike Inf. Criteria Multivariate Div. yield & CBI		Schwartz Inf. Criteria Univariate Div. yield	Schwartz Inf. Criteria Multivariate Div. yield & CBI
		Dividend Yield and CBI - Business Optimism							
3		0.111	0.102		1013.7	1015.7		1018.9	1023.6
6	Jan & July	0.093	0.083		485.1	486.6		489.0	492.4
6	Apr & Oct	0.346	0.335		513.3	515.3		517.3	521.2
12	October	0.544	0.555	*	249.4	249.7		252.0	253.5
12	January	0.272	0.287	*	238.0	238.4		240.5	242.2
12	April	0.282	0.252		242.8	244.8		245.3	248.6
12	July	0.173	0.161		246.7	248.0		249.2	251.7
24	October	0.388	0.360		245.7	247.7		248.1	251.3
24	January	0.401	0.378		237.6	239.4		240.0	243.1
24	April	0.344	0.322		240.1	240.9		242.5	244.6
24	July	0.344	0.332		248.8	250.1		251.2	253.8
36	October	0.745	0.756	*	240.3	242.2		242.6	245.7
36	January	0.554	0.555	*	236.0	236.8		238.3	240.4
36	April	0.371	0.376	*	239.2	239.9		241.6	243.4
36	July	0.429	0.412		252.7	254.2		255.0	257.8
		Dividend Yield and CBI - Investment in Buildings							
3		0.111	0.112	*	1013.7	1014.8		1018.9	1022.4
6	Jan & July	0.093	0.164	*	485.1	483.9	*	489.0	489.8
6	Apr & Oct	0.346	0.341		513.3	514.7		517.3	520.7
12	October	0.544	0.527		249.4	251.3		252.0	255.1
12	January	0.272	0.301	*	238.0	237.9	*	240.5	241.6
12	April	0.282	0.270		242.8	244.2		245.3	247.9
12	July	0.173	0.228	*	246.7	245.8	*	249.2	249.6
24	October	0.388	0.417	*	245.7	247.5		248.1	251.2
24	January	0.401	0.387		237.6	239.2		240.0	242.9
24	April	0.344	0.321		240.1	241.8		242.5	245.4
24	July	0.344	0.323		248.8	250.5		251.2	254.1
36	October	0.745	0.732		240.3	242.2		242.6	245.7
36	January	0.554	0.518		236.0	238.0		238.3	241.5
36	April	0.371	0.342		239.2	241.2		241.6	244.7
36	July	0.429	0.409		252.7	254.4		255.0	257.9

The objective is to maximise R bar squared or to minimise the Akaike or Schwartz information criteria. Where the inclusion of the CBI series is indicated by the statistic, the series is marked by an *.

Multiple Regressions
Model Selection Criteria 1966 - 1993

Return Horizon Months	Returns following CBI surveys	R-bar Sq Uni-variate Div. yield	R-bar Sq Multi-variate Div. yield & CBI		Akaike Inf. Criteria Uni-variate Div. yield	Akaike Inf. Criteria Multi-variate Div. yield & CBI	Schwartz Inf. Criteria Uni-variate Div. yield	Schwartz Inf. Criteria Multi-variate Div. yield & CBI
		Dividend Yield and CBI - Investment in Plant -						
3		0.111	0.109		1013.7	1014.9	1018.9	1022.9
6	Jan & July	0.093	0.107	*	485.1	485.2	489.0	491.1
6	Apr & Oct	0.346	0.334		513.3	515.3	517.3	521.2
12	October	0.544	0.526		249.4	251.3	252.0	255.1
12	January	0.272	0.283	*	238.0	238.5	240.5	242.3
12	April	0.282	0.262		242.8	244.4	248.2	251.0
12	July	0.173	0.186	*	246.7	247.2	249.2	251.0
24	October	0.388	0.360		245.7	247.7	248.1	251.3
24	January	0.401	0.387		237.6	239.1	240.0	242.7
24	April	0.344	0.331		240.1	241.4	242.5	245.1
24	July	0.344	0.315		248.8	250.8	251.2	254.4
36	October	0.745	0.735		240.3	242.0	242.6	245.6
36	January	0.554	0.574	*	236.0	237.9	238.3	241.5
36	April	0.371	0.358		239.2	240.6	241.6	244.1
36	July	0.429	0.430	*	252.7	253.5	255.0	257.0
		Dividend Yield and CBI - Future Orders						
3		0.111	0.102		1013.7	1015.7	1018.9	1023.6
6	Jan & July	0.093	0.075		485.1	487.1	489.0	492.9
6	Apr & Oct	0.346	0.337		513.3	515.0	517.3	520.9
12	October	0.544	0.551	*	249.4	249.9	252.0	253.7
12	January	0.272	0.253		238.0	239.6	240.5	243.4
12	April	0.282	0.252		242.8	244.7	245.3	248.6
12	July	0.173	0.157		246.7	248.1	249.2	251.9
24	October	0.388	0.415	*	245.7	247.6	248.1	251.3
24	January	0.401	0.401		237.6	238.5	240.0	242.1
24	April	0.344	0.334		240.1	241.3	242.5	245.0
24	July	0.344	0.316		248.8	250.7	251.2	254.4
36	October	0.745	0.736		240.3	241.9	242.6	245.4
36	January	0.554	0.535		236.0	237.9	238.3	241.4
36	April	0.371	0.352		239.2	240.8	241.6	244.3
36	July	0.429	0.403		252.7	254.6	255.0	258.1

The criteria is to maximise R bar squared and to minimise the Akaike or Schwartz information criteria. Where the inclusion of the CBI series in a regression is indicated by the statistic, the series is marked by an *.

APPENDIX 10

Explanatory Note

In appendix 10 the headings are as follows:

O.L.S. *p*	The p values of the regression coefficient estimated by O.L.S
HCSE *p*	The p values for the heteroscedasticity adjusted standard errors, see White (1980).
HHNW p	The p values for the heteroscedasticity and serial correlation corrected standard errors using the method of Hansen (1982) and Newey West (1987).
Simple random	The p values where returns are randomised but the actual dividend yield is used as the explanatory variable.
G&J random	The p values of the OLS β where the methodology described in Chapter 3.4.4 is used
Stratified random	The p values of the OLS β where the methodology described in Chapter 3.4.5 is used.
W.L.S. random	The p values of the OLS β where the methodology described in Chapter 3.4.5 is used.

p values from randomisation tests for β

1966 - 1993

Return Horizon Months	Returns following CBI surveys	Beta	O.L.S *p*	HCSE *p*	HHNW *p*	Simple random *p*	G&J random *p*	Stratified random *p*	W.L.S random *p*
				Dividend Yield					
3		3.927	0.000	0.008		0.002	0.047	0.251	0.116
6	Jan & July	4.710	0.016	0.006		0.021	0.207	0.675	0.080
6	Apr & Oct	10.665	0.000	0.000		0.001	0.010	0.061	0.020
12	October	17.634	0.000	0.000		0.001	0.029	0.109	0.052
12	January	11.544	0.004	0.003		0.021	0.127	0.452	0.096
12	April	15.303	0.003	0.000		0.006	0.052	0.196	0.023
12	July	9.553	0.020	0.004		0.024	0.204	0.654	0.061
24	October	14.634	0.000	0.002	0.002	0.020	0.396	0.895	0.163
24	January	18.039	0.000	0.000	0.003	0.048	0.268	0.697	0.240
24	April	19.933	0.001	0.000	0.003	0.050	0.211	0.607	0.222
24	July	18.186	0.001	0.000	0.000	0.035	0.264	0.731	0.211
36	October	33.505	0.000	0.000	0.000	0.005	0.184	0.455	0.251
36	January	28.544	0.000	0.000	0.000	0.048	0.274	0.679	0.322
36	April	25.251	0.001	0.000	0.000	0.096	0.361	0.869	0.348
36	July	28.750	0.000	0.000	0.000	0.040	0.265	0.698	0.242
Number of series significant at 1%			**13**	**15**		**6**	**0**	**0**	**0**
Number of series significant at 5%			**15**	**15**		**14**	**3**	**0**	**2**
				CBI - Business Optimism					
3		-1.163	0.018	0.043		0.009		0.017	0.125
6	Jan & July	-0.845	0.287	0.422		0.178		0.198	0.151
6	Apr & Oct	-3.374	0.006	0.290		0.002		0.004	0.114
12	October	-5.771	0.051	0.091		0.013		0.016	0.082
12	January	-1.900	0.195	0.385		0.151		0.133	0.128
12	April	-3.829	0.078	0.018		0.068		0.084	0.225
12	July	-3.816	0.050	0.044		0.052		0.078	0.097
24	October	-6.508	0.025	0.026	0.093	0.081		0.074	0.146
24	January	-4.954	0.008	0.011	0.005	0.083		0.038	0.142
24	April	-3.827	0.162	0.147	0.298	0.209		0.174	0.382
24	July	-3.527	0.224	0.205	0.212	0.180		0.164	0.387
36	October	-15.117	0.001	0.006	0.039	0.017		0.007	0.060
36	January	-6.031	0.024	0.043	0.000	0.106		0.026	0.139
36	April	-4.814	0.159	0.151	0.250	0.236		0.189	0.452
36	July	-6.282	0.134	0.115	0.099	0.122		0.088	0.238
Number of series significant at 1%			**3**	**1**		**2**		**2**	**0**
Number of series significant at 5%			**7**	**7**		**4**		**6**	**0**

APPENDIX 10.1.2

p values from randomisation tests for β

1966 - 1993

Return Horizon Months	Returns following CBI surveys	Beta	O.L.S p	HCSE p	HHNW p	Simple random p	G&J random p	Stratified random p	W.L.S random p
CBI Investment in Buildings									
3		-2.268	0.007	0.006		0.004		0.006	0.099
6	Jan & July	-3.817	0.006	0.002		0.015		0.021	0.025
6	Apr & Oct	-5.103	0.009	0.024		0.003		0.004	0.016
12	October	-8.290	0.057	0.148		0.011		0.021	0.047
12	January	-7.578	0.005	0.005		0.025		0.024	0.016
12	April	-6.772	0.040	0.044		0.044		0.044	0.035
12	July	-7.544	0.015	0.028		0.023		0.033	0.044
24	October	-7.749	0.083	0.065	0.080	0.123		0.156	0.014
24	January	-9.140	0.013	0.006	0.004	0.098		0.053	0.101
24	April	-5.117	0.213	0.099	0.166	0.239		0.192	0.234
24	July	-8.560	0.062	0.027	0.062	0.101		0.097	0.149
36	October	-15.799	0.039	0.056	0.039	0.391		0.579	0.068
36	January	-12.830	0.015	0.000	0.001	0.432		0.417	0.046
36	April	-8.139	0.118	0.020	0.015	0.209		0.193	0.158
36	July	-8.304	0.233	0.112	0.140	0.164		0.218	0.219
Number of series significant at 1%			**4**	**5**		**2**		**2**	**0**
Number of series significant at 5%			**9**	**10**		**7**		**7**	**7**
CBI Investment in Plant									
3		-1.520	0.017	0.039		0.010		0.012	0.135
6	Jan & July	-2.382	0.023	0.011		0.034		0.039	0.052
6	Apr & Oct	-3.291	0.030	0.084		0.000		0.000	0.001
12	October	-5.233	0.134	0.289		0.040		0.053	0.019
12	January	-5.316	0.009	0.009		0.000		0.000	0.001
12	April	-4.545	0.064	0.028		0.060		0.041	0.101
12	July	-4.189	0.080	0.108		0.071		0.070	0.182
24	October	-4.972	0.159	0.147	0.181	0.170		0.179	0.324
24	January	-7.032	0.009	0.002	0.002	0.091		0.042	0.159
24	April	-3.074	0.320	0.205	0.281	0.276		0.195	0.435
24	July	-3.877	0.270	0.213	0.277	0.213		0.186	0.438
36	October	-1.087	0.072	0.138	0.098	0.410		0.521	0.178
36	January	-9.102	0.018	0.000	0.000	0.094		0.036	0.119
36	April	-4.059	0.298	0.142	0.151	0.285		0.214	0.387
36	July	-1.754	0.737	0.730	0.667	0.376		0.402	0.597
Number of series significant at 1%			**2**	**3**		**2**		**2**	**2**
Number of series significant at 5%			**6**	**6**		**5**		**7**	**2**

APPENDIX 10.1.3

p values from randomisation tests for β

1966 - 1993

Return Horizon Months	Returns following CBI surveys		O.L.S p	HCSE p	HHNW p	Simple random p	G&J random p	Stratified random p	W.L.S random p
				Future Orders					
3		-1.274	0.039	0.053		0.017		0.030	0.113
6	Jan & July	-1.418	0.151	1.348		0.116		0.144	0.082
6	Apr & Oct	-2.961	0.058	0.058		0.015		0.021	0.099
12	October	-3.648	0.303	0.375		0.100		0.108	0.265
12	January	-3.245	0.086	0.164		0.094		0.098	0.106
12	April	-5.205	0.047	0.023		0.046		0.072	0.083
12	July	-4.110	0.074	0.100		0.064		0.092	0.138
24	October	-5.675	0.102	0.173	0.274	0.163		0.180	0.302
24	January	-7.371	0.002	0.003	0.004	0.057		0.036	0.114
24	April	-4.844	0.135	0.184	0.296	0.208		0.225	0.407
24	July	-4.677	0.165	0.233	0.334	0.172		0.198	0.388
36	October	-13.504	0.021	0.024	0.060	0.063		0.052	0.129
36	January	-10.151	0.002	0.001	0.000	0.057		0.025	0.070
36	April	-9.672	0.013	0.006	0.046	0.132		0.146	0.219
36	July	-9.274	0.055	0.016	0.070	0.107		0.112	0.207
Number of series significant at 1%			**2**	**3**		**0**		**0**	**0**
Number of series significant at 5%			**6**	**6**		**3**		**4**	**0**

APPENDIX 10.2.1

p values from randomisation tests for R^2

1966 - 1993

Dividend Yield

Return Horizon Months	Returns following CBI surveys	R^2	O.L.S R squared p	Simple random p	G&J random p	Stratified random p	W.L.S random p
3		0.1195	0.000	0.002	0.101	0.085	0.146
6	Jan & July	0.1108	0.016	0.015	0.179	0.583	0.030
6	Apr & Oct	0.3590	0.000	0.000	0.001	0.003	0.002
12	October	0.5625	0.000	0.000	0.001	0.005	0.012
12	January	0.3013	0.004	0.004	0.055	0.224	0.002
12	April	0.3109	0.003	0.002	0.048	0.229	0.004
12	July	0.2062	0.020	0.017	0.181	0.590	0.050
24	October	0.4135	0.000	0.000	0.124	0.368	0.016
24	January	0.4258	0.000	0.002	0.111	0.333	0.026
24	April	0.3720	0.001	0.004	0.178	0.517	0.031
24	July	0.3710	0.001	0.007	0.174	0.509	0.069
36	October	0.7560	0.000	0.000	0.006	0.018	0.016
36	January	0.5735	0.000	0.000	0.086	0.240	0.021
36	April	0.4399	0.001	0.005	0.321	0.731	0.059
36	July	0.4535	0.000	0.004	0.225	0.567	0.149
Number of series significant at 1%			**13**	**13**	**3**	**2**	**3**
Number of series significant at 5%			**15**	**15**	**4**	**3**	**11**

CBI - Business Optimism

Return Horizon Months	Returns following CBI surveys	R^2	O.L.S R squared p	Simple random p	G&J random p	Stratified random p	W.L.S random p
3		0.0571	0.018	0.013		0.032	0.241
6	Jan & July	0.0266	0.287	0.239		0.364	0.257
6	Apr & Oct	0.1374	0.006	0.007		0.010	0.238
12	October	0.1499	0.051	0.051		0.064	0.151
12	January	0.0659	0.195	0.200		0.337	0.187
12	April	0.1240	0.078	0.077		0.147	0.515
12	July	0.1511	0.050	0.050		0.091	0.200
24	October	0.2000	0.025	0.047		0.069	0.195
24	January	0.2682	0.008	0.019		0.058	0.144
24	April	0.0831	0.162	0.232		0.305	0.586
24	July	0.0636	0.224	0.253		0.310	0.768
36	October	0.3740	0.001	0.042		0.004	0.036
36	January	0.2117	0.024	0.036		0.067	0.185
36	April	0.0880	0.159	0.224		0.217	0.927
36	July	0.0582	0.134	0.272		0.249	0.497
Number of series significant at 1%			**3**	**1**		**1**	**0**
Number of series significant at 5%			**7**	**7**		**3**	**1**

p values from randomisation tests for R^2
1966 - 1993

Return Horizon Months	Returns following CBI surveys	R^2	O.L.S R squared p	Simple random p	G&J random p	Stratified random p	W.L.S random p
			CBI - Investment in Buildings				
3		0.0678	0.007	0.009		0.015	0.089
6	Jan & July	0.1406	0.006	0.007		0.011	0.014
6	Apr & Oct	0.1241	0.009	0.010		0.019	0.013
12	October	0.1418	0.057	0.056		0.116	0.070
12	January	0.2814	0.005	0.007		0.007	0.004
12	April	0.1659	0.040	0.041		0.057	0.041
12	July	0.2220	0.015	0.014		0.033	0.048
24	October	0.1247	0.083	0.114		0.189	0.147
24	January	0.2379	0.013	0.032		0.035	0.032
24	April	0.0665	0.213	0.301		0.301	0.273
24	July	0.1430	0.062	0.092		0.135	0.165
36	October	0.1789	0.039	0.042		0.066	0.047
36	January	0.2402	0.015	0.025		0.014	0.009
36	April	0.1073	0.118	0.173		0.127	0.097
36	July	0.0638	0.233	0.241		0.262	0.381
Number of series significant at 1%			**4**	**4**		**1**	**2**
Number of series significant at 5%			**9**	**9**		**7**	**8**
			CBI - Investment in Plant				
3		0.0535	0.017	0.018		0.031	0.270
6	Jan & July	0.0990	0.023	0.026		0.038	0.084
6	Apr & Oct	0.0861	0.030	0.043		0.066	0.286
12	October	0.0909	0.134	0.138		0.217	0.431
12	January	0.2547	0.009	0.040		0.040	0.061
12	April	0.1354	0.064	0.068		0.075	0.209
12	July	0.1224	0.080	0.078		0.106	0.379
24	October	0.0844	0.159	0.207		0.271	0.592
24	January	0.2590	0.009	0.025		0.030	0.136
24	April	0.0430	0.320	0.406		0.402	0.800
24	July	0.0530	0.270	0.333		0.349	0.821
36	October	0.1399	0.072	0.085		0.088	0.284
36	January	0.2277	0.018	0.030		0.019	0.097
36	April	0.0491	0.298	0.362		0.300	0.664
36	July	0.0052	0.737	0.761		0.750	0.822
Number of series significant at 1%			**2**	**0**		**0**	**0**
Number of series significant at 5%			**6**	**6**		**5**	**0**

p values from randomisation tests for R^2
1966 - 1993

Return Horizon Months	Returns following CBI surveys	R^2	O.L.S R squared p	Simple random p	G&J random p	Stratified random p	W.L.S random p
			CBI - Future Orders				
3		0.0405	0.039	0.038		0.055	0.357
6	Jan & July	0.0408	0.151	0.149		0.213	0.203
6	Apr & Oct	0.0682	0.058	0.061		0.067	0.346
12	October	0.0441	0.303	0.307		0.317	0.604
12	January	0.1180	0.086	0.080		0.139	0.150
12	April	0.1550	0.047	0.050		0.078	0.252
12	July	0.1270	0.074	0.076		0.096	0.339
24	October	0.1119	0.102	0.194		0.194	0.556
24	January	0.3544	0.002	0.008		0.012	0.103
24	April	0.0946	0.135	0.218		0.267	0.859
24	July	0.0822	0.165	0.238		0.262	0.774
36	October	0.2189	0.021	0.076		0.076	0.196
36	January	0.3607	0.002	0.005		0.006	0.052
36	April	0.2491	0.013	0.042		0.046	0.374
36	July	0.1576	0.055	0.112		0.109	0.427
Number of series significant at 1%			**2**	**2**		**1**	**0**
Number of series significant at 5%			**6**	**5**		**3**	**0**

APPENDIX 10.3.1

Weighted Average of p values

		Beta				R^2			
Months	OLS p	Simple random p	G&J random p	Stratified random p	WLS random p	Simple random p	G&J random p	Stratified random p	WLS random p
				Dividend yield					
3	0.000	0.002	0.047	0.251	0.116	0.002	0.101	0.085	0.146
6	0.008	0.011	0.109	0.368	0.050	0.008	0.090	0.293	0.016
12	0.007	0.013	0.103	0.353	0.058	0.006	0.071	0.262	0.017
3 to 12	0.006	0.011	0.097	0.343	0.064	0.006	0.081	0.246	0.035
24	0.001	0.038	0.285	0.733	0.209	0.003	0.147	0.432	0.036
36	0.000	0.047	0.271	0.675	0.291	0.002	0.160	0.389	0.061
24 to 36	0.000	0.043	0.278	0.704	0.250	0.003	0.153	0.410	0.048
3 to 36	0.003	0.028	0.193	0.535	0.163	0.004	0.119	0.333	0.042
				CBI - Business Optimism					
3	0.018	0.009		0.017	0.125	0.013		0.032	0.241
6	0.147	0.090		0.101	0.133	0.123		0.187	0.248
12	0.094	0.071		0.078	0.133	0.095		0.160	0.263
3 to 12	0.098	0.068		0.076	0.132	0.091		0.149	0.256
24	0.105	0.138		0.113	0.264	0.138		0.186	0.423
36	0.080	0.120		0.078	0.222	0.144		0.134	0.411
24 to 36	0.092	0.129		0.095	0.243	0.141		0.160	0.417
3 to 36	0.095	0.100		0.086	0.191	0.117		0.155	0.342
				CBI Investment in Buildings					
3	0.007	0.004		0.006	0.099	0.009		0.015	0.089
6	0.008	0.009		0.013	0.021	0.009		0.015	0.014
12	0.029	0.026		0.031	0.036	0.030		0.053	0.041
3 to 12	0.020	0.018		0.022	0.040	0.021		0.037	0.040
24	0.093	0.140		0.125	0.125	0.135		0.165	0.154
36	0.101	0.299		0.352	0.123	0.120		0.117	0.134
24 to 36	0.097	0.220		0.238	0.124	0.128		0.141	0.144
3 to 36	0.061	0.125		0.137	0.085	0.082		0.100	0.096

Weighted Average of p values

		Beta				R^2			
Months	OLS p	Simple Random p	G&J random p	Stratified random p	WLS random p	Simple Random p	G&J random p	Stratified random p	WLS random p
Investment in Plant									
3	0.017	0.010		0.012	0.135	0.018		0.031	0.270
6	0.027	0.017		0.020	0.027	0.035		0.052	0.185
12	0.072	0.043		0.041	0.076	0.081		0.110	0.270
3 to 12	0.051	0.031		0.031	0.070	0.059		0.082	0.246
24	0.190	0.188		0.151	0.339	0.243		0.263	0.587
36	0.281	0.291		0.293	0.320	0.310		0.289	0.467
24 to 36	0.235	0.239		0.222	0.330	0.276		0.276	0.527
3 to 36	0.149	0.142		0.133	0.209	0.175		0.185	0.396
CBI - Future Orders									
3	0.039	0.017		0.030	0.113	0.038		0.055	0.357
6	0.105	0.066		0.083	0.091	0.105		0.140	0.275
12	0.128	0.076		0.093	0.148	0.128		0.158	0.336
3 to 12	0.108	0.065		0.081	0.127	0.109		0.138	0.322
24	0.101	0.150		0.160	0.303	0.165		0.184	0.573
36	0.023	0.090		0.084	0.156	0.059		0.059	0.262
24 to 36	0.062	0.120		0.122	0.230	0.112		0.122	0.418
3 to 36	0.084	0.094		0.103	0.181	0.110		0.129	0.373

APPENDIX 11

Randomisation
RATS Program -1

* This appendix shows the OLS and weighted least squares randomisation program written in
* *RATS* 4.10. Details are given for one variable dividend yield, and for one time period, 3 months.

* Code relating specifically to weighted least squares is shown in *italics.*
* Stratified randomisation operates by limiting the shuffling, see section 9.00x.
* RATS ignores lines starting with *.

*** 1.00X INITIALISES PROGRAM AND LOADS DATA**

```
CALENDAR(IRREGULAR)
ALLOCATE 338
* DIVI05B.RAT contains the data in appendix 1
OPEN DATA DIVI05B.RAT
DATA(FORMAT=RAT,ORG=OBS) / DANO CBI INVB INVP FORD RETIND PRIND QTR
VOLAT
```

*** 2.00X INITIAL TRANSFORMATIONS**

```
* Calculates number of days between observations
SET DA = DANO-DANO{1}
* Calculates arithmetic total returns
SET TRET = (RETIND-RETIND{1}) / RETIND{1}
* Calculates arithmetic capital returns
SET CR = (PRIND - PRIND{1}) / PRIND{1}
* Computes income return
SET IR = ((1+TRET)/(1+CR))-1
* Adjusts income returns for unequal periods between CBI surveys
SET AIR = (IR/DA)*365/12
* Aggregates a pseudo price index from capital returns
SET(FIRST=100) PI 1 329 = PI{1}*(1+CR)
* Computes monthly dividends
SET DIV = AIR*PI{1}
* Accumulates monthly dividends to annual dividends
SET ADIV = DIV + DIV{1} + DIV{2} + DIV{3} + DIV{4} + DIV{5} + DIV{6} $
      + DIV{7} + DIV{8} + DIV{9} + DIV{10} + DIV{11}
```

*** 3.00X SET COUNTERS TO ZERO -**

```
* Beta coefficient
COMPUTE CO101=0.0
* R Squared
COMPUTE CR101=0.0
```

APPENDIX 11

Randomisation
RATS Program - 2

```
* 4.00X  INPUTS CALCULATED BETA & R SQUARED


COMPUTE AB101=3.927  1.699
COMPUTE AR101=0.1195   0.0785


* 7.00X  SETS NUMBER OF REPLICATIONS

COMPUTE NDRAWS = 8000


* 8.00x  SETS COUNTER FOR NUMBER OF DRAWS

SET TEST101 1 NDRAWS = 0.0
SET TEST101R 1 NDRAWS = 0.0

* 9.00x          RANDOMISATION PROGRAM

* Start of randomisation loop
DO DRAWS=1,NDRAWS
*   Sets a new variable RA3Z to a random variable in a uniform distribution between zero and
one.
SET RA3Z = %UNIFORM(0,1)

*  Sort for simple randomisation.  The line below sorts RA3Z into ascending order.  The
variables DA TRET and CR are sorted in ascending order of RA3Z
ORDER RA3Z 2 336 RA3Z DA TRET CR

*  Sort for stratified randomisation.  The 5 lines below sorts RA3Z into ascending order.  The
*  Variables DA TRET and CR are sorted in ascending order of RA3Z.

* ORDER RA3Z 2 80 RA3Z DA TRET CR
* ORDER RA3Z 81 130 RA3Z DA TRET CR
* ORDER RA3Z 131 230 RA3Z DA TRET CR
* ORDER RA3Z 231 280 RA3Z DA TRET CR
* ORDER RA3Z 281 336 RA3Z DA TRET CR

*  The code below calculates dividend yield.  It ensures that the price series used to calculate
*  Dividend yield is based on a continuous history of capital returns. (See Goetzmann and Jorion
*  (1993)).
*  Aggregates a pseudo price index from capital returns
SET(FIRST=100) PI 1 329 = PI{1}*(1+CR)
SET DYA = (ADIV/PI)*100
```

APPENDIX 11

Randomisation
RATS Program - 3

```
* The code below compounds arithmetic returns to a 3 months horizon.
SET R3 = ((1+TRET{-1}) * (1+TRET{-2}) * (1+TRET{-3})-1) * 100

* The code below compounds volatility to a 3 months horizon - see McQueen (1992).
SET V3 = ((VOLAT{-1}) + (VOLAT(-2)) + (VOLAT{-3}))*0.5

* 10.00X  EXTRACTS DATA

*   Extracts quarterly data

SAMPLE(INTERVAL=3) R3 4 338 REX
SAMPLE(INTERVAL=3) V3 4 338 V3X
SAMPLE(INTERVAL=3) DY 4 338 DYX
SAMPLE(INTERVAL=3) CBI 4 338 CBIX


*  11.00X  WEIGHTING OF VARIABLES


*  3 months series

SET REXW = REX / V3X
SET DYXW = DYX / V3X


* 15.00X  REGRESSIONS -

* 101
 LINREG(NOPRINT) REXW 7 111
 # CONSTANT DYXW

 COMPUTE TEST101(DRAWS) = %BETA(2)
 IF %BETA(2)>AB101
 COMPUTE CO101=CO101+1

 COMPUTE TEST101(DRAWS) = %RSQUARED
 IF %RSQUARED>AR101
 COMPUTE CR101=CR101+1


* Ends Randomisation Loop
 END DO DRAWS
```

APPENDIX 11

Randomisation
RATS Program - 4

*** 17.00 PRINT STATISTICS**

```
* 101
DISPLAY @29 'P value B'  @47  'P Value  R'

DISPLAY  @1 'Reg No 1.01'   @15 'P-Val B'  @25 ##.###### $
    ((CO101+1)/(NDRAWS+1)) @15 'P-Val R'@43 ##.###### $
    ((CR101+1)/(NDRAWS+1))

* End
```

Regressions of returns on dividend yields and CBI data
Split sample periods - 1

Return Horizon Months	Returns following CBI survey	1966 -1980 Beta	Beta p	R^2	DW	1981-1993 Beta	Beta p	R^2	DW
				Dividend Yields					
3		4.404	0.003	0.156	1.80	3.126	0.099	0.058	2.20
6	Jan & July	5.200	0.041	0.163	1.46	4.804	0.187	0.071	2.38
6	Apr & Oct	12.308	0.000	0.440	1.64	4.138	0.166	0.075	2.48
12	October	19.611	0.001	0.648	2.05	4.695	0.384	0.070	2.04
12	January	15.531	0.012	0.450	1.70	4.569	0.357	0.077	2.19
12	April	20.055	0.014	0.437	1.65	4.032	0.508	0.041	2.01
12	July	11.115	0.042	0.316	1.47	6.657	0.407	0.063	2.34
24	October	15.749	0.009	0.478	1.60	10.158	0.152	0.194	0.58
24	January	22.736	0.002	0.616	1.27	11.287	0.131	0.213	1.08
24	April	23.706	0.007	0.504	1.80	14.533	0.133	0.211	0.76
24	July	20.716	0.002	0.582	1.16	15.747	0.190	0.165	0.94
36	October	35.691	0.000	0.860	1.89	24.927	0.035	0.406	0.71
36	January	32.665	0.000	0.755	1.42	26.626	0.016	0.494	0.71
36	April	27.882	0.003	0.675	1.92	25.723	0.080	0.301	0.61
36	July	32.042	0.000	0.757	1.21	28.378	0.153	0.213	1.15
Number of series significant at 1 %			**11**				**0**		
Number of series significant at 5%			**15**				**2**		
				Confederation of British Industries - Business Optimism					
		x 10							
3		-1.265	0.079	0.059	1.89	-0.991	0.140	0.043	2.28
6	Jan & July	-0.907	0.376	0.033	1.60	-0.882	0.575	0.013	2.56
6	Apr & Oct	-5.318	0.019	0.210	2.19	-1.146	0.227	0.058	2.41
12	October	-12.472	0.023	0.387	3.11	1.043	0.563	0.031	2.41
12	January	-3.072	0.175	0.160	2.31	1.110	0.545	0.034	2.48
12	April	-6.370	0.073	0.264	2.00	1.271	0.563	0.031	2.32
12	July	-4.215	0.113	0.213	1.63	-2.691	0.448	0.053	2.24
24	October	-12.099	0.017	0.417	1.83	-0.025	0.992	0.000	0.68
24	January	-6.874	0.006	0.509	1.07	0.104	0.972	0.000	0.95
24	April	-7.101	0.068	0.270	2.23	3.203	0.408	0.069	1.04
24	July	-5.318	0.149	0.179	1.39	2.091	0.711	0.014	1.15
36	October	-25.725	0.001	0.661	2.33	-2.609	0.564	0.038	0.99
36	January	-7.911	0.019	0.403	1.52	-1.680	0.735	0.013	0.66
36	April	-9.232	0.026	0.377	1.52	4.437	0.465	0.061	0.64
36	July	-8.661	0.076	0.259	0.84	1.114	0.904	0.002	1.20
Number of series significant at 1 %			**2**				**0**		
Number of series significant at 5%			**7**				**0**		

Regressions of returns on dividend yields and CBI data
Split sample periods - 2

Return Horizon Months	Returns following CBI survey	1966 -1980 Beta	Beta p	R^2	DW	1981 -1993 Beta	Beta p	R^2	DW
Confederation of British Industries - Investment in Buildings									
		x 10							
3		-3.110	0.016	0.109	2.08	-0.788	0.454	0.011	2.37
6	Jan & July	-5.237	0.005	0.286	1.92	-1.164	0.604	0.011	2.66
6	Apr & Oct	-9.615	0.008	0.260	2.42	-0.428	0.780	0.003	2.74
12	October	-16.232	0.048	0.311	3.26	-0.011	0.997	0.000	2.34
12	January	-11.263	0.011	0.460	2.04	-1.656	0.576	0.029	2.39
12	April	-13.735	0.019	0.405	2.50	0.387	0.887	0.002	2.16
12	July	-10.248	0.015	0.424	2.08	-1.901	0.711	0.013	2.55
24	October	-10.730	0.185	0.154	1.83	-3.513	0.367	0.082	0.88
24	January	-10.838	0.069	0.270	1.39	-5.961	0.180	0.172	1.20
24	April	-8.451	0.233	0.126	2.16	-1.414	0.759	0.010	0.99
24	July	-10.275	0.101	0.226	1.17	-4.479	0.566	0.034	0.98
36	October	-20.887	0.121	0.204	1.90	-8.344	0.225	0.159	1.12
36	January	-18.124	0.147	0.181	1.10	-14.622	0.404	0.389	1.27
36	April	-9.612	0.217	0.135	1.13	-6.447	0.385	0.085	0.69
36	July	-11.827	0.172	0.163	0.87	0.330	0.980	0.000	1.14

Number of series significant at 1 % — 1966-1980: **2**; 1981-1993: **0**
Number of series significant at 5% — 1966-1980: **7**; 1981-1993: **0**

Return Horizon Months	Returns following CBI survey	1966 -1980 Beta	Beta p	R^2	DW	1981 -1993 Beta	Beta p	R^2	DW
Confederation of British Industries - Investment in Plant									
		x 10							
3		-2.090	0.032	0.087	2.03	-0.503	0.528	0.008	2.36
6	Jan & July	-3.378	0.017	0.216	1.84	-0.524	0.753	0.004	2.66
6	Apr & Oct	-6.893	0.016	0.220	2.30	0.185	0.871	0.001	2.77
12	October	-12.230	0.071	0.266	3.18	1.415	0.495	0.043	2.27
12	January	-8.390	0.011	0.457	2.00	-0.772	0.716	0.012	2.35
12	April	-10.444	0.017	0.418	2.22	1.336	0.511	0.040	2.10
12	July	-6.347	0.053	0.300	1.74	0.795	0.841	0.004	2.65
24	October	-8.034	0.224	0.131	1.71	0.204	0.658	0.020	0.78
24	January	-8.997	0.039	0.332	1.25	-3.928	0.221	0.146	1.06
24	April	-5.682	0.287	0.102	2.03	-0.111	0.974	0.000	0.93
24	July	-5.141	0.282	0.104	1.17	-0.659	0.914	0.001	1.06
36	October	-16.549	0.130	0.195	1.84	-4.005	0.440	0.068	1.13
36	January	-8.959	0.128	0.197	1.05	-9.107	0.074	0.319	1.08
36	April	-5.766	0.329	0.087	1.05	-1.915	0.727	0.014	0.62
36	July	-3.677	0.578	0.029	0.78	3.094	0.756	0.011	1.15

Number of series significant at 1 % — 1966-1980: **0**; 1981-1993: **0**
Number of series significant at 5% — 1966-1980: **6**; 1981-1993: **0**

Regressions of returns on dividend yields and CBI data
Split sample periods - 3

Return Horizon Months	Returns following CBI survey	1966 -1980 Beta	Beta *p*	R^2	DW	1981 -1993 Beta	Beta *p*	R^2	DW
		Confederation of British Industries - Future Orders							
		x 10							
3		-1.322	0.128	0.044	1.93	-1.122	0.263	0.025	2.32
6	Jan & July	-1.336	0.286	0.047	1.63	-1.544	0.439	0.025	2.54
6	Apr & Oct	-4.856	0.078	0.123	2.27	-0.654	0.659	0.008	2.66
12	October	-10.653	0.143	0.184	3.30	2.178	0.346	0.081	2.34
12	January	-4.317	0.142	0.186	2.38	-0.120	0.959	0.000	2.32
12	April	-7.382	0.062	0.282	2.12	2.576	0.484	0.045	2.24
12	July	-4.697	0.117	0.209	1.73	-1.427	0.792	0.007	2.52
24	October	-10.636	0.115	0.210	1.95	-0.477	0.882	0.002	0.70
24	January	-8.867	0.007	0.496	1.23	-2.701	0.465	0.055	0.91
24	April	-6.069	0.179	0.157	2.18	2.091	0.741	0.011	0.92
24	July	-5.946	0.152	0.177	1.46	3.648	0.658	0.020	1.07
36	October	-23.668	0.286	0.365	2.29	-3.393	0.553	0.041	1.02
36	January	-10.717	0.017	0.434	1.69	-7.690	0.186	0.185	0.70
36	April	-11.082	0.015	0.433	1.58	-0.685	0.946	0.001	0.54
36	July	-10.431	0.054	0.296	0.88	-1.290	0.924	0.001	1.12
Number of series significant at 1 %			**1**				**0**		
Number of series significant at 5%			**3**				**0**		

Randomisation - Split Sample Periods - 1
p factors from randomisation tests for β

Dividend Yield

Return Horizon Months	Returns following CBI surveys	1966 - 1980 O.L.S p	1966 - 1980 G&J random p	1981 - 1993 O.L.S p	1981 - 1993 G&J random p
3		0.003	0.197	0.099	0.276
6	Jan & July	0.041	0.504	0.187	0.372
6	Apr & Oct	0.000	0.080	0.166	0.450
12	October	0.001	0.146	0.384	0.704
24	October	0.009	0.756	0.152	0.700
36	October	0.000	0.409	0.035	0.479

Confederation of British Industries - Business Optimism

Return Horizon Months	Returns following CBI surveys	O.L.S p	Simple random p	O.L.S p	Simple random p
3		0.079	0.025	0.140	0.131
6	Jan & July	0.376	0.081	0.575	0.310
6	Apr & Oct	0.019	0.003	0.227	0.231
12	October	0.023	0.046	0.563	0.387
24	October	0.017	0.003	0.992	0.494
36	October	0.001	0.080	0.564	0.395

Confederation of British Industries - Investment in Buildings

3		0.016	0.003	0.454	0.284
6	Jan & July	0.005	0.015	0.604	0.341
6	Apr & Oct	0.008	0.001	0.780	0.431
12	October	0.048	0.004	0.997	0.491
24	October	0.185	0.111	0.367	0.371
36	October	0.121	0.014	0.225	0.297

Note. Randomised p factors were not calculated for the series following the CBI surveys published in January, July and April for 12 months, 24 months and 36 months periods since it was considered that this would add little to the conclusions

APPENDIX 13.1

Randomisation - Split Sample Periods - 2
p factors from randomisation tests for β

Confederation of British Industries - Investment in Plant

Return Horizon Months	Returns following CBI surveys	1966 - 1980 O.L.S p	1966 - 1980 Simple random p	1981 -1993 O.L.S p	1981 -1993 Simple random p
3		0.032	0.007	0.528	0.312
6	Jan & July	0.017	0.025	0.753	0.399
6	Apr & Oct	0.016	0.000	0.871	0.451
12	October	0.071	0.008	0.495	0.368
24	October	0.224	0.001	0.658	0.496
36	October	0.130	0.018	0.440	0.355

Confederation of British Industries - Future Orders

3		0.128	0.038	0.263	0.194
6	Jan & July	0.286	0.135	0.439	0.264
6	Apr & Oct	0.078	0.013	0.659	0.384
12	October	0.143	0.026	0.346	0.323
24	October	0.115	0.063	0.882	0.474
36	October	0.286	0.011	0.553	0.399

Randomisation - Split Sample Periods - 3
p factors from randomisation tests for R^2

Dividend Yield -

		1966 - 1980		1981 -1993	
Return Horizon Months	**Returns following CBI surveys**	**O.L.S** p	**G & J random** p	**O.L.S** p	**G & J random** p
3		0.003	0.044	0.099	0.426
6	Jan & July	0.041	0.287	0.187	0.589
6	Apr & Oct	0.000	0.013	0.166	0.572
12	October	0.001	0.013	0.384	0.753
24	October	0.009	0.295	0.152	0.664
36	October	0.000	0.020	0.035	0.500

Confederation of British Industries - Business Optimism

Return Horizon Months	**Returns following CBI surveys**	**O.L.S** p	**Simple random** p	**O.L.S** p	**Simple random** p
3		0.079	0.075	0.140	0.145
6	Jan & July	0.376	0.370	0.575	0.586
6	Apr & Oct	0.019	0.020	0.227	0.228
12	October	0.023	0.023	0.563	0.562
24	October	0.017	0.021	0.992	1.000
36	October	0.001	0.001	0.564	0.675

Confederation of British Industries - Investment in Buildings

3		0.016	0.013	0.454	0.473
6	Jan & July	0.005	0.005	0.604	0.618
6	Apr & Oct	0.008	0.007	0.780	0.795
12	October	0.048	0.046	0.997	1.000
24	October	0.185	0.193	0.367	0.483
36	October	0.121	0.036	0.225	0.411

Randomisation - Split Sample Periods - 4
p factors from randomisation tests for *R* squared

Confederation of British Industries - Investment in Plant

Return Horizon Months	Returns following CBI surveys	1966 -1980 O.L.S *p*	1966 -1980 Simple random *p*	1981 -1993 O.L.S *p*	1981 -1993 Simple random *p*
3		0.032	0.025	0.528	0.541
6	Jan & July	0.017	0.015	0.753	0.763
6	Apr & Oct	0.016	0.015	0.871	0.873
12	October	0.071	0.069	0.495	0.493
24	October	0.224	0.241	0.658	0.730
36	October	0.130	0.052	0.440	0.594

Confederation of British Industries - Future Orders

3		0.129	0.247	0.263	0.269
6	Jan & July	0.286	0.287	0.439	0.445
6	Apr & Oct	0.078	0.078	0.659	0.655
12	October	0.143	0.142	0.346	0.344
24	October	0.115	0.144	0.882	0.908
36	October	0.029	0.024	0.553	0.681

APPENDIX 14.1

Arithmetic v Continuously Compounded Returns

Regressions of returns on dividend yields

1966 - 1993

Return Horizon Months	Return following CBI Survey	Arithmetic returns Beta	Beta p	R^2	Log. returns Beta	Beta p	R^2
3		3.927	0.000	0.120	3.521	0.002	0.094
6	Jan &	4.710	0.016	0.111	7.806	0.015	0.114
6	Apr &	10.665	0.000	0.359	8.391	0.000	0.251
12	October	17.634	0.000	0.563	13.868	0.001	0.393
24	October	14.634	0.000	0.414	12.626	0.003	0.319
36	October	33.505	0.000	0.756	20.294	0.000	0.546

1966 - 1980

Return Horizon Months	Return following CBI Survey	Arithmetic returns Beta	Beta p	R^2	Log. returns Beta	Beta p	R^2
3		4.404	0.003	0.156	3.911	0.010	0.122
6	Jan &	5.200	0.041	0.163	5.210	0.046	0.156
6	Apr &	12.308	0.000	0.440	9.748	0.003	0.314
12	October	19.611	0.001	0.648	15.773	0.009	0.472
24	October	15.479	0.009	0.478	14.037	0.026	0.377
36	October	35.691	0.000	0.860	21.994	0.001	0.645

1981 -1993

Return Horizon Months	Return following CBI Survey	Arithmetic returns Beta	Beta p	R^2	Log. returns Beta	Beta p	R^2
3		3.126	0.099	0.058	3.256	0.080	0.060
6	Jan &	4.804	0.187	0.071	5.274	0.137	0.090
6	Apr &	4.138	0.166	0.075	3.943	0.169	0.074
12	October	4.695	0.384	0.070	3.709	0.453	0.052
24	October	10.158	0.152	0.194	7.385	0.161	0.187
36	October	24.927	0.035	0.406	15.266	0.040	0.390

APPENDIX 14.2

Regressions of returns on CBI - Business Optimism

1966 - 1993

Return Horizon Months	Return following CBI Survey	Arithmetic returns Beta	Beta *p*	R^2	Log. returns Beta	Beta *p*	R^2
3		-0.116	0.019	0.053	-0.104	0.029	0.046
6	Jan &	-0.085	0.287	0.023	-0.074	0.330	0.019
6	Apr &	-0.337	0.006	0.137	-0.274	0.013	0.115
12	October	-0.577	0.051	0.145	-0.472	0.072	0.128
24	October	-0.651	0.025	0.200	-0.622	0.020	0.214
36	October	-1.512	0.001	0.374	-0.965	0.003	0.339

1966 - 1980

Return Horizon Months	Return following CBI Survey	Arithmetic returns Beta	Beta *p*	R^2	Log. returns Beta	Beta *p*	R^2
3		-1.265	0.079	0.059	-1.111	0.107	0.050
6	Jan &	-0.907	0.376	0.030	0.753	0.451	0.024
6	Apr &	-5.318	0.019	0.210	-4.211	0.038	0.168
12	October	-12.472	0.023	0.387	-9.821	0.050	0.306
24	October	-12.099	0.017	0.417	-11.174	0.020	0.400
36	October	-25.725	0.001	0.661	-15.644	0.004	0.546

1981 - 1993

Return Horizon Months	Return following CBI Survey	Arithmetic returns Beta	Beta *p*	R^2	Log. returns Beta	Beta *p*	R^2
3		-0.991	0.140	0.043	-0.971	0.139	0.04
6	Jan &	-0.882	0.575	0.013	-0.882	0.520	0.01
6	Apr &	-1.146	0.227	0.058	-1.033	0.234	0.05
12	October	1.043	0.563	0.031	-1.012	0.518	0.03
24	October	-0.025	0.992	0.000	-0.129	0.942	0.00
36	October	-2.609	0.564	0.038	-1.853	0.048	0.05

APPENDIX 15

Dates of Samples

Return Horizon Months	Series	Start	End	No. of Obs.
3	1	15-06-1966	22-10-1993	105
6	1	19-10-1966	23-07-1993	52
6	2	15-06-1966	22-10-1993	53
12	1	15-06-1966	23-10-1992	26
12	2	19-10-1996	22-01-1993	26
12	3	7-02-1967	23-04-1993	26
12	4	16-06-1967	23-07-1993	26

1966 - 1980

Return Horizon Months	Series	Start	End	No. of Obs.
3	1	15-06-1966	24-10-1980	53
6	1	19-10-1966	29-07-1980	26
6	2	15-06-1966	25-04-1980	26
12	1	15-06-1966	29-10-1979	13
12	2	19-10-1996	1-02-1980	13
12	3	7-02-1967	25-04-1980	13
12	4	16-06-1967	29-07-1980	13

1981 - 1993

Return Horizon Months	Series	Start	End	No. of Obs.
3	1	23-01-1981	22-10-1993	52
6	1	23-01-1981	23-07-1993	26
6	2	24-10-1980	22-10-1993	27
12	1	24-10-1980	23-10-1992	13
12	2	23-01-1981	22-01-1993	13
12	3	24-04-1981	23-04-1993	13
12	4	29-07-1981	23-07-1993	12

The starting date for 24 and 36 months series is the same as that for annual series

Industrial Trends Survey

January 1996

Confidential

Number 139

CBI

Confederation of British Industry
Economic Trends Department
Centre Point
103 New Oxford Street
London WC1A 1DU

Telephone 0171-379 7400
Facsimile 0171-836 5856

For office use only

		1	1-10

Please return by 11.00 am
WEDNESDAY 11 JANUARY 1996

APPENDIX 16

Please use space overleaf for any comments you would like to make on points not covered by your replies.

1 Are you more, or less, optimistic than you were four months ago about THE GENERAL BUSINESS SITUATION IN YOUR INDUSTRY

More	Same	Less	
			11

2 Are you more, or less, optimistic about your EXPORT PROSPECTS for the next twelve months than you were four months ago

More	Same	Less	N/A	
				12

3 Do you expect to authorise more or less capital expenditure in the next twelve months than you authorised in the past twelve months on:

	More	Same	Less	N/A	
a. buildings					13
b. plant & machinery					14

4 Is your present level of output below capacity (i.e., are you working below a satisfactory full rate of operation)

Yes	No	N/A	
			15

4a What is your current rate of operation as a percentage of full capacity
(Please tick one box below. All Survey participants should answer this question.)

1-5 ☐	6-10 ☐	11-15 ☐	16-20 ☐	21-25 ☐	26-30 ☐	31-35 ☐
36-40 ☐	41-45 ☐	46-50 ☐	51-55 ☐	56-60 ☐	61-65 ☐	66-70 ☐
71-75 ☐	76-80 ☐	81-85 ☐	86-90 ☐	91-95 ☐	96-100 ☐	>100% ☐ (ie overtime/ extra shifts)

5 **Excluding seasonal variations,** do you consider that in **volume** terms:

	Above Normal	Normal	Below Normal	N/A	
a. Your present total order book is					16
b. Your present export order book is					17

(firms with no order book are requested to estimate the level of demand)

	More than Adequate	Adequate	Less than Adequate	N/A	
c. Your present stocks of finished goods are					18

Excluding seasonal variations, what has been the trend over the PAST FOUR MONTHS, and what are the expected trends for the NEXT FOUR MONTHS, with regard to:

	Trend over PAST FOUR MONTHS				Expected trend over NEXT FOUR MONTHS				
	Up	Same	Down	N/A	Up	Same	Down	N/A	
6 Numbers employed									19 20
7 **Volume** of total new orders									21 22
of which: a. domestic orders									23-24
b. export orders									25-26
8 **Volume** of output									27-28
9 **Volume** of: a. domestic deliveries									29-30
b. export deliveries									31-32
10 **Volume** of stocks of: a. raw materials and brought in supplies									33-34
b. work in progress									35-36
c. finished goods									37-38
11 **Average** costs per unit of output									39-40
12 **Average** prices at which: a. domestic orders are booked									41 42
b. export orders are booked									43-44

13 Approximately how many months' production is accounted for by your present order book or production schedule.

Less than 1	1-3	4-6	7-9	10-12	13-18	More than 18	N/A	
								45
1	2	3	4	5	6	7	8	

14 What factors are likely to limit your OUTPUT over the next four months.
Please tick the **most** important factor or factors. If you tick more than one factor it would be helpful if you could rank them in order of importance.

Orders or Sales	Skilled Labour	Other Labour	Plant Capacity	Credit or Finance	Materials or Components	Other	
							46-52

15 What factors are likely to limit your ability to obtain EXPORT ORDERS over the next four months.
Please tick the **most** important factor or factors. If you tick more than one factor it would be helpful if you could rank them in order of importance.

Prices	Delivery Dates (compared with overseas competitors)	Credit or Finance	Quota & Import Licence Restrictions	Political or Economic Conditions Abroad	Other	
						53-58

15 a. Excluding seasonal variations, what has been the trend in your COMPETITIVENESS over the past four months, and what are the expected trends for the next four months, with regard to:
(Please tick one box on each line)

	Past four months				Next four months			
	Improved	Unchanged	Worsened	N/A	Improved	Unchanged	Worsened	N/A
UK market only								
Other EU* markets								
Non EU* markets								

*European Union formerly known as The European Community

16 a. In relation to expected demand over the next twelve months is your present fixed capacity:

More than adequate	adequate	less than adequate	
			59

b. What are the main reasons for any expected CAPITAL EXPENDITURE AUTHORISATIONS ON BUILDINGS, PLANT OR MACHINERY over the next twelve months.
If you tick more than one factor it would be helpful if you could rank them in order of importance.

to expand capacity		60	other (please specify)		63
to increase efficiency		61	N/A		64
for replacement		62			

c. What factors are likely to limit (wholly or partly) your capital expenditure authorisations over the next twelve months. If you tick more than one factor it would be helpful if you could rank them in order of importance.

Inadequate net return on proposed investment		65	Uncertainty about demand		69
Shortage of internal finance		66	Shortage of labour including Managerial and Technical Staff		70
Inability to raise external finance		67	Other (Please specify)		71
Cost of finance		68	N/A		72

17 Do you expect to authorise more or less expenditure in the NEXT twelve months than you authorised over the PAST twelve months on:

	More	Same	Less	N/A	
a. Product and Process Innovation (inc. mkt research, R & D, product/process dev.)					73
b. Training and Retraining					74

Please enter here the code number of the ***main*** manufacturing activity covered by this return. ☐ 75-78
(If unsure of your correct Industrial Classification, please state clearly below your main manufacturing activity being as specific as possible.)

....

How many EMPLOYEES are covered by this return

(a) 0 – 199 ☐ (b) 200 – 499 ☐ (c) 500 – 4,999 ☐ (d) 5,000 and over ☐ 79

What is the annual ex-works value of your **direct** EXPORTS

Nil-£75th	£75th-£1m	£1m-£3m	£3m-£8m	£8m-£15m	£15m-£25m	£25m-£40m	£40m-£60m	£60m-£100m	£100m-£150m	Over £150m	
											80
0	1	2	3	4	5	6	7	8	9	10	

Please enter here the appropriate regional code according to the main geographic location of your manufacturing activities. Please see list overleaf. ☐ 81

Signature ....

Company (Please see overleaf) ....

Address ....

APPENDIX 16

Space for comments on points not covered by your replies.

Regional Codes 1-11

Code 1 Wales (Counties)
- Clwyd
- Dyfed
- Gwent
- Gwynedd
- Mid Glamorgan
- Powys
- South Glamorgan
- West Glamorgan

Code 2 Scotland (L A Region)
- Borders
- Central
- Dumfries and Galloway
- Fife
- Grampian
- Highland
- Lothian
- Strathclyde
- Tayside
- Islands

Code 3 Northern Ireland (Borders)
- Belfast
- South Eastern
- Southern
- North Eastern
- Western

Code 4 North
- Cleveland
- Cumbria
- Durham
- Northumberland
- Tyne and Wear

Code 5 Yorkshire and Humberside
- Humberside
- North Yorkshire
- South Yorkshire
- West Yorkshire

Code 6 East Midlands
- Derbyshire
- Leicestershire
- Lincolnshire
- Northamptonshire
- Nottinghamshire

Code 7 East Anglia
- Camb
- Norfolk
- Suffolk

Code 8 South East
- Bedfordshire
- Berkshire
- Buckinghamshire
- East Sussex
- Essex
- Greater London
- Hampshire
- Hertfordshire
- Isle of Wight
- Kent
- Oxfordshire
- Surrey
- West Sussex

Code 9 South West
- Avon
- Cornwall
- Devon
- Dorset
- Gloucester
- Somerset
- Wiltshire

Code 10 West Midlands
- Hereford and Worcs.
- Shropshire
- Staffordshire
- Warwickshire
- West Midlands (met. county)

Code 11 North West
- Cheshire
- Greater Manchester
- Lancashire
- Merseyside

* If you are unaware of your correct Standard Industrial Classification, please refer to this abbreviated 2 digit code listing and enter the most appropriate code for your main manufacturing activity.

Standard Industrial Classification Categories (2 digit)

11	Coal extraction and manufacture of solid fuels
21	Extraction of minerals and metalliferous ores
22	Metal manufacturing
23	Extraction of minerals, not elsewhere specified
24	Manufacture of non-metallic mineral products
25	Chemical industry
26	Production of man-made fabrics
31	Manufacture of metal goods not elsewhere specified
32	Mechanical engineering
33	Manufacturing of office machinery and data processing equipment
34	Electrical and electronic engineering
35	Manufacture of motor vehicles and parts thereof
36	Manufacture of other transport equipment
37	Instrument engineering
41/2	Food, drink, tobacco manufacturing industries
43	Textile industry
44	Manufacture of leather and leather goods
45	Footwear and clothing industries
46	Timber and wooden furniture industries
47	Manufacture of paper and paper products: printing and publishing
48	Processing of rubber and plastics
49	Other manufacturing industries

Note: If you wish your reply to remain anonymous, please detach this slip and return it under separate cover.