ANOMALIES ON THE LONDON STOCK EXCHANGE: *The Influence of the Bid-Ask Spread and Nonsynchronous Trading*

Thesis submitted for PhD degree

by

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October 1994

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ACKNOWLEDGEMENTS

Firstly, I would like to thank my supervisor Dr. Ian Garrett for his attention to detail and ideas both empirical and theoretical. Additionally, I am grateful to Professor Tony Antoniou for his supervision and producing the right environment for successful research. Also Professor Len Skerratt has provided invaluable FORTRAN programming expertise and has been the inspiration for this use of data methodology. Both my examiners, Professor Pradeep Yadav and Dr. Andrew Clare, deserve a mention for suggesting amendments that have added clarity to this thesis.

On a more personal note I am extremely grateful to Denise Foreman for her encouragement with my work throughout the last two years. Her proof reading has been invaluable on earlier drafts and has enabled me to write more clearly. Also my thanks go to Richard Priestley for his help and encouragement. Mike Kagwa, Dr. Andy Foster, Dr. John Hunter and Norma Bowes also deserve a mention for their support.

I would like to thank Professor Martin Cave and Professor Tony Antoniou in their capacity as Heads of the Department of Economics for employing me in a teaching and research capacity. Finally, I would like to thank my mother and father for their financial and moral support as well as others not mentioned here.

ABSTRACT

"ANOMALIES ON THE LONDON STOCK EXCHANGE: *The Influence of the Bid-Ask Spread and Nonsynchronous Trading*"

This thesis tests for seasonal anomalies and daily predictability on the UK stock market and investigates how mispricing caused by the bid-ask spread, known as the 'touch' and nonsynchronous trading in portfolio returns may explain these anomalies. By using constructed portfolios within a time-series regression framework, I show that seasonality, in the first instance, is prominent in returns around the turn of the week and the turn of the year. However, this seasonal returns behaviour disappears when the touch is accounted for. Indeed, seasonality seems to occur in the touch rather than returns. Despite this touch explanation, lagged returns remain significant, suggesting return predictability. In fact, when using a price adjustment model returns are predictable across portfolios. This predictability, while to some extent dependent upon firm size and the touch, may be accounted for by nonsynchronous trading. First-order autocorrelation and cross-autocorrelation found in returns proves more indicative of infrequent trading than return predictability. Thus, these results confirm that mismeasurement in portfolio returns caused by market microstructure and nonsynchronous trading can create false inferences about the extent of stock market anomalies in the UK and subsequently, market efficiency.

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1. INTRODUCTION

Market efficiency has been one of the most widely researched areas in financial economics. The debate between so-called "believers" and "non-believers" is important, since if markets are considered to be inefficient investors should be able to make consistent abnormal returns. Nevertheless, Bachelier, as long ago as 1900, showed that speculation in an efficient market should be a "fair game" so that only zero abnormal profits would accrue to investors. However, only relatively recently has the efficiency debate come to the fore.

One of the most prominent papers has been Fama (1970) who introduced the idea of the Efficient Markets Hypothesis (EMH). Here, markets are efficient if asset prices fully reflect all information. Jensen (1978) later categorised market efficiency in terms of price reflecting an information set up to the point where the marginal benefit of profitably utilizing information does not exceed its marginal cost. Jensen was so confident that securities were efficiently priced that he made the following statement:

> *"I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis."*

This, as we shall investigate, may not be too bold a statement.

With the advent of more sophisticated data sets and econometric modelling techniques it was realised that many of the original studies were incorrectly testing for market efficiency. Subsequent studies, which have become known as the anomalies literature[1], were able to refute this evidence of efficient markets. In the light of these mainly US studies, this thesis investigates some aspects of the anomalies question for the UK, while simultaneously correcting for mismeasurement in portfolio returns. The results seem to refute the initial "non-believer" claim that market efficiency is dead.

The contribution this thesis makes to the literature is in several areas:

1) A number of anomalies tested for in the US are examined using UK data.

2) While most studies use indices, this thesis constructs portfolios that mimic investment behaviour. By using varying sizes and classifications of portfolios, tests for the economic effects of, for example, a firm size and small price effect are made.

3) Using time-series analysis, tests for day of the week and monthly calendar anomalies, as well as return predictability on the London Stock Exchange (LSE), are undertaken using these portfolios and various empirical models.

These empirical models in the first instance capture seasonal investor behaviour, and secondly show how efficiently investors adjust prices on the receipt of information. The results initially reveal a positive end of year effect which may pre-empt a January effect, little evidence of a tax effect and a Monday and Friday effect due to the influence of the settlement system. Additionally, they show that when using a model that mimics investors' price adjustment behaviour, portfolio return predictability is

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[1] See for example French (1980) who found seasonality across days of the week, and Keim (1983) who showed January experiences higher returns, especially in small firms [Banz (1981)]. Shiller (1981) theorised that share prices were too volatile compared to underlying dividends. Later, DeBondt & Thaler (1985, 1987) showed how shares that had recently fallen in price, overreact, especially at the turn of the year. Finally, Poterba & Summers (1986) showed that returns are predictable in short-run periods.

prominent.

The main innovation in this thesis is the account made for the influence that the bid-ask spread, known as the touch, and 'thin' or nonsynchronous trading has on UK stock market anomalies. The results show that daily seasonal behaviour is more prominent in the touch than portfolio returns. Additionally, portfolio return predictability appears weak when nonsynchronous trading is accounted for. This rebut of stock market anomalies is due to the influence of mismeasurement in portfolio returns caused by both the touch and nonsynchronous trading. Consequently, returns may be over-estimated and so the results should coincide with the market efficiency view of security pricing.

This thesis is divided into seven further chapters. Chapter 2 provides an overview of the literature on stock market anomalies, the bid-ask spread, nonsynchronous trading and the influence of market trading systems. The overview chronologically shows how the finance literature, throughout the 1970's, firstly supported the hypothesis that stock markets efficiently price securities, and then later refutes the original claims. This is due to the advent of more rigorous empirical and theoretical investigations of the way the markets operate. Subsequent chapters test many of the issues raised in this literature including tests for calendar anomalies, portfolio return predictability and the influence mispricing caused by the touch and nonsynchronous trading has on market inefficiency.

Chapter 3, examines the way portfolios are constructed using at least 5 years of daily data from the LSE. These portfolios are initially classified by various economic categories, including firm size, transaction price, the touch and turnover by volume and then sorted by size. Differing constructed portfolios rather than indices enable a more robust examination of the anomalies literature, as well as tests for mismeasurement in portfolio returns.

In the first empirical analysis of the thesis, chapter 4 tests for monthly seasonality on the LSE using high frequency daily data. Using dummy variable regression analysis, initial tests are made for monthly and intra-monthly seasonality in portfolio returns. Evidence supports the existence of a positive December and January effect, as well as other monthly effects. However, contrary to some studies, a January effect appears more prominent in the last few days of the month. Further tests that account for the influence of the touch refute these anomalies and suggest that it is seasonality in the touch, which may reflect investors' buying and selling behaviour, that is driving seasonal returns.

Chapter 5, using a similar methodology, tests for day of the week and institutional settlement effects on the LSE. In contradiction to US studies, day of the week effects are not as prominent on the LSE, except for a Monday and Friday settlement effect. Again, the touch is found to explain these seasonal effects. However, it is seasonality in the touch reflecting investors' behaviour on these Mondays and Fridays that predominates. In both these aforementioned empirical chapters, daily returns rather than being dependent on seasonal returns appear dependent upon daily lagged returns which is indicative of short run predictability.

Due to the prominence of these daily lagged returns the portfolio return predictability question is examined more closely in chapter 6 using a partial price adjustment model (PAM). This model provides a framework that enables investors to minimise the cost of price adjustment and so mimic their decision making process more closely. Tests for predictability using the PAM evolve from a restricted multi-lag linear regression model. Interestingly, predictability is prominent in daily, weekly and two weekly cycles, and mispricing in price adjustment behaviour occurs across many of the portfolios. The results also indicate that portfolio returns are influenced by the touch and are negatively related to firm size.

Chapter 7 examines mismeasurement of portfolio return predictability due to nonsynchronous trading effects. First-order autocorrelation, a common measure of predictability in portfolio returns, appears prominent. This predictability is, however, overstated since it is synonymous with infrequent trading. Additionally, cross-correlations between small and large lagged sized portfolios also point to nonsynchronous trading. In further analysis, the models from chapter 6 are re-estimated using nonsynchronous trading consistent variables. The results show that the daily, weekly and two weekly cyclical predictability found previously, seems dependent upon nonsynchronous trading in portfolio returns.

Hence, this thesis while confirming anomalies in the first instance finds that mismeasurement caused by the touch and nonsynchronous trading provides explanations to support market efficiency. The overall conclusions and implications for further research are shown in chapter 8.

2. ANOMALIES, THE BID-ASK SPREAD AND NONSYNCHRONOUS TRADING FRICTIONS: AN OVERVIEW OF THE LITERATURE

2.1. INTRODUCTION

The efficiency debate has long been researched in the area of financial economics. Equally debatable has been the definition of market efficiency, Fama being among the first to provide a formal definition in 1970. He theorised that an efficient market price always "fully reflects" all available information. Tests for market efficiency were undertaken with respect to three information levels: weak form, semi-strong form and strong form. Most of the literature at this time found support for at least weak form efficiency. With time this definition proved to be too general to be testable and led Fama, in 1976, to redefine efficient prices as reflecting all relevant information. Notable contributions were also made by Jensen (1978) and Grossman & Stiglitz (1980) who respectively incorporated transaction costs and the cost of information into the definition of efficiency.

The early consensus regarding market efficiency was becoming increasingly difficult to support by the 1980's. Much of the 'new' literature started to refute weak form market efficiency in favour of evidence on so-called market anomalies. This literature included evidence in support of excess volatility in stock prices, portfolio return predictability and calendar anomalies.

Evidence on stock market volatility mainly centred around two path-breaking US papers by Shiller and LeRoy & Porter both in 1981. They implied when using a variance-bounds methodology that stock prices were too volatile compared to some underlying value. While these studies, at the time, seemed to show that the markets were inefficient or at least characterised by explainable anomalies, subsequent studies tried to refute this evidence. Much of the criticism of Shiller's work centred upon statistical and econometric problems. However, recent evidence by Campbell (1991) in the US and Bulkley & Tonks (1989) in the UK has supported evidence of volatile markets and refuted market efficiency.

Similar studies which compared prices to some underlying value highlighted an overreaction problem in stock returns, where the path of stock returns follows a mean-reverting process. This meant that returns moved away from underlying value on a periodic basis. Indeed, Fama & French (1988) found that mean-reverting behaviour occurred over a 3-5 year period implying that returns were predictable since they exhibited negative autocorrelation. Predictability in stock returns clearly provides some evidence against market efficiency.

Furthermore, cyclical predictability can be found in the form of calendar anomalies. In fact, calendar anomalies show predictable above average returns at differing times of the year. Indeed, Rozeff & Kinney (1976) were one of the first to show that returns are higher in January. Explanations for this monthly seasonality have centred on many factors including a firm size effect, a tax effect, and portfolio window dressing. Evidence suggests that apart from yearly and monthly seasonal effects, shorter run calendar anomalies exist. Examples include the US studies on intra-monthly effects [Ariel (1987)] and day of the week effects [French (1980)]. French specifically found that Mondays taken as a single day have negative returns. Board & Sutcliffe (1988) in the UK suggest that this Monday effect occurs because of the influence of the settlement system on the UK stock market.

While the above literature documents anomalies on the stock market, more recently a body of evidence has developed which casts doubt on the reliability of these results. More specifically, stock return mispricing due to the influence of the bid-ask spread seems to account for much of the anomalies evidence. Indeed, in the US, Kaul & Nimalendran (1990) have shown that part of security return overreaction can be explained by mismeasurement in returns due to the bid-ask spread. For turn of the year effects, Keim (1989) has shown that seasonality can be explained by movements between the bid and ask price.

Despite the prominence of the spread explanation, mispricing errors due to nonsynchronous trading may also account for predictable anomalies. US evidence from Perry (1985) and Lo & MacKinlay (1990a and 1990b) amongst others, suggest that nonsynchronous trading induces positive first-order autocorrelation in portfolio returns which may mistakenly be indicative of return predictability.

The following chapter aims to overview many of these and other areas in greater detail and show how the consensus regarding evidence of market efficiency has changed quite noticeably over the past twenty-five years. Of most interest to this thesis is the influence the touch and nonsynchronous trading has on predictable cyclical and lagged portfolio returns and hence market efficiency.

2.2. AN OVERVIEW OF MARKET EFFICIENCY

The criteria of what is efficient has changed with time. Economists in the 1930's introduced the idea of the "intrinsic" or fundamental value of a security. This implied that a security was valued on information represented by the future discounted cash flow of its earnings. In his review study, LeRoy (1989) cited Cowles (1933), who showed that brokerage house recommendations based on fundamental analysis appeared *not* to out-perform the market. In a similar analysis of efficiency in the capital markets, Roberts (1959), implied that information assimilated about a stock's earnings potential would be incorporated into its price by the market through the process of arbitrage. Hence, if and when this potential information became public the stocks would not exhibit abnormal returns.

In his review study, Fama (1970) theorised that market prices "fully reflect" all available information - the so-called efficient markets model. Fama's work, along with Samuelson's in 1965, highlighted the link between the random walk model, the martingale model and capital market efficiency. Fama's main contribution to the efficiency debate was the analysis of market efficiency on three main information levels. These levels included: *weak form* tests where historical prices only are used, *semi-strong* form tests where prices reflect all publicly available information including historical prices and *strong form* tests where prices reflect both asymmetric (private) and non-asymmetric information.

In his analysis of these information levels, Fama highlighted three main models that could be used to form a representation of weak form efficiency (the easiest to substantiate) in the capital markets. These were as follows:

(i) *Expected Returns or "Fair Game" Model.*

From Fama's definition of market efficiency, clearly establishing what constitutes the term "fully reflects" is important, if efficiency tests are to be made. Under the assumption of investor risk-neutrality and perfect capital markets, Fama theorised a model (given an information set) based on the value of an equilibrium expected return. He used expected returns purely as an arbitrary means of showing how prices fully reflect information. In Fama's notation this is shown in (2.1) below

$$E(\tilde{p}_{j,t+1} \mid \phi_t) = [1 + E(\tilde{r}_{j,t+1} \mid \phi_t)] p_{jt} \qquad (2.1)$$

where E is the expected value operator; p_{jt} is the price of security j at time t; $p_{j,t+1}$ is the price in time t+1; $r_{j,t+1}$ is the one-period percentage return; ϕ represents an information set that is fully reflected in prices at time t. The tilde indicates that $p_{j,t+1}$ and $r_{j,t+1}$ are random variables at time t.

However, the principle problem when using expected returns for stating the market equilibrium, is that it rules out the chance of making excess profits above equilibrium expected profits. Evidence in favour of the fair game model is that of runs; successive price changes in the same direction. Fama cited Niederhoffer & Osbourne (1965) who confirmed the existence of this problem since they found that price reversal were up to three times more common than price continuations (runs). Patterns of this systematic nature are contrary to the fair game model which implies that the excess market price of a security is a fair game with respect to an information set. In contradiction to this evidence, Fama showed that a more empirically useful model for tests of market efficiency is the submartingale model.

(ii) *The Submartingale Model.*

The submartingale model implies that the expected price (given an information set) is equal to or greater than the current price such that

$$E(\tilde{p}_{j,t+1} \mid \phi_t) \geq p_{jt} \tag{2.2}$$

or that

$$E(\tilde{r}_{j,t+1} \mid \phi_t) \geq 0 \tag{2.3}$$

When (2.2) and (2.3) are equalities the model becomes a martingale. Fama made this assumption about the price formation process without much explanatory foundation, and hence assumed that stock prices would always rise. The submartingale process was assumed to have one important empirical implication, that is, strategies such as the buy and hold strategy cannot be outperformed by the submartingale price sequence. Clearly, this implies that under the submartingale representation of the market, it is impossible to test for efficiency. Given these shortcomings, Fama then proceeded to test efficiency under the random walk hypothesis.

(iii) *The Random Walk Model.*

This model arises in the context of the fair game model but further assumes market equilibrium as well as being stated in terms of expected returns, can also be stated in terms of a stochastic process generating returns. This assumes that prices fully reflect information and hence that successive price changes are independent and identically distributed. This formally describes a random walk with drift model (since price changes can be non-zero, Fama (1970), pp386). Equation (2.4) shows the random walk without drift model

$$f(r_{j,t+1} \mid \phi_t) = f(r_{j,t+1}) \qquad (2.4)$$

which according to Fama is "the usual statement that the conditional and marginal probability distributions of an independent random variable are identical" [Fama (1970) pp386]. The advantage of this equation over the expected returns model, is that the random walk model says the entire returns distribution $r_{j,t+1}$ is independent of ϕ_t rather than just the mean of the distribution. Even though this model was assumed to give much information about the economic environment and details of the stochastic process generating returns, the random walk model is however, following Samuelson (1965), too restrictive because of the independence between price changes.

Later, Fama in 1976, refined his assumption that prices fully reflect available information because it was realised to be too general to be testable. Instead Fama assumed that capital market efficiency implied that prices reflect *all* relevant information and that agents in the market have or (act as if) they have rational expectations (RE), of the form theorised by Muth (1961). This describes an hypothesis that implies that economic agents do not waste scarce information, that the formation of expectations is dependent on the structure of the relevant system describing the economy and "public prediction" will not influence the operation of the economic system unless there is asymmetric information. As a result, investors will learn from their mistakes.

Jensen (1978) re-examined Fama's definitions of efficiency and concluded that by trading on an information set, θ_t, it must be impossible to make "economic profits" if the market is efficient. The economics underlying this assumption is that a market is efficient when a price reflects an information set up to the point where the marginal benefit of profitably utilizing information does not exceed its marginal costs.

More recently, Beaver in 1981 and 1989 described market efficiency in terms of price, reflecting people's ability to observe an information set. One shortcoming of this definition is that not all economic agents observe the same information set, or act as if they do. Finally, in Fama's 1991 paper he re-iterated his original 1970 version of the efficient markets hypothesis. The three categories of market efficiency (weak form, semi-strong form, and strong form) were updated to take account of the research literature that proceeded 1970. Weak form tests became *tests for return predictability* which includes tests on asset-pricing models, as well as anomalies. This in contrast to the tests of weak form efficiency which solely examined historical information in asset pricing. Semi-strong tests, while still examining the adjustment of prices to publicly available information, were deemed *event studies* and strong form tests became *tests for private information.*

Even under these new categories of market efficiency there still remains the problem of what reflects return predictability. For example, the problem of establishing whether predictable variance of returns are rational or irrational remains. Equally the problem of data-dredging and chance sample-specific conditions could explain, for example, calendar anomalies. These scenarios however, seem very anecdotal in the light of evidence on inefficiency to date.

Grossman & Stiglitz (1980) examined the "impossibility of informationally efficient markets" by proposing a model that implies that arbitrageurs who spend resources to obtain information receive compensation for doing so. Hence, individuals who are ex-ante identical, are either informed or uninformed, depending if they spend money to obtain information. By assuming disequilibrium in the information market, i.e. that informed individuals do not convey all information to uninformed individuals, Grossman and Stiglitz assumed that information asymmetry exists. The model they used to represent this observation was an extension of the Lucas noisy rational expectations model, a two asset model comprising of a "safe asset" providing R returns and a "risky asset" providing random returns, u_t, as follows

$$u_t = \theta_t + \varepsilon_t \tag{2.5}$$

where θ_t is observable at a cost, and ε_t is the unobservable component, both being random variables.

Informational inefficiency arises because informed traders are able to gather better information about the market than uninformed traders. Grossman and Stiglitz conclude that when the market is efficient and information is costly, competitive markets break down. This implies that the variance of returns is zero, hence informed investors will not need to buy information in order to earn at least as good a return as uninformed investors.

In similar work, Stein (1987) examines what happens when more informed investors enter the market. Here more information improves risk sharing, but existing investors gain negative externalities since they have no knowledge of this new (private) information and consequently have misinformation. This information asymmetry can also occur due to the "herding" of investors over private favourable information, where consequently rational short-term speculators disregard other equally valuable information.

In recent studies since the early 1980's, there has been strong evidence to refute capital market efficiency. Much research has found excess volatility in prices when compared to changes in dividends, in so-called variance-bounds tests, as well as portfolio return predictability and calendar anomalies. A review of the subsequent debate on whether these anomalies imply capital market inefficiency follows.

2.3. EVIDENCE OF MARKET INEFFICIENCIES: THE ANOMALIES LITERATURE

2.3.1. *Volatility*

One of the first innovative papers in what has come to be known as the anomalies literature was the work done by Shiller in 1981 on price volatility. Shiller assimilated an efficient markets hypothesis model as one where real stock prices are equal to rationally expected or optimally forecasted discounted dividends. The conjecture made was that stock prices are too volatile to be attributed to new information, so implying market inefficiency.

The initial evidence cited was that a long-weighted moving average de-trended stock price index, p_t^*, fluctuates significantly more than p_t, p_t^*'s ex-post rational "counterpart" (the present discounted value of subsequent dividends). The model which shows this (assuming a fair game) is as follows

$$p_t^* = p_t + x_t \tag{2.6}$$

where

$$p_t = \sum_{i=n}^{n} (1 + \rho)^{-i} d_{t+i} \tag{2.7}$$

and

$$x_t = \sum_{i=1}^{n} (1 + \rho)^{-i} e_{t+i} \tag{2.8}$$

Here d_{t+i} represents dividends, e_{t+i} is the unexpected component of the one-period return on the stock, x_t is the difference between the ex-post rational price and the actual price, and ρ is the discount rate. By taking conditional expectations of (2.6) we have the following

$$p_t = E(p_t^* \mid \phi_t) \tag{2.9}$$

This implies that p_t is a forecast of p_t^* given an information set ϕ_t. Under the assumption of (2.9), we can say that (2.6) shows that p_t^* is the sum of the forecast p_t and the forecast error x_t. Since optimal forecasting implies forecasts and their errors are uncorrelated, (2.9) can be expressed (in the ensuing paragraph on variance-bounds methodology) in terms of variance.

Work carried out simultaneously, but independently by LeRoy & Porter in 1981, examined the question of volatility from the variance-bounds perspective in a similar way to that of Shiller's work. Following on from (2.6) and (2.9) and using variance representations, optimal forecasting implies that

$$V(p_t^*) = V(p_t) + V(x_t) \tag{2.10}$$

where V is the variance. Since the variance of a forecast error is always non-negative the following holds

$$V(p_t) \leq V(p_t^*) \tag{2.11}$$

Equation (2.11) holds since the upper bound is not dependent on agents' information set but on dividends and the discount factor only. Rejection of (2.11) implies the rejection of the martingale model as a representation of agents' information set.

Under this framework of the variance of forecasts, LeRoy and Porter conclude that (2.10) could imply that more informative agents induce greater price variance and lower discounted returns variance. However, equally the above implies that returns are more volatile under a less informative information set than agents' actual information set. These two points imply that price and return variances are negatively related. The difference between Shiller's and LeRoy and Porter's variance-bounds tests is that Shiller saw violation of variance-bounds as evidence against efficiency and for irrationality in the market. LeRoy and Porter thought the variance-bounds tests suggested explainable anomalies.

The volatility work done by Shiller sparked a flurry of explanations for his results, as well as criticisms of the methodology used. Indeed, Copeland (1983) sort to explain Shiller's results through a dividends argument, whereby excess stock price volatility could depend on whether dividends are permanent, i.e. reflect fundamental changes, or are transitory. In addition, by analysing the *rate of growth* of dividends, small changes in dividends can represent large percentage changes in growth rates and so contribute to volatility.

Other well known criticisms of Shiller's volatility work include, Flavin (1983) who found small-sample bias and Kleidon (1986) who found that econometric problems existed; dividends were non-stationary and had a unit root. Marsh & Merton (1986) as before, assumed that stock prices are rational but assumed that dividends follow a different stochastic process. Since the tests are a joint hypothesis, and rationality was not questioned, Marsh & Merton believed that their variance-bounds tests show that Shiller's tests incorrectly show excess volatility and that his tests become tests for efficiency.

The claims and counter claims sparked by Shiller and his critics (incidentally the criticism of poor dividend de-trending and econometric bias seemed not to apply to the LeRoy and Porter work) were partially solved by a second round of variance-bounds tests which found excess volatility but to a lesser degree - see Mankiw, Romer & Shapiro (1985) and West (1988) as examples.

More recently, Mankiw, Romer & Shapiro (1991) examined a statistical appraisal of the volatility question. They suggested that a "naive forecast" can be used to outperform the market price as a predictor of the perfect foresight price (present discounted value of dividends plus the discounted terminal price). Explanations for Shiller's observations extend to the fact that dividends may be slow to reflect new information about the profitability of a company. The theoretical implication of this is that events that are *out-of-sample* will determine fluctuations in stock prices. Dividends on the other hand are *within sample* so are an inadequate test of market rationality. The results of the Mankiw et al study proved inconclusive probably due to changing expectations about naive forecasts of dividends and, an inability to make inferences about whether excess volatility exists.

Additionally in the UK, Bulkley & Tonks (1989) used the original and second generation variance-bounds tests to show that de-trended dividends are stationary and, that positive excess returns over a buy and hold strategy can be made in a market with excess volatility. They found that this was evidence against the joint weak form market efficiency/rationality hypothesis.

The second generation tests concentrated on return orthogonality conditions (that is exogenous tests of parameters). Hence, by applying (2.6), (2.7) and (2.8) shown previously, we have the following

$$\begin{aligned} p_t^* &= p_t + x_t \\ &= p_t + \sum_{i=1}^{n} (1+\rho)^{-i} e_{t+i} \end{aligned} \tag{2.12}$$

These orthogonality tests of p_t and x_t, say that the weighted-average of p_t and future returns must be uncorrelated. Excess volatility implies negative correlation in these parameters. Further evidence regarding correlations are reviewed later in this chapter.

Some of the problems highlighted above have been addressed from a different angle by Campbell (1991). He assumed that unexpected stock returns can be attributed to news about future dividends and future returns. By assuming expected returns and dividends are constant and applying a log-linear asset pricing framework, the impact that a news innovation has on stock prices was shown. Another problem with the studies highlighted above, is that they use univariate time-series models that ignore information variables since they use only past returns.

Additionally, ex-post autocorrelations are small for expected returns since innovations in these returns cause movements in ex-post returns in the opposite direction. The resulting negative serial correlation offsets positive serial correlation from persistent expected returns. The result of these tests can result in white noise, i.e. zero autocorrelation. Campbell overcomes these problems by using the following representation of stock returns

$$h_{t+1} - E_t h_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j h_{t+1+j} \quad (2.13)$$

where h_{t+1} is the log real return on a stock held between the end of period t and t+1, d_{t+1+j} is the log real dividend paid on security j, in period t+1, E_t are expectations formed at the end of period t, with Δ, a one period backward difference operator and ρ, a number $\leq$ 1.

Equation (2.13) implies that if unexpected stock returns are negative, expected future dividend growth is lower or expected future returns are higher or both. Campbell's analysis of stock returns focuses on a vector autoregression approach (VAR) rather than that of an autocovariance. A VAR persistence measure, P_h, is defined as

$$P_h \equiv \frac{\sigma(\eta_{h,t+1})}{\sigma(u_{t+1})} \quad (2.14)$$

where the numerator is the variance in news about future returns in t+1 and the denominator is the variance in the news innovation in t+1. The results suggest using this analysis that only 33-50% of the variance in unexpected stock returns is accounted for by a variance in news about fundamentals. News about future expected returns makes up the remaining variance. The lack of independence between these two news variables was suggested as an explanation for volatility in stock prices.

Differences between so-called conventional efficiency tests and variance-bounds tests stem from tests of the orthogonality of returns over differing time intervals. The evidence to explain this phenomena centres around the observation of permanent and temporary components in stock prices and hence evidence of mean reversion in stock prices[2]. An explanation for volatility in the form of mean reversion stems from the theory that price, rather than acting as a martingale model of the Fama (1970) type, should follow a random walk and a "fads" model[3], fads being modelled in the form of a slowly mean-reverting stationary series. This is the subject of the subsequent section.

2.3.2. *Mean Reversion*

Tests of market efficiency could be classed as tests of whether stock prices reflect (under the assumption of investor rationality) an underlying fundamental value. Tests of market efficiency seem weak as unpredictable valuation errors result. This is perhaps evidence against the first round of efficient market/volatility tests which used return forecasting regressions that disregard the unpredictable parts of returns, i.e the error terms[4]. However, investor irrationality may be present because prices do not necessarily reflect fundamentals, since there could be volatility in prices around fundamental value.

In a typical paper in this area, Fama & French (1988) show that fundamentals can be expressed as a permanent component of stock prices and volatility as a temporary component. Autocorrelation tests using a price/dividends ratio of random walk and AR(1) models were run to find whether returns are predictable over differing time periods. These tests were expressed as the following stock price model

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[2] See Fama & French (1988), Poterba & Summers (1988) for example.

[3] See Summers (1986).

[4] See the review paper by Cochrane (1990).

$$p(t) = q(t) + z(t) \qquad (2.15)$$

where p(t) is the logged stock price p in time period t, q(t) is a random walk and z(t) a stationary component where

$$q(t) = q(t-1) + \mu + \eta(t) \qquad (2.16)$$

with μ being a drift factor and $\eta(t)$ white noise. The stationary component can be expressed as a mean-reverting or slowly decaying component expressed as an AR(1) process

$$z(t) = \phi\, z(t-1) + \varepsilon_t \qquad (2.17)$$

where $\varepsilon(t)$ is white noise and $\phi < 1$. Equations (2.15) to (2.17) imply that stock prices follow a non-stationary process where the permanent gain from periodic price shocks are less than 1, and a predictable temporary component that reverts to fundamental value.

Under the assumption that negative autocorrelation is consistent with a slowly mean-reverting component in stock prices, Fama & French (1988) found autocorrelation in returns of the order of -0.35 in 3-5 year periods, but not in short (less than 3 years) or long (10 years) periods. Hence, this negative correlation implies forecastability of future returns over this 3-5 year period. In an earlier study, Poterba & Summers (1988) while confirming that the result above may be due to the presence of fads, use similar tests to Fama and French, and find additionally in short horizons, non-trading effects i.e. positive serial correlation due to infrequent trading. This is a matter we will examine later.

Furthermore in a similar study, Lo & MacKinlay (1988) suggest that stock returns follow a random walk process rather than a mean reversion process. This is confirmed by the positive serial correlation for weekly and monthly returns they find in US securities. Finally, they cite the lack of correct statistical data as a reason for the invalidation of some mean reversion studies.

Tests for volatility can be seen as only one part of tests for return predictability and hence market efficiency. There is much evidence to suggest that predictable returns, at differing times of the calendar year, are prominent in the US as well as in the UK. These issues on calendar anomalies are examined below in section 2.2.3.

2.3.3. *Calendar Anomalies*

Seasonality in stock returns is perhaps one of the best known tests for stock market inefficiency and implies above average or even excessive returns in specific periods of the year. Rozeff & Kinney (1976) is one of the best known earlier papers documenting so-called calendar anomalies. They found that when using an equal weighted index of NYSE monthly prices over a 70 year period, that January had returns 7 times higher than the average monthly return. The use of autocorrelation tests in the Box & Jenkins (1970) style found non-seasonality and a random walk in the first instance. However, non-parametric tests found seasonality and pairwise monthly returns. This latter finding implied that, for example, January and July had similar high returns, and February and August similar low returns. Additionally, November and December had similar higher returns than the average month.

Explanations for this monthly seasonal effect have centred on many factors. Some studies[5] have cited larger risk premiums in January as an explanation for a turn of the year effect. Other explanations for seasonality have centred on examining the returns for differing sizes of firms[6]. Indeed, Ritter & Chopra (1989) showed that small firms were found to have higher returns compared to other firms and that these returns were concentrated in January. Furthermore, the timing of earnings information announcements could contribute to calendar based seasonality, see Penman (1987).

Further explanations for monthly seasonal behaviour has centred upon a tax-loss effect. In the US the financial year end is generally December. During this month investors may sell securities in order to realise capital tax-losses or adjust the make up of portfolios; so-called window dressing. Clearly investors could buy stocks in the New Year which are now cheap relative to the ex-ante tax-loss stock prices. Obviously, the implication of this could be market irrationality, since non tax-loss investors may anticipate this seasonal effect and buy at the end of the previous year.

Additionally, evidence from Cadsby & Ratner (1992) suggests that in countries such as Japan where there is no capital gains tax, as well as countries where the financial year end is not January (eg the UK which has an April financial year end), seasonality exists. Chan (1986) examines this hypothesis and finds that tax-loss selling in any time period does not shed light on the January effect and concludes therefore that investors are irrational tax-sellers as a result. In a similar study, Ritter & Chopra

[5] See Fama & MacBeth (1973).

[6] See Banz (1981), who reviews evidence on the firm size effect.

(1989) refuted the seasonality anomaly using a CAPM framework and a value weighted portfolio as opposed to an equally-weighted portfolio which was common in previous tests. They find that tax-loss selling is not an explanation of seasonality, and that the CAPM positive risk-return relationship is prevalent in small firms. Such firms have positive returns in January when the market has a negative return.

Apart from the yearly seasonal effects there is evidence to suggest that shorter run calendar anomalies exist including a monthly effect and a day of the week effect. Ariel (1987) is credited with examining intra-monthly seasonality and suggests that mean returns on stocks are concentrated in the first half of the calendar month for both equal and value weighted portfolios. Specifically, Ariel found that the last day of the previous month and the first 5 days of the current month account for nearly all the returns of that month. Interestingly, evidence is found to suggest that there exists a small firm effect, but only when the returns from these firms under-perform those of the large firms.

One reason for a monthly effect could be the timing of information announcements in the first part of the month. Penman (1984) shows that reports or announcements made late (usually more than 4 days late) generally bring bad news and hence result in share price under-performance. Clearly, the near zero returns found by Ariel in the second half of the month could be the result of this late announcement effect smoothing returns. However, studies such as this could be open to data mining whereby data is manipulated to be conducive to the anomaly in question. The Ariel study could be open to such criticisms given that the last day of the previous month is added to the returns of the proceeding month, simply because this day had positive returns.

In even shorter time periods calendar anomalies such as the so-called day of the week effects or weekend effects have been documented. In an early example, French (1980) tested a so-called calendar time hypothesis which theorised that Monday represents a three calendar-day investment and hence should experience returns three times as great as on other days of the week. In contradiction to this hypothesis, French showed that stock returns seem to vary between days of the week, with Monday taken as a single day experiencing negative returns. This was theorised to occur due to the effects of the weekend - even while taking into account any so-called holiday effects. The implication of this seems to be that non-trading over the two day weekend period causes uncertainty and that the weekend can be characterised by bad news.

Many other factors have been documented to explain the weekend effect. These include settlement dates and ex-dividend effects on Mondays in the UK Stock Market [Board & Sutcliffe (1988) and Theobald & Price (1984)]. Condoynni, O'Hanlon & Ward (1987) test for an international weekend effect and suggest that correlations across world stock markets exist. In fact, they showed that the significance of a negative Monday effect diminishes the further away from the US trading time zone a stock is traded. Hence, as a result of this movement of a single information set, the Far East, for example which opens after the US market closes, is characterised by a Tuesday effect. Of course this assumes that the US has a large informational dominance on the world's stock markets. Clearly the overlapping of market trading times in the US and Europe could explain the Monday effect in the UK.

Finally, it is important to remember that explanations for calendar seasonals may be dependent upon the reliability of asset pricing models. These, could be subject to errors in prices leading to biased returns and estimated coefficients. Notwithstanding this, many of the issues on long and short run seasonality will be examined in greater detail in chapters 4 and 5.

2.3.4. *Evidence of Interdependence between Anomalies*

In the previous section we have highlighted, amongst other things, the link between seasonality and firm size. This interdependence between anomalies is not uncommon. Indeed, DeBondt & Thaler (1985 and 1987) showed the link between firm size and market overreaction. This is whereby a loser (winner) portfolio of stocks previously exhibiting abnormal negative (positive) returns in period t-1, earns positive (negative) returns in period t due to overreaction to news events. Specifically, DeBondt and Thaler found that there can be over- or under-performance against the market resulting in loser and winner portfolios.

Identifying a size effect where small companies [loser portfolios] outperform the market in subsequent periods has been assumed to be an overreaction phenomenon. However, the returns pattern of small size firms in the DeBondt and Thaler studies proved to be consistent with seasonal effects in January. DeBondt and Thaler also suggest that when under-performing companies are matched with over-performing companies of the same size their returns are approximately equal. Clearly this seems to refute the news overreaction hypothesis in favour of a size effect.

Further tests have shown that overreaction could not be permanent as suggested by DeBondt and Thaler, but mean-reverting, since consistent over-performance of this nature could imply irrationality in the market[7]. More recently, Jegadeesh (1991) again in the US, used equal and value weighted portfolio regression tests and examines a fads model, a slow mean-reverting process. The results indicate that mean reversion occurs mainly in January, and that there exists negative serial correlation in returns when prices have a slowly decaying temporary component.

While section 2.3. shows evidence of predictable inefficiencies in the market such as volatility, mean reversion, calendar anomalies and even a firm size effect, there is more recent evidence to refute evidence of such market inefficiencies. Much of the recent debate has centred on the bid-ask spread and nonsynchronous trading explanations for market efficiency. The influence of these two explanations on stock market anomalies is examined in the next two sections.

2.4. BID-ASK SPREAD EXPLANATIONS FOR MARKET INEFFICIENCY

2.4.1. *The Bid-Ask Spread and Market Overreaction*

Much of the US literature on the overreaction phenomenon fails to take account of some important problems that may have biased the results. Examples of these biases

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[7] See Lo & MacKinlay (1988) and Fama & French (1988).

include transaction costs (measured by the bid-ask spread, referred to as the "spread"), portfolio selection techniques, noise trading and illiquidity inefficiencies in the market (both reflected in the spread)[8].

In tests for overreaction, Atkins & Dyl (1990) found using a mean-adjusted return and two market models that percentage returns were less than the size of the bid-ask spread. The innovation in this study was that the data originated from a set of randomly selected security prices free from calendar anomalies. This was instead of the sophisticated stock selection techniques using historical data that is commonly used and is unavailable to investors during the period studied. Even though a statistically significant return-spread relationship was found, overreaction could be partially explained by overreaction to bad and under-reaction to good news by risk averse investors.

As we have established, overreaction induces price reversals and hence negative autocorrelation. Many of the studies, highlighted above, on overreaction failed to take account of measurement errors (the bid-ask spread) in returns. Kaul & Nimalendran (1990) propose the following model which tries to overcome this problem.

$$R_{it} = \mu + \eta_t + \varepsilon_t \qquad (2.18)$$

This differentiates between a spread and overreaction component in the security returns process, where R_{it} is the return on security i in period t, μ is the mean of R_{it},

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[8] See Atkin & Dyl (1990), Black (1986), Kaul & Nimalendran (1990), Harris (1990), Dubofsky (1991), Roll (1984), Amihud & Mendelson (1987), Lehmann (1990) for a review of this evidence.

η_t is the idiosyncratic white noise, where $\eta_t \sim N(0,\sigma^2)$, and ε_t is the error component dependent on either the spread or overreaction.

If ε_t is entirely due to the spread, the results should confirm Roll (1984) who observes the following: $Cov(\varepsilon_t,\varepsilon_{t-j}) = -s^2/4$ if j=1, 0 otherwise; $Var(\varepsilon_t) = s^2/2$ and $\rho_\varepsilon = -0.5$, where s is the bid-ask spread. If the spread accounts for all the error term, then the covariance equation above induces negative serial autocorrelation at lag 1 for an MA(1) process. Indeed, in order to test the errors for the influence of the touch on the LSE we can use closing prices (R_t) which contain the touch and overreaction errors, and bid-bid prices (R_b) which are not influenced by the touch errors.

In related work Fama & French (1988), Lo & MacKinlay (1988) and Cochrane (1991), amongst others, use the variance-ratio test to measure both variance and autocorrelations of returns. These measure overreaction effects and bid-ask spread errors respectively. Following Poterba & Summers (1988) the variance-ratio measure for overreaction can be defined as

$$VR(k) = \frac{Var(R_t^k)/k}{Var(R_t^n)/n} \qquad (2.19)$$

where Var is the variance of returns, R_t, in time t, over the period k, say (in this case) a month, and n is the total number of periods, say 12 months. Equation (2.19) illustrates the ratio between the variance of k period returns and n period returns i.e. the variance between one months returns and 12 months returns. Expressed in the form of (2.20) below, the variance-ratio can be shown as a function of autocorrelations, which, can measure spread effects on the error term[9].

$$VR(k) \approx 1 + \frac{2(k-1)}{k}\hat{\rho}_1 + \frac{2(k-2)}{k}\hat{\rho}_2 + \ldots.. + \frac{2}{k}\hat{\rho}_{k-1} \qquad (2.20)$$

Results from Lo & MacKinlay (1988) for transaction-transaction returns (R_t) and bid-bid returns (R_b) [i.e. returns devoid of the spread], indicate that bid-ask errors explain between 50% and 23% of the variance of one day returns and 16% to 5% of one week returns.

Another way of analysing return variance is in the form of a partial adjustment model from Amihud & Mendelson (1987) - (A&M hereafter). This model implies that returns consist of an intrinsic value and a noise component shown in (2.21).

$$P_t - P_{t-1} = g.[V_t - P_{t-1}] + \mu_t \qquad (2.21)$$

where P_t is the observed price in period t, V_t is the intrinsic value in period t, g is the adjustment coefficient and μ_t is a noise component, where $\mu_t \sim N(0,\sigma^2)$. The noise component can be due to two main sources: noise trading such as transitory liquidity needs, and errors in the analysis and interpretation of information, as well as the impact of the trading mechanism in which prices are set.

In a continuous trading - dealership market, fluctuation between the bid and ask price are pronounced and may explain a large proportion of the return variance. Other trading mechanism effects include the random arrival of buy/sell orders and

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9 See Lo & MacKinlay (1988) for an exposition.

discreteness in stock prices[10]. Clearly, the value of the so-called adjustment coefficient, g, will determine the form of (2.21).

When g=1

$$P_t = V_t + \mu_t \tag{2.22}$$

and

$$V_t = V_{t-1} + \varepsilon_t + m \tag{2.23}$$

where V_t follows a random walk process, given m is the expected daily value return, and ε_t is independent of μ_t, with mean zero and variance v^2. Using (2.21), (2.22) and (2.23), A&M define the observed returns variance as

$$Var(R_t) = \frac{g}{2-g} v^2 + \frac{2}{2-g} \sigma^2 \tag{2.24}$$

where the first term on the right hand side is the contribution of the value return variance and the second term is the contribution of the noise to the observed return variance.

The following conditions on g can explain the extent to which return variance is prevalent. When 0<g<1, there is a partial adjustment of prices to value and greater noise. However, from (2.24) we can see that the variance of returns is less than the variance of value, implying under-reaction. For g=1, the full adjustment of value return variance and observed return variance, there is some overreaction due to noise. When g>1, the variance of value is greater than the variance of returns implying an overreaction and volatility.

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[10] See section 6.3.1. for a fuller description of these effects.

Hence, the larger the coefficient g, the larger the transmission of noise to the observed return variance. Consequently, there is a bias in the measured return variance which is dependent on the adjustment coefficient, g and noise variance, σ^2. As a result the volatility of price exceeds the volatility of value. For $0<g<1$, there is downward bias in the measurement of value variance and upward bias from the noise variance.

A&M also considered the first-order autocovariance and autocorrelation function, given by them in equations (2.25) and (2.26) below

$$Cov(R_t, R_{t-1}) = \frac{g}{2-g}[(1-g)v^2 - \sigma^2] \tag{2.25}$$

$$Corr(R_t, R_{t-1}) = \frac{g(1-g)v^2 - g\sigma^2}{gv^2 + 2\sigma^2} \tag{2.26}$$

We can see that the noise variance autocorrelation contribution is always negative apart from when $0<g<1$, when it is positive. The sign of the autocorrelation is therefore dependent on the size of g and the relationship between the value and noise variances. Under the assumption that the variance in noise is due to fluctuations between bid and ask prices, hence $\sigma^2 = s^2$, where s is the spread. Using the measure of the spread derived from the partial adjustment model we can show that

$$s = \sqrt{(1-\frac{2}{g})\,Cov(R_t, R_{t-1}) + (1-g)v^2} \tag{2.27}$$

When $g=1$, we have Roll's 1984 result, that is, $s = [-Cov(R_t,R_{t-1})]^{0.5}$. When using close-to-close returns [which is consistent with a continuous trading dealership market such as in the London market] A&M found positive autocorrelation. This indicated that the adjustment factor g is between 0 and 1. We can clearly see from (2.27) that

A&M's measure of the spread is greater than that of Roll's, implying that the use of return covariances alone underestimates the spread. Using returns variances for the spread supports a positive relationship between such variances and close-to-close return variances. Hence, return variances are a biased estimator of the value return variance, the bias being the spread.

This evidence from the US above, points to the fact that mean reversion or overreaction tests may have data problems due to measurement errors in prices caused by the bid-ask spread. In a recent study, Kaul & Nimalendran (1990) show that short run price reversals may be heavily influenced by the bid-ask spread since spread errors in security returns are positively autocorrelated. They found that bid-ask errors in prices may explain up to 50% of all daily return variances and hence cause price reversals. Such evidence points against the overreaction hypothesis.

As we have implied the spread additionally may be able to explain size effects and the variances in returns. Likewise, seasonal predictability may occur due to the influence of the spread. This is the subject of section 2.3.2.

2.4.2. *The Bid-Ask Spread and Calendar Anomalies*

As Kaul & Nimalendran (1990) have shown, calculating stock returns using closing transaction prices may introduce measurement errors represented by the bid-ask spread. Furthermore, Keim (1989) shows that the turn of the year is characterised by a shift from transactions at the bid to transactions at the ask. The bias in returns is defined as the difference between transaction and bid priced returns. The following model enabled Keim to calculate the probability of trading at the bid or ask price and so tests for the influence of the spread. Here, the closing price of a stock is given as

$$\begin{aligned}\tilde{P}_{it} &= \tilde{x}_{it}[\tilde{w}_{it}\tilde{P}_{Bit} + (1 - \tilde{w}_{it})\tilde{P}_{Ait}] + [(1 - \tilde{x}_{it})(\tilde{P}_{Bit} + \tilde{P}_{Ait})/2] \\ &= \tilde{x}_{it}[\tilde{w}_{it}\tilde{P}_{Bit} + (1 - \tilde{w}_{it})(1 + \tilde{s}_{it})\tilde{P}_{Bit}] \\ &\quad + (1 - \tilde{x}_{it})[\tilde{P}_{Bit} + (1 + \tilde{s}_{it})\tilde{P}_{Bit}]/2\end{aligned} \tag{2.28}$$

where $\tilde{P}_{Bit}$ is the final bid price for stock i on day t, $\tilde{P}_{Ait}$ is the final ask price for stock i on day t, $\tilde{s}_{it}$ is the bid-ask spread in relation to the bid price i.e. $(\tilde{P}_{Bit} - \tilde{P}_{Ait})/\tilde{P}_{Bit}$. Also $\tilde{w}_{it}$ is 1 with probability q if the closing price is a bid at t, 0 otherwise with probability (1 - q). $\tilde{x}_{it}$ is 1 with probability p if the stock trades on day t, 0 otherwise with probability (1 - p).

The term in the first set of square brackets shows that the transaction price depends on the probability of the closing price occurring at the bid or ask. The term in the second set of square brackets represents the possibility of non-trading and reflects a price mid-way between the bid and ask. When testing the model in (2.28) on US data, Keim shows that for small firms, with a spread of 6%, a movement from the bid to the ask results in a 4.9% one day return when there is no change in the bid price. Differing probabilities of changes in the bid or ask prices induces less, though significant, sized intra-spread movements.

Keim also showed that there is a tendency for December prices to occur at the bid (lower) price with a ratio of two bids to one ask price. January is characterised by a ratio of 0.61 implying more transactions occur at the ask (higher) price. In order to calculate the within spread location of the closing transaction price the following formula was used

$$L_{it} = \frac{Closing\ Price\ (P_{it}) - Bid\ Price\ (P_{Bit})}{Ask\ Price\ (P_{Ait}) - Bid\ Price\ (P_{Bit})} \tag{2.29}$$

where $0 \leq L_{it} \leq 1$, and when L=0, closing transactions occur at the bid price, and when L=1, the closing transaction is at the ask price.

Keim's results indicate that on the last trading day of the year, L ranges from 46% to 0.29% for the lowest to highest priced portfolios and from 23% to 5.5% for the same portfolios on the first trading day of the year. Other days of the year were found to have no such biases. The influence of intra-spread movements were seen as being consistent with the large returns that occur either side of the turn of the year, especially in the light of the large spreads that occur for low priced stocks. In the light of this, the spread bias produces a 1.1% and 2% turn of the year effect on these two days. Further tests using bid-bid prices find no seasonality of returns and substantiates the claim that the spread effect explains at least part of the turn of the year effect in the US.

For all firms in the Keim study, January returns exceed all other monthly returns. However, there seems to be an inverse relationship between firm size and returns in January. The size of the spread suggests that investors cannot profit from seasonality in small firm returns. By cross-classifying firms by spread and firm size, excess January returns increase with spread and decrease with firm size and can jointly explain 88% of excess January returns. Nevertheless, neither of these phenomena can explain February to December returns.

Other studies such as Lamoureux & Sanger (1989) have linked the turn of the year effect with firm size. Here returns on stocks are computed at the midpoint of the bid-ask spread so avoiding much of the measurement errors caused by movements in transactions between bid and ask prices. The results from this study using the US based NASDAQ stock market suggest that share price and firm size have a positive relationship, and that firm size is negatively related to the spread.

For daily data, Keim, again in his 1989 paper, examines returns on each day of the week using transaction returns and mid-spread returns in the US. The difference between these two return values is the bid-ask bias, which was found to be negative on a Monday and positive and rising throughout the rest of the week. This may contribute to the day-of-the-week effect. Fortin (1990) takes the seasonality issue further by examining the relationship between increasing returns during the week [starting with negative Monday returns] and the bid-ask spread in the US markets. His analysis suggests that during the week the spread remains constant while returns rise, so contradicting Keim's 1989 study. Additionally, the spread was found to be a linearly increasing function of returns, with the smallest stocks having the largest spread and returns.

With the availability of more and more high frequency data, intra-day analysis of day of the week effects has become increasingly popular. Porter (1992) examining US stocks showed that closing prices are closer to the ask price on Friday than on other days of the week. When using portfolios classified by price, the results indicate that higher priced portfolios have a higher probability that the closing transaction is at the ask price regardless of the day of the week. Porter concludes that up to 20% of the weekend effect in the US can be explained by bid-ask price behaviour.

While the studies above highlight some of the problems associated with corroborating a turn of the year effect and a day of the week effect they form just part of the literature which shows the influence of the bid-ask spread on calendar anomalies. Chapters 4 and 5 examine this literature in greater detail and give empirical evidence on monthly calendar anomalies and the day of the week effect in the UK when accounting for the effects of the touch.

The final part in this section examines evidence of the influence mismeasurement of the spread plays in calculating the level of return predictability. Clearly, given the importance of the spread in the literature, it is important to recognise that such mispricing should be correctly accounted for.

2.4.3. *Evidence of Mispricing in the Bid-Ask Spread*

It is well recognised that the bid-ask spread is a cost accruing to investors who transact in securities. Since illiquidity in the market implies that investors generally have to buy securities at the ask (upper) price and sell securities at the bid (lower) price. This occurs because an investors sell requests of a stock requires a market maker to buy a stock, and vice-versa for buy requests. The spread component of a stock price is hence the profit that accrues to a market maker in compensation for his or her agreement to make a market in a stock.

So far we have shown evidence to suggest that anomalies depend to a great extent on the size of the spread. Generally it is recognised, following George, Kaul & Nimalendran (1991), that the quoted spread covers three main costs faced by dealers. Firstly, inventory holding costs show the risk borne by the dealer. Secondly, order-processing costs could be seen as the compensation market makers accrue for providing so-called liquidity services and thirdly, adverse information or selection costs represent compensation from uninformed investors to market makers for losses caused by informed traders. It is the identification and the magnitude of these components that may help to determine the size of the spread in security returns.

Previously, measures of the spread have focused on examining transaction returns. Roll (1984) assumed that market makers only face order processing costs and measured the spread in terms of autocovariance. He finds that weekly and daily estimates of the spread are downward biased. In contrast to this, Stoll (1989) finds that an adverse selection component cost makes up 43% of the spread, an order processing component 47% and an inventory processing component cost 10%. Clearly, the first two components are the two main sources of downward bias in the spread estimates. Revisions of bid to ask prices may be due to movements in the adverse selection component. This can imply that rational market makers' actions can be anticipated due to a change in expectations made on a buy/sell transaction.

Models of the spread have generally implied that the only source of autocorrelation in transaction returns is the order-processing cost component of the quoted spread. Measures of the spread in the Roll (1984) and Glosten (1987) tradition, imply that R_{iTt}, the continuously compounded returns on security i, based on transaction prices are

$$R_{iTt} = E_{it} + B_{it} + U_{it} \tag{2.30}$$

where

$$B_{it} = \pi_i (s_{qi}/2) [Q_{it} - Q_{it-1}] + (1 - \pi_i) (s_{qi}/2) Q_{it} \tag{2.31}$$

and π_i is the unobservable proportion of the quoted spread due to order-processing costs and s_{qi} is the quoted spread of the market maker. Q_{it} is the unobservable indicator for the bid-ask classification of P_t, and E_{it} is the unobservable expected return for the period between transactions t-1 and t, based on all public information up to transaction t-1. U_{it} is the unobservable innovation in true prices due to the arrival of public information between transactions t-1 and t, and finally $(1-\pi_i)$ is the unobservable proportion of the quoted spread due to adverse selection (market information asymmetry). Using this measure we find that the quoted spread is

$$SP_{1i} = 2\sqrt{- [Cov(R_{iTt}, R_{iTt-1}) - Cov(E_{it}, E_{it-1})]} = \sqrt{\pi_i S_{qi}}$$

which Roll (1984) further assumed becomes

$$SP_{1i} = 2\sqrt{-Cov(R_{iTt}, R_{iTt-1})} \tag{2.32}$$

under the assumption of no adverse selection effects. However Glosten (1987) has proved that Roll's measure will underestimate the true quoted spread if the spread contains this adverse selection component.

In further work, Conrad & Kaul (1988) suggest that expected returns on portfolios vary through time and induce positive autocorrelation which effects both the level and components of the spread. The assumption of time-varying returns can be represented by an AR(1) process as follows

$$E_{it} = \mu_i + \phi_i E_{it-1} + \varepsilon_{it} \qquad (2.33)$$

where $0<\phi_i<1$, μ_i is a constant and E_{it} is unobservable. In order to account for the time variation in E_{it} two techniques can be used. Firstly, the continuous compounded transaction returns R_{iTt} can extract the expected return from each security as follows

$$R_{iTt} = \gamma_{0i} + \gamma_{1i} E_{pt} + \eta_{it} \qquad (2.34)$$

where $E_{pt} = \mu_p + \phi_{pe} E_{pt-1} + \varepsilon_{pt}$ and equals the expected return of portfolio p and η_{it} is the error term representing mismeasurement in returns, in this case due to the spread, which therefore is defined as

$$SP_{2i} = 2\sqrt{-Cov(\eta_{it}, \eta_{it-1})} \qquad (2.35)$$

Equation (2.35) comes about due to the fact that the spread errors are cross-sectionally uncorrelated, expected returns are positively correlated[11] and as a result the average positive covariance is measured by γ_{1i}. This will enable E_{pt} to extract expected returns from a security's realised returns. When $E_{pt} = E_{it}$, equation (2.35) will be free of all time-varying expected returns.

Secondly, by analysing the difference (RD_{it}) between transaction and bid returns, where bid returns are given as

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[11] This could be due to nonsynchronous trading.

$$R_{iBt} = E_{it} + (1 - \pi_i)(s_{qi}/2)Q_{it} + U_{it} \tag{2.36}$$

and the difference between R_{iTt} and R_{iBt} is RD_{it}, where $RD_{it} = \pi_i(s_{qi}/2)[Q_{it} - Q_{it-1}]$, we can measure the spread as

$$SP_{3i} = 2\sqrt{-Cov(RD_{it}, RD_{it-1})} = \pi_i s_{qi} \tag{2.37}$$

The difference between Roll's measure of the spread and equation (2.37) is that RD_{it} is unaffected by any positive autocovariance induced by time-varying expected returns, and if there is adverse selection in the security market $[\pi_i < 1]$, SP_{3i} will be downward biased by π_i but Roll's measure (SP_{1i}) will be downward bias by $\sqrt{\pi_i}$. This implies that Roll's spread measure has a greater variance than this new estimator. Conrad and Kaul's results indicate that this measure of the spread is comprised of only a 9-13% adverse selection component which is positively related to the size of each trade.

George, Kaul & Nimalendran (1991) adopt a different approach and construct a spread measure based on the serial covariance of the difference between transaction returns and returns calculated using bid prices. This will mean that the spread is not affected by any positive autocorrelation caused by market friction and time-varying returns. Additionally the variance of this spread estimator is lower due to no unexpected return components in the difference between transaction and bid returns.

Following Glosten & Harris (1988) only adverse selection and order processing cost components are used in George et al's 1991 spread measure. The latter component is regarded as transitory in nature and causes price changes to be negatively autocorrelated. Under the equal probability of a trade at the bid or ask price and unit size trades, the following model is proposed where the transaction price of a stock can be shown as

$$\begin{aligned} P_t &= M_t + \pi(S_{qi}/2)Q_t \\ M_t &= E_t + M_{t-1} + (1-\pi)(s_{qi}/2)Q_t + U_t \end{aligned} \tag{2.38}$$

where P_t is the price of transaction t, M_t is the unobservable "true" price reflecting all available public information immediately following transaction t, and the other variables are the same as given in (2.31) above. Under this framework George et al have shown that existing spread estimates have a large downward bias, and between 77 and 97% of this bias is due to time-varying expected returns.

What section (2.4) shows is that the bid-ask spread (despite any mismeasurement problems in its components) enables full, or, at worst partial explanation of many aspects of the literature on anomalies including calendar anomalies, volatility and mean reversion studies. However, before these explanations are examined empirically there is the issue of the influence differing markets may have on the measure of the spread used. This is examined in the following section.

2.4.4. *Measures of the Spread on the US and UK Stock Markets.*

The review of the literature above, mainly documents the influence of microstructure on stock market anomalies in the largest of the US markets, the NYSE. At first sight this evidence appears to be applicable to other stock markets both in the US and around the world. However, the applicability of the results, using NYSE data, for other markets is dependant upon differences in the rules governing stock market trading systems. This is because differing markets operate in autonomous ways and therefore the prices quoted at the end of business each day reflect these differences. Hence, an overview of the main difference between the NYSE and LSE trading systems follows, so that the distinction can be made between the way closing prices and spread values are calculated. Clearly, this has important implications when testing for anomalies and their microstructure explanations.

The NYSE is characterised as what is commonly termed an auction market, where market specialists' orders are executed immediately through what Pagano & Roell (1991) refer to as a central auction mechanism. Trades of differing quantities and prices are executed at a common market clearing price and displayed on screens so that the order flow of stock transactions can be seen by market participants. Consequently trades are executed at a transaction price by market makers who impose their own bid-ask spread around some notional mid-price. The size and direction of each trade will determine whether the transaction price is close to the mid-price or to the bid or ask price. Clearly this may explain why US studies have found that the bid-ask bounce may explain some anomalies, for example Keim's (1989) paper on calendar effects.

The LSE however operates a different trading system, what Hansch & Neuberger (1993) refer to as a quote-driven or electronic dealership market. Here market makers display bid and ask price schedules that they are prepared to trade on. However, as Naik, Neuberger & Viswanathan (1994) point out, trades are typically negotiated between the dealers and investors. This implies that transactions can be traded at prices that are inconsistent with the quoted bid-ask spread. Furthermore, due to the riskier nature of larger trades, market makers are allowed a longer time before disclosing such transactions on the SEAQ system. Hence, end of day prices on the dealership system of the LSE may not necessarily reflect closing trades. Prior to 1991 notification of larger trades could be delayed for anything upto 24 hours, but since 1991, generally delays have been limited to just 90 minutes. Clearly, this has implications for tests of market anomalies when using closing prices.

All equity markets are subject to some level of illiquidity when investors trade. Typically, this is reflected in the spread around some notional transacting price. However, because the LSE is a quote-driven system, closing prices reflect market makers quoted prices. This quoted price is usually the mid-price half way between the upper (ask) and lower (bid) prices. In the US, the closing or transaction price can occur at either the bid or the ask price or somewhere in between. Whereas, at the close on the LSE, prices can only reflect a price near the mid value of the quoted *touch*, the UK equivalent of the spread and not at some bid or ask price. The LSE is hence, not characterised by any US style bid-ask bounce in equity prices that may move trading prices away from transaction prices[12], or by movements between the bid and ask price at calendar turning points.

The illiquidity costs faced by investors means that they trade at the bid or ask price and not at the quoted closing price. This implies that closing prices used in tests for market anomalies may overstate true stock market returns. This over-estimation is equivalent to the value of the touch. Hence this thesis tries to rectify this problem for

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[12] See Amihud & Mendelson (1987).

tests using LSE data. Despite differences between end of day prices and spreads on the LSE and NYSE, anomalies can be explained by other mis-specifications in portfolio returns, including the effects of infrequent or nonsynchronous trading. An overview of this literature follows.

2.5. NONSYNCHRONOUS TRADING EXPLANATIONS FOR MARKET INEFFICIENCY

Fisher gave the theory of nonsynchronous trading most prominence in his 1966 paper. He showed that infrequent trading by some of the constituent companies of a portfolio may cause these prices to lag behind more frequently traded stocks and hence experience so-called "thinness" in trading. The following example may explain this phenomenon. Firstly, let us assume that stock A trades frequently and at the close of business each day and that stock B trades only once during the day - in the morning, say. Secondly, assume that there is a relevant news event that effects both stock A and B in the market, and which occurs after stock B has traded for the day. The result of this scenario will be that stock A reacts immediately, on day t, and its closing price reflects the news event that has come to the market. However, stock B will react with a lag to the news event the next morning, on day t+1. Only at the close of business on day t+1 will stock B reflect yesterday's news event. Hence A appears to lead B, but solely because of non-trading.

When such infrequent trading transpires within a portfolio of securities, this induces positive first-order autocorrelation into the returns process and therefore perhaps mistakenly implies predictability in portfolio returns. Indeed much of the most recent evidence cites high autocorrelation and high cross-autocorrelation in short-horizon portfolio returns as evidence of predictability. In the light of the nonsynchronous trading problem, attaching meaning to these predictable portfolio correlations perhaps remains an obstacle.

However, following Boudoukh, Richardson & Whitelaw (1993) the strength of any correlation and hence predictability in portfolio returns has been reconciled through three schools of thought: the *loyalist*, *revisionist* and *heteric* schools. The *loyalist* school believes that correlations are economically spurious and occur for the following reasons: measurement error (for example nonsynchronous trading or the bid-ask spread); institutional structures (for example trading mechanisms); or microstructure effects (for example systematic changes in information flows). The *revisionist* school believes that correlation is consistent with time-varying short interval economic risk premiums. They believe that these risk premiums can be explained by variations in risk factors such as past returns. Therefore they believe that markets are efficient. Finally, the *heterics* believe in irrationality in the market and that correlations can be explained by, say, investor overreaction or partial adjustment to information flows.

This compartmentalising of the literature on short-horizon correlations is a useful exercise, since it enables us to judge the strength of any inferences we make about the level of portfolio return predictability. This literature is highlighted in chapter 7 and is mainly related to the *loyalist* school. Initially however, the nonsynchronous trading literature examined the biases infrequent trading imposed on asset pricing models and therefore in some ways follows the evidence from the *revisionist* school.

While the effects of nonsynchronous trading on asset pricing models is important, it is of secondary interest to this research. This chapter in keeping with evidence of stock market anomalies, is more concerned with the influence of nonsynchronous trading on the predictability of short run portfolio returns. As we have indicated, predictability can be measured as the level of autocorrelation and cross-autocorrelation in portfolio returns. However, these correlations can also come about due to the effects of nonsynchronous trading. These seemingly contradictory statements are the subject of a brief overview in this section.

2.6.1. *Nonsynchronicity, Autocorrelation and Predictable Portfolio Returns*

Evidence of the *loyalists* belief that short run predictability measured by autocorrelation and/or cross-correlation is economically spurious is supported by many studies. Some of the earlier ones examine nonsynchronous trading from the correlation perspective and found some interesting digressions in their results.

One of the first studies in this area was Perry (1985), who examined explanations for serial correlation in portfolio returns and found correlation levels to be larger for a portfolio of large sized firms than for the sum of the correlations of the individual firms that made up the portfolio. This seems to contradict the theory on nonsynchronicity i.e. that infrequent trading occurs only in smaller firm portfolios.

Additionally, Atchinson, Butler & Simonds (1987) used the Schwartz & Whitcomb (SW hereafter) (1977) model of nonsynchronous trading in order to compare the implied theoretical portfolio autocorrelation with the observed market autocorrelation of US equally and value weighted portfolios. They find that the equally weighted portfolios have a correlation approximately twice as high as for the value weighted portfolios. This difference in correlation would be expected given that smaller sized securities (which generally experience higher autocorrelation due to infrequent trading) in the portfolio have the same weighting as larger, more frequently traded securities.

Additionally, Atchinson et al's results indicate that measures of observed autocorrelation rise to much higher levels than is predicted by SW's theoretical model, as the number of firms in the portfolio rises. Even after using the nonsynchronous consistent SW model of transaction returns, autocorrelation of the order of 15% remains, again implying that other factors are contributing to autocorrelation.

Similar tests for index correlation were estimated by Berglund & Liljeblom (1988) who compared the serial correlation of the market index and individual securities on the Helsinki Stock Exchange. Their results demonstrate that the reported first-order market index autocorrelation is greater than the average first-order serial correlation across the individual stocks in the market. Suggested explanations for this additional market correlation centred upon institutional structures specifically, the procedure of 'calling out' security transaction prices during the first half of the day, one by one from a list operating in the Helsinki market.

In a US study, Lo & MacKinlay (1988) test for the random walk hypothesis with weekly data using variance ratio analysis. Consistent with previous studies they find that portfolio returns are characterised by significant positive serial correlation and individual stocks experience insignificant negative serial correlation - the opposite effect. This supports the hypothesis that the procurability of company specific information on individual securities makes it difficult to forecast returns. However, the formation of portfolios tends to diminish this 'idiosyncratic' noise and therefore make returns more predictable. For smaller sized portfolios they find serial correlation up to 49%, and for larger sized portfolios as low as 9%, implying that such high levels of predictability may be induced by biases associated with nonsynchronous trading.

In a later paper, Lo & MacKinlay (1990a) refined their nonsynchronous trading explanation of return predictability by examining the overreaction problem in terms of contrarian investment strategies. Most of the literature on portfolio overreaction had documented negative autocorrelation as evidence for some form of mean-reverting behaviour in stock returns[13]. Lo and MacKinlay approach this issue from another angle. By examining cross-autocorrelation effects in portfolios they document positive autocorrelation due to these cross-effects. What is equally as interesting from this study is that these cross-effects generally always occur when large firms lead smaller sized firms. This is the requirement for portfolios to be nonsynchronously traded. Therefore, Lo and MacKinlay's conclusion is that it is the lead-lag behaviour (i.e.

[13] See Poterba & Summers (1988) and Fama & French (1988) for two of the best known examples.

nonsynchronous trading) between differing sized portfolios that seems to determine contrarian investment strategies.

In further work, Conrad, Kaul & Nimalendran (1991) refute Lo & MacKinlay's (1988 & 1990a) results. They show that securities can be made up of a positively autocorrelated common component as well as a negatively autocorrelated idiosyncratic component related to the bid-ask spread, and a white noise component. Under this framework Conrad et al (1991) show that for NASDAQ weekly returns that the expected common component reflects asymmetric lagged cross-correlations between large and small firms. In addition the bid-ask spread can explain the individual negative autocorrelation in security returns. This suggests that evidence of nonsynchronous trading is prominent after taking account of the effects of the bid-ask spread in returns, a result which is consistent with Roll's (1984) finding that the effective bid-ask spread can be measured by $2\sqrt{-cov}$, where -cov is the negative first-order autocorrelation in price changes.

In a more recent study, Sentana & Wadhwani (1992) examine the link between return autocorrelation and share price volatility. Their results suggest that when stock price volatility is low, short run stock returns exhibit positive serial correlation. However, when volatility is high, returns exhibit negative autocorrelation, due to the influence of positive feedback trading on prices. This positive feedback trading is also greater following price declines, rather than price rises.

In their review study, Boudoukh et al (1993) question the strength of any cross-autocorrelation between portfolios. They suggest that the strength of any cross-effects perhaps is determined by the level of contemporaneous correlation between small and large sized portfolios. Clearly, under this scenario lagged large firms portfolios may be just proxying for small firm portfolio's returns if this correlation is high.

What the evidence in section (2.5) shows is that from the *loyalist* perspective, short run predictability measured by portfolio autocorrelation or cross-correlation can be seen as evidence of nonsynchronous trading rather than evidence of inefficiency such as overreaction or portfolio returns predictability, in the market. This is consistent with the evidence on the influence of the bid-ask spread, since it also shows that anomalies can be explained by mismeasurement in returns. The final section, that follows, concludes and summaries this overview of the literature.

2.6. CONCLUSIONS

This overview examines whether anomalies, in contradiction to evidence presented on the so-called Efficient Markets Hypothesis (EMH), are present in the stock market. To this end, this chapter examines evidence, mainly from the US, where much of the research has been undertaken, predictable anomalies, including mean reversion, volatility, portfolio return predictability, calendar effects and even a firm size effect. Furthermore, the more recent US evidence on market anomalies cites mispricing in the form of the bid-ask spread and nonsynchronous trading as a full, or at worst, partial explanation for this market inefficiency.

What is evident from the finance literature published over the past twenty-five years, is that there has been numerous definitions of what constitutes market efficiency. One of the first versions was Fama's path-breaking 1970 paper, in which he theorised that efficient market prices fully reflect all available information. Despite the importance of this work the definition of what constitutes market efficiency has changed with time due to continuing attempts to make the original 'strict' theory, due to Fama, more testable. While many of the earlier studies during the 1970's supported market efficiency, much of the subsequent evidence in the 1980's refuted Fama's original conclusions.

Due to the availability of higher frequency data, much improved statistical and econometric techniques, as well many studies into this area of financial economics, more recent work has highlighted varying degrees of market inefficiency. Indeed many showed the ostensible empirical regularity of stock prices and/or returns being too volatile compared to some underlying fundamental value.

Many of the studies such as Fama & French (1988) and Poterba & Summers (1988) highlighted predictable overreaction in stock returns where stock prices followed a slowly mean-reverting process (in the medium term) represented by a negative correlation. This correlation implies predictability of future returns and hence perhaps evidence of inefficiency.

Tests for volatility can be seen as only one part of the anomalies literature. There is much evidence to suggest that predictable, above average returns, at differing times of the calendar year, are prominent in the US as well as in the UK. Explanations for a so-called seasonal effect have centred on many factors including a firm size effect. Many studies including Ritter & Chopra (1989), for example, showed that small US firms, especially in January were found to have higher returns compared to other firms. Additionally, there is evidence to suggest that tax-loss selling and portfolio window dressing account for this seasonal behaviour. In the UK superior stock returns have been found to some extent in April as a result of the tax-loss phenomenon.

Apart from the yearly seasonal effects, evidence suggests that shorter run calendar anomalies exist including a monthly and so-called day of the week effect. Indeed, Ariel (1987) found intra-monthly seasonality possibly due to the timing of good and bad information releases to the market. In even shorter time series, day of the week effects or weekend effects have been found by French (1980), amongst others. Here Monday taken as a single day had negative returns due to the effects of the non-trading weekend period. In addition, many other factors have been documented to explain the weekend effect. These, in the UK, include account settlement dates and ex-dividend effects on Mondays.

Despite this seemingly overwhelming evidence in support of the existence of anomalies in the market, much of the literature has refuted many of the previous tests for market inefficiency. Indeed, stock mispricing exemplified by the bid-ask spread, measured by the touch in the UK, as well as nonsynchronous trading, seems to espouse market efficiency. For example studies such as Atkins & Dyl (1990) and

Kaul & Nimalendran (1990) in the US have shown that security return overreaction may occur because of mismeasurement due to the bid-ask spread. Furthermore, Keim (1989) in the US advocates turn of the year seasonality as a shift from transactions at the bid price to transactions at the ask price. Other studies such as Lamoureux & Sanger (1989) have linked such seasonality with a negative firm size effect.

Despite the prominence of spread explanations, anomalies can be explained by other mispricing errors including nonsynchronous trading. Indeed, as Perry (1985) and Lo & MacKinlay (1988) have shown, infrequent trading can induce positive first-order autocorrelation and therefore perhaps mistakenly imply predictability in the portfolio returns process. In the light of the nonsynchronous trading problem, attaching meaning to these predictable portfolio correlations perhaps remains an obstacle.

As we have already seen from the so-called *loyalist* perspective, short run predictability measured by portfolio correlations supports a nonsynchronous trading explanation of market inefficiency. Clearly, this and the impact of the bid-ask spread has influenced the market efficiency debate. The work that follows hopes to add to this debate by examining short- and long run calendar anomalies as well as portfolio return predictability in the UK stock market. The results will show, in an innovative way, that UK market anomalies perhaps can be accounted for by the touch (reflecting market maker behaviour) as well as nonsynchronous trading within portfolio returns.

The following chapter describes the means by which, the data used in this thesis is sorted into varying classifications and sizes of portfolios. Clearly, portfolios constructed by firm size or even price level for example, may have differing influences on tests for stock market anomalies. Additionally, simple descriptive statistics try to show the influence these classifications and sizes may have on portfolio returns.

3. THE EFFECTS OF PORTFOLIO CONSTRUCTION: SOME DESCRIPTIVE STATISTICS

3.1. INTRODUCTION

This chapter provides a preliminary analysis of the seasonal anomalies highlighted in the literature of the previous chapter. Clearly, the evidence in this literature supports the likelihood that rational investors will diversify away their firm specific risk using portfolios. Many of the tests for market efficiency explicitly use portfolios because they are more representative of investor behaviour; the work presented here is no different.

Generally, in this thesis the emphasis of the empirical research is to test for anomalies on the London Stock Exchange (LSE) including, for example, monthly seasonality, day of the week effects and daily predictability in portfolio returns. In order to test for the robustness of these anomalies, varying classifications of portfolios calculated using daily data supplied by DATASTREAM INTERNATIONAL are used. This data was sorted into varying classifications, including market value, closing price, the touch and turnover by volume. It was then ranked by size to form portfolios using a FORTRAN program. The use of differing classifications enables us to test whether portfolio construction influences the empirical results. The table below shows the economic implications of each portfolio classification used.

Portfolio Weighting Classifications and the Likely Economic Effects From Their Use

Classification	Economic Effect[14]
1. Market Value	Enables the examination of a firm size effect
2. Closing Price	Tests for a low-price effect
3. Touch	Measure of risk or illiquidity
4. Volume	A measure of information flows

To avoid bias associated with co-movement between stock prices and the portfolio classification or variable of interest, the portfolios are re-ordered periodically[15]. The method by which a portfolio is classified is important since the type of classification will effect each portfolios returns series. The most commonly used weight is market value. So, for example, sorting portfolios based on a market value classification enables us to document the influence of the so-called firm size effect on portfolio returns. The results from this analysis, and analysis of the other sizes and classifications of portfolios are shown in the descriptive statistics. These statistics show differing returns behaviour across days of the week and throughout the days of each month.

Finally, this chapter is organised as follows: Section 3.1 examines why investors use portfolios, section 3.2 shows the influence of, and link between, portfolios of differing classifications, with section 3.3 showing descriptive statistics for each of the portfolios.

[14] Evidence supporting these economic effects is widespread and includes Banz (1981) who showed an inverse relationship between firm size and average returns. Bhardwaj & Brooks (1992) used price-sorted portfolios to test for US turn of the year effects. Roll (1984) implied that the bid-ask spread (touch) is a measure of illiquidity and Merton (1987) theorised volume as a measure of information flow.

[15] This is in light of evidence on so-called data-snooping biases characterised by Lo & MacKinlay (1990c).

3.2. WHY USE PORTFOLIOS?

The desire of all rational investors is to maximise their wealth, i.e. earn the highest return available for a given level of risk. The optimal way to achieve this is to invest in portfolios. Portfolios are constructed from a number of securities and following Markowitz (1991), represent .. "a balanced whole, providing investors with protections and opportunities with respect of a wide range of contingencies". This implies that generally investors require a well diversified portfolio of securities.

The total risk an investor encounters can usually be measured by the variance of a portfolio's return. This risk comprises two components: *systematic* and *unsystematic* risk. Systematic risk is the part of an asset's total risk that cannot be eliminated by forming a diversified portfolio of all assets in the market. However, investors by forming portfolios are able to diversify away their unsystematic risk; the proportion of total risk which is firm specific.

Many studies have been undertaken to establish what the optimum risk - return trade-off is. Fama (1976) in the US, and Poon, Taylor & Ward (1992) in the UK, suggest that diversifying beyond 15 stocks will not reduce risk significantly, and any abnormal returns will be offset by transaction costs and portfolio management problems. Given this evidence, portfolios for the purpose of this research have been constructed in a similar fashion. As has been implied, this thesis is not primarily interested in the risk-return trade-off when using portfolios with a different number of constituent securities, but with the influence each of the four classification types have on portfolio returns.

The next section describes some of the empirical and theoretical relationships that might occur when using these differing portfolio classifications, while the penultimate section presents evidence on how the type of portfolio classification can influence seasonal returns.

3.3. THE INFLUENCE OF PORTFOLIO CLASSIFICATION

3.3.1. *Portfolios Classified by Market Value*

Market value, being a measure of security size, enables the examination of the so-called small firm effect found by Banz (1981) and Reinganum (1981), amongst others. Initially, Banz (1981) found a negative relationship between average risk adjusted stock returns and market value. This initial evidence perpetuated many studies which tried to explain the likely causes and consequences of the firm size effect.

Roll (1981) found smaller firms are less frequently traded than larger firms implying that systematic risk estimates from daily stock returns will be biased estimates of abnormal returns. More recent studies on the size effect by Chan, Chen & Hsieh (1985) found that the bottom 5% of the NYSE companies (i.e. the smallest firms) had returns 12% higher than the top 5% of firms (i.e the largest firms), but when these returns are risk-adjusted, the difference in returns narrowed to 2%. This implies that the size effect is consistent with the risk-return trade-off and is therefore not an anomaly. Later, seemingly contradictory evidence by Jegadeesh (1992), again in the US, found that even with a beta risk adjustment the size effect remained, but deemed other risk factors as a likely cause of this effect.

Even though firm size may in effect be risk related, there have been many other factors cited that may explain this phenomenon. In tests for the influence of firm size on calendar seasonals, both Roll (1983) and Reinganum (1983) tried to explain if the so-called 'January size effect' could be explained by tax-loss selling. Clearly, equities that are sold to minimise tax-losses must be those that have fallen in price and so are smaller in value. Under the US scenario of a December tax *and* calendar year end, such 'cheap' equities may subsequently be bought in the next month, resulting in positive returns in January. These results are similar to other studies[16], most noticeably Keim (1983), who found that for small firms the first five days in January had large risk adjusted returns, and that about half of the annual firm size effect occurred in January.

Clearly, the tax-loss selling hypothesis and firm size effect seem connected due to the behaviour of investors, who close their account books at the year end. However, the assumption that the January seasonal, or for that matter the March/April tax year end in the UK, are small firm effects, opens up the possibility that seasonals could be affected by the touch. Indeed, US evidence from Stoll & Whaley (1983) suggests that a size effect can be at least partially explained by the negative relationship between firm size and the bid-ask spread. This relationship for the UK is reviewed in section 3.3.3.

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[16] See Leong & Zaima (1991) and Lamoureux & Sanger (1989) who also implied that the size effect was a calendar anomaly.

3.3.2. *Portfolios Classified by Closing Price*

Intuitively, small firms are assumed to have lower relative share prices compared to their larger counterparts. The bid-ask spread, as its name suggests, is calculated using bid and ask prices. Its size therefore is dependent more upon the level of share price than of firm size, due to problems of price discreteness. Small priced shares in the UK therefore, are more likely to experience greater mispricing due to the influence of the touch on prices.

Following Demsetz (1968), who suggested that lower priced stocks exhibit a departure from proportionality due to the higher commission charges on such stocks, we can imply that lower priced stocks must have larger spreads. Furthermore, Porter (1992) shows that the turn of the year effect is dependent upon a small price effect rather than a firm size effect. Despite this evidence it is clear that closing price classified portfolios may proxy for a small firm effect, since market value is directly dependent upon share price[17]. Perhaps the effects of classifying by turnover by volume and the touch, described below, may be of more interest.

3.3.3. *Portfolios Classified by the Percentage Touch.*

The LSE operates on a dealership basis with market makers and dealers offering quotations of price and volume in stocks. Market makers are stock dealers who agree to make a market in a stock at any price and for any volume of transaction, and in return are guaranteed first right of access to public buy and sell orders. Market

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[17] In fact, market value equals transaction price times the number of shares in circulation.

makers earn their profit from the commission they charge investors for transacting in the market, and from the profit they earn from buying securities at a lower price than they sell at. The difference between this buy and sell price is known as the market makers touch, defined as

$$\frac{(P_a - P_b)}{[0.5(P_a + P_b)]/100} \qquad (3.1)$$

The denominator in (3.1) is assumed to be the closing (or equilibrium) price - the price quoted on the market, which should lie somewhere between the bid price, P_b, and ask price, P_a.

Furthermore, Garbade (1982) implied that transactions in securities are executed by a market maker immediately when both buy and sell orders from investors coincide. This will be at a known equilibrium price. Market makers will probably be only willing to wait for, say a public sale order, if they can purchase a security, and hence complete the transaction at a price lower than equilibrium, i.e. at the bid price. The ask price (a price above equilibrium) arises when there is an arrival of a unilateral purchase order. The longer the market maker has to wait to complete a transaction the more divergent the price will be from equilibrium i.e. there will be a larger touch. This is the cost paid by investors in exchange for the liquidity provided by market makers in security prices and reflects price risk associated with holding an equity over a period of time.

In terms of classifying portfolio return series, using the touch enables examination of many empirical relationships. Following the US evidence from Amihud & Mendelson

(1986) who found that the spread is positively related to security returns, since due to illiquidity (the spread clientele effect) a larger spread implies a longer holding period of securities by market makers and so higher returns. Hence, UK portfolios characterised by the touch should exhibit differing returns behaviour[18].

Demsetz (1968) in the US suggested that lower priced stocks are small in firm size and must have larger spreads because they are more infrequently trading. However, under the hypothesis of at least moderately efficiently traded securities, the value of the spread may adjust more rapidly and more frequently on the receipt of a public transaction order than price. This is because market makers can adjust the spread, so changing the level of risk of a security without adjusting its price. Consequently, using a touch classification for UK data may introduce more variance in the weighted returns series especially in the larger sized portfolios which are less frequently traded. Trading frequency, more commonly referred to as turnover by volume, is however the subject of the next section.

3.3.4. *Portfolios Classified by Turnover by Volume*

Every security in a portfolio has its own unique percentage touch and since each security has different trading patterns, the touch, as we have already inferred, is therefore inversely related to a market makers holding period. Low levels of

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[18] Clearly, illiquidity in security prices has as much to do with the touch as it has to do with the efficiency of the trading system by which securities are transacted. On the LSE, normal sized transactions have to be logged onto the SEAQ information system within 3 minutes of execution. In addition the use of 'alpha' stocks has traditionally implied since 'Big Bang' in 1986 that 2 market makers must provide immediate transacting information on price and volume. This provides a high degree of liquidity and hence a continuous market in a security.

transactions in the market may mean that there are fewer buyers and sellers. As we have seen, this makes it more expensive for market makers to provide liquidity services, due to the risk of holding an equity in an incomplete transaction.

Transactions provide information on the size (value) *and* direction of a share price movement and therefore provide vital information on its trading pattern. Volume hence provides information to market makers. The smaller (larger) the volume the less (more) information there is about investors' supply and demand functions. Market makers are unable to estimate the current equilibrium price accurately due to the lack of information[19], and so widen the touch. Infrequently traded stocks are hence characterised by more uncertainty, have a larger touch, and by implication may experience large price adjustments on the arrival of transaction orders.

Such low volume and low information securities therefore have specific characteristics. Merton (1987) in the US implies that the spread relates to the number of shares in circulation which in turn reflects the availability of information about the firm. Demsetz (1968) showed that the spread is inversely related to the number of shareholders and that shareholder numbers are directly related to the turnover or volume of shares in the market. Conversely, smaller sized securities will have fewer issued shares, and so less shareholders who are able to transact.

Commission charges and the touch will also discourage investors from periodically 'turning over' their portfolios. So portfolios characterised by volume size should have

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[19] See Garbade (1982) for an overview of this area.

a relationship with the touch and subsequently security returns. This is because portfolios classified by different volumes are classified on an information level, where securities in portfolios with the highest informational levels will be less susceptible to mispricing and inefficiency.

3.3.5. Equally verses Value Weighted Portfolios

The method by which a portfolio is weighted is important since the type of weighting will affect each portfolio's returns series. Since a portfolio consists of a number of securities, say 15, then intuitively one could imply that the returns on that portfolio are the summation of all 15 security returns. This implies that the securities carry an equal weighting within the portfolio, defined as (1/N), where N is the number of securities in a portfolio. In terms of calculating an index, this weighting has limited economic usefulness, since differing sized firms have differing risk and return levels which should be reflected in the index.

The way the financial markets determine the performance of a security is through its price activity. The change in price (plus dividends) equals returns which, as we have shown, is empirically related to the market value of a company's equity. Portfolios can reflect this characteristic by being formulated using a value weighting for each security's return. Value weighting in portfolios takes into account the relative economic significance of each constituent security. The value weighting (such as market value) is constructed as follows: $P_i/\Sigma P_j$, where P_i is the i securities classification value, and ΣP_j is the sum of the market's classification value.

Even though value weighting is nearly always used in the construction of indices, it is rarely used to construct investor portfolios. This is because calculating a value weighted portfolio is time consuming and complicated. The following section describes the data used in this thesis and shows the influence of portfolio classification on seasonal returns.

3.4. DESCRIPTIVE STATISTICS

3.4.1. *Data Description for Testing Monthly Effects*

In order to test for January and monthly effects on the LSE, 6 years of daily data was collected over the period 1 September, 1987 until 23 August 1993 from DATASTREAM. Data on bid and ask prices, as well as turnover by volume was not available before this period from the LSE. Given the need for this specific data in the construction of portfolios, six years represents the total period for which data could be used. The data, which represents 1512 observations, was divided into 6 equal years of data, each year having 252 observations. Eighty five of a possible ninety companies (shown in Appendix 1) from the old style 'alpha stocks'[20] were available for use in these tests, and were sorted into 5 equally sized portfolios of 18 stocks each[21]. Portfolios were constructed on an equally weighted basis[22] where returns

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[20] The SEAQ (Stock Exchange Automated Quotations) information system now classifies stocks as a 'normal market size' (NMS) banding system for 12 differing turnover by volume categories.

[21] This follows Fama (1976) and Poon, Taylor & Ward (1990) who found that diversifying beyond around 15 stocks per portfolio does not reduce risk significantly, and would incur additional transaction costs and portfolio management problems.

were calculated as follows

$$R_t = \ln P_t + [\ln(DY_t * P_{t-1})/100] - \ln P_{t-1} \tag{3.2}$$

where P_t is the daily closing price of each security in the portfolio in time t, DY_t is the dividend yield[23] in time t from which dividends are calculated. Closing prices reflected the mid-market price from the best market maker's bid and offer quotations on the LSE SEAQ trading system. All prices are adjusted for scrip and rights issues under the assumption that capital structure changes do not alter company value.

Four classifications [market value, closing price, touch, and turnover by volume] were used to sort portfolios into differing sizes in order to test for the robustness of monthly effects across differing sizes and classifications of portfolios. Following the portfolio construction methodology used by Fama & MacBeth (1973), the first year of 252 observations were used to form the portfolio weightings and the last 5 years were used to construct returns[24]. The first year of portfolio classifications are therefore paired off, on a yearly basis, with each of the following 5 years return series. Portfolio re-ordering avoids the problems of so-called 'data-snooping biases' examined by Lo & MacKinlay (1990c). Such biases occur when different sized portfolios are classified and weighted by a value, in the same time period that is directly related to a variable

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22 See Jegadeesh (1991) and Ritter & Chopra (1989) who use these indices to test for turn of the year effects.

23 DATASTREAM does not carry daily company dividend data only dividend yield.

24 Clearly, even though generally the out of sample period should be the same length as the in sample period, data requirements for tests of yearly and monthly effects mean that 5 years of returns data is needed in the in sample period.

of interest, such as closing returns. Convention dictates that portfolios are normally classified by a market value weighting[25]. Since market value is the number of shares in issue multiplied by the price per share, market value is therefore related to returns.

Hence, using the example of a falling market value implies that either the number of shares in circulation has decreased[26], or more plausibly that the closing price is lower. Accordingly, there is an intuitive and statistical relationship between firm size and the stochastic behaviour of closing returns. Portfolio re-ordering clearly avoids these problems and should increase the power of any tests using portfolios constructed in such a manner. Hence in order to make the portfolio construction more realistic, and so mimic the actions of investors more closely, each year is divided into 6 sub-periods of 42 days each, since investors on the whole periodically buy and sell equities (in this case every 5-6 weeks during the year) and so alter the constituents of their portfolios. The portfolios are numbered 1-6 and are classified in ascending order.

3.4.2. *Data Description for Testing Day of the Week Effects*

To test for day of the week effect and daily return predictability, the following data set was used. Again daily closing security market data on the LSE was collected from

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[25] See Fama & MacBeth (1973), Reinganum (1990), and Lo & MacKinlay (1990b) for example.

[26] This is probably unrealistic given that Mayer (1988) documents the fact that only 6% of the gross source of UK corporate capital financing comes from share issues. This suggests that the volume of shares in circulation for each company remains fairly constant.

DATASTREAM, this time over a 5-year period between 1 August 1987 and 23 July 1992, which provides 1260 observations. For this period 90 alpha stocks [shown in Appendix 1] were available with the relevant data over the entire period, and these formed the basis for portfolio construction[27].

Again portfolio weights are calculated from a period before the returns period. In this case the data sample was split *equally* into a period taken from 1 August 1987 until 26 January 1990 which formed the basis for the portfolio weighting classifications. The returns data was taken from the period 27 January 1990 to 23 July 1992. Hence, there is a 2½ year lag between returns and their weighting value. Portfolio construction in this case, hence involved forming 6 portfolios of 15 stocks each, which were equally weighted by the four classifications highlighted previously. Following Kaul & Nimalendran (1990), the weightings and hence constituent companies, are re-sorted every 70 days (approximately 3 months). The following sections show descriptive statistics for tests of seasonality

3.4.3. *Testing the Effects of Portfolio Construction on Seasonal Returns*

(a) *Monthly Seasonality*

In Figure 3.1 we show the influence that portfolio classification size has on seasonal returns. The results suggest that portfolio size causes the previous robust seasonal results across portfolio classifications to breakdown. For example, we can see that December returns now seem comparable to January returns, in all the smaller sized

[27] At the time of portfolio construction this represented the maximum time period and number of companies available.

portfolios apart from those classified by closing price. Intuitively, this may show that investors are buying smaller sized securities at the end of December in anticipation of higher returns in the new calendar year.

In contradiction to some of the seasonality studies in the US, January returns do not appear to be a function of firm size, but rather, following Bhardwaj & Brooks (1992) and Porter (1992), a function of closing price, even though the results suggest that investors buy small firms in December. Also, the seemingly spuriously large May returns appear consistent across all classifications of portfolios.

With regard to any tax-motivated trading by investors, on average the results show that March is characterised by returns at least half the level of April, across all classifications and sizes of portfolios[28]. The implication here is that investors may be more willing to buy at the start of a new UK tax year in April, than in March, the end of the previous tax year. This, following Ritter & Chopra (1989), is perhaps because investors re-balance their portfolios around the turn of the tax year by trading equities so as to minimise any tax liability.

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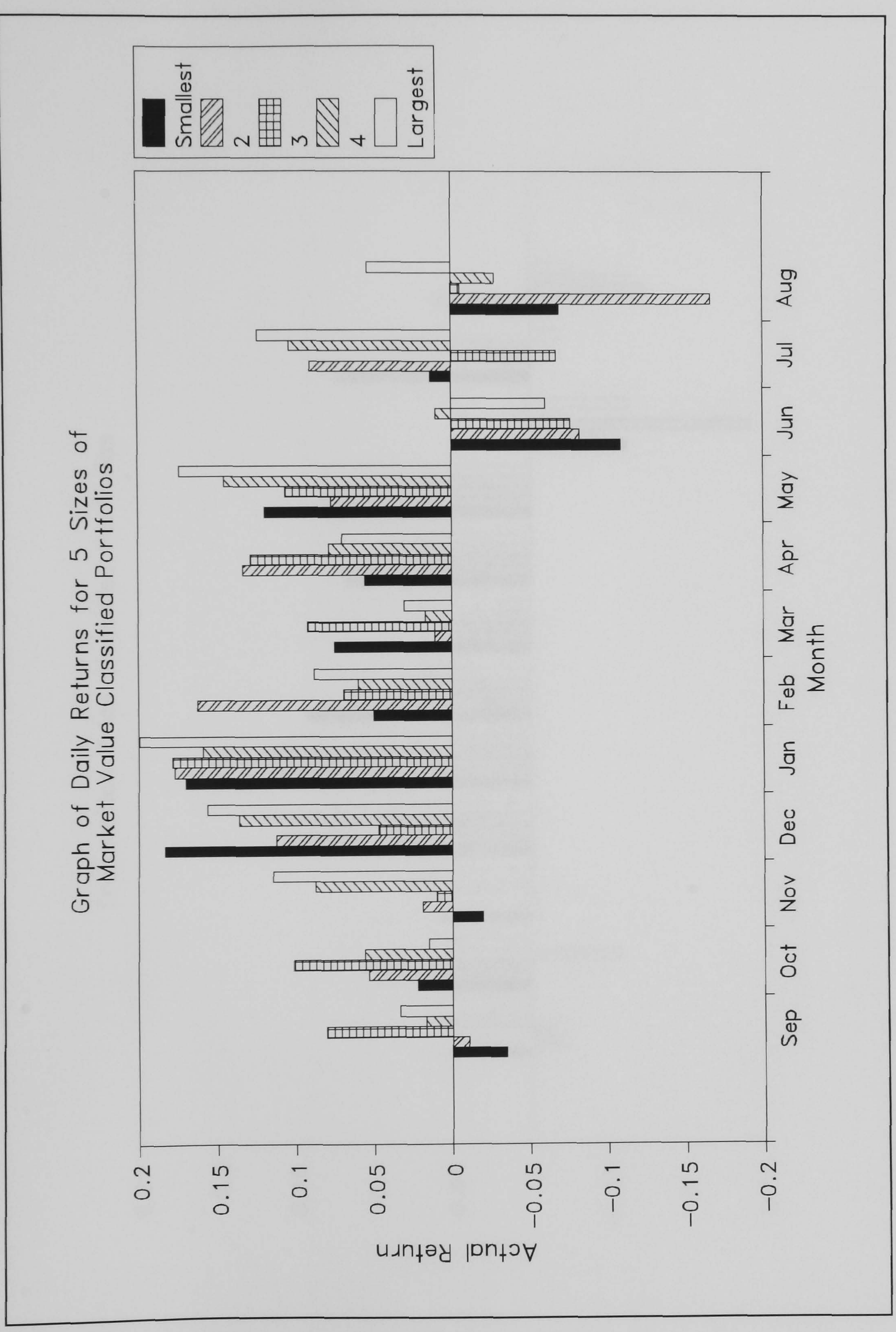
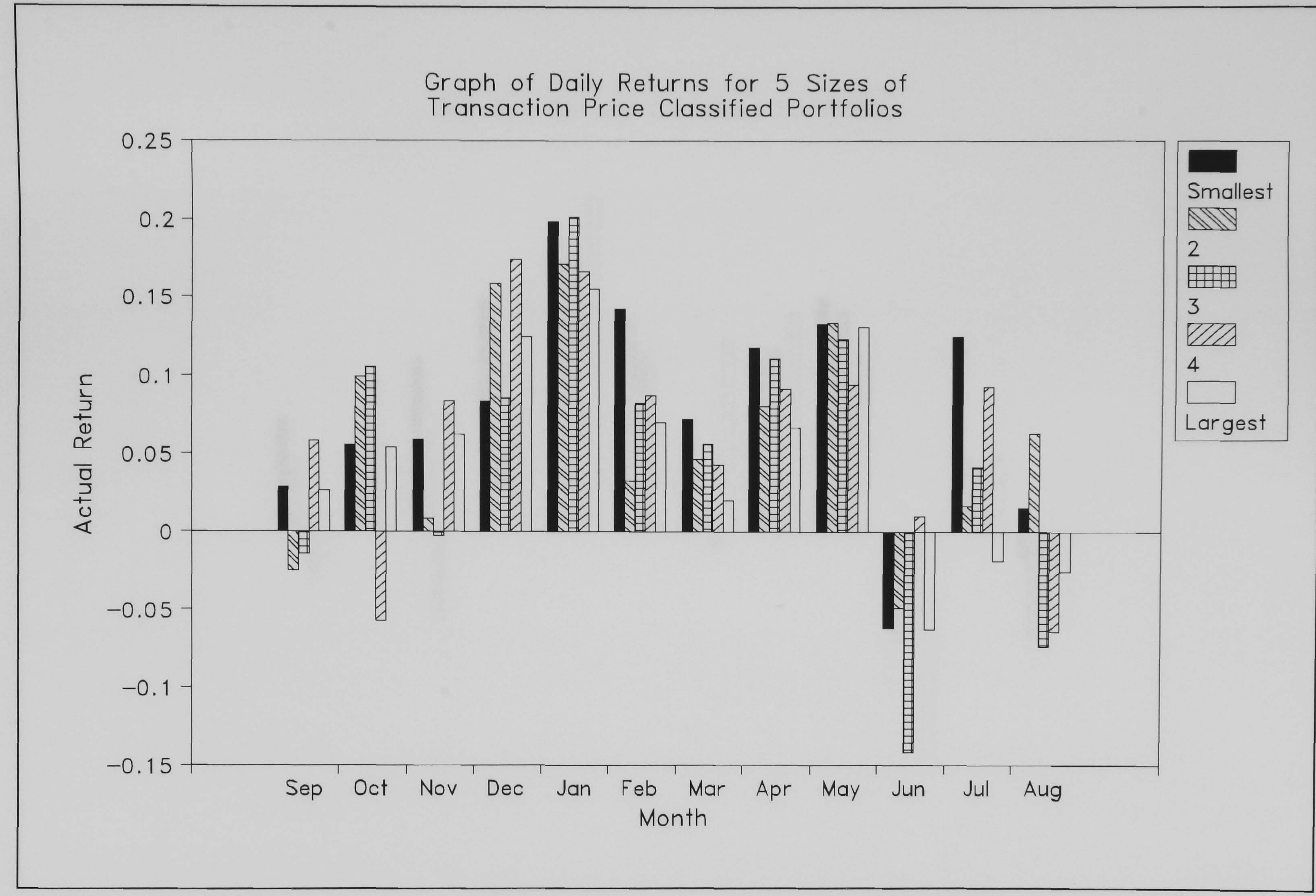
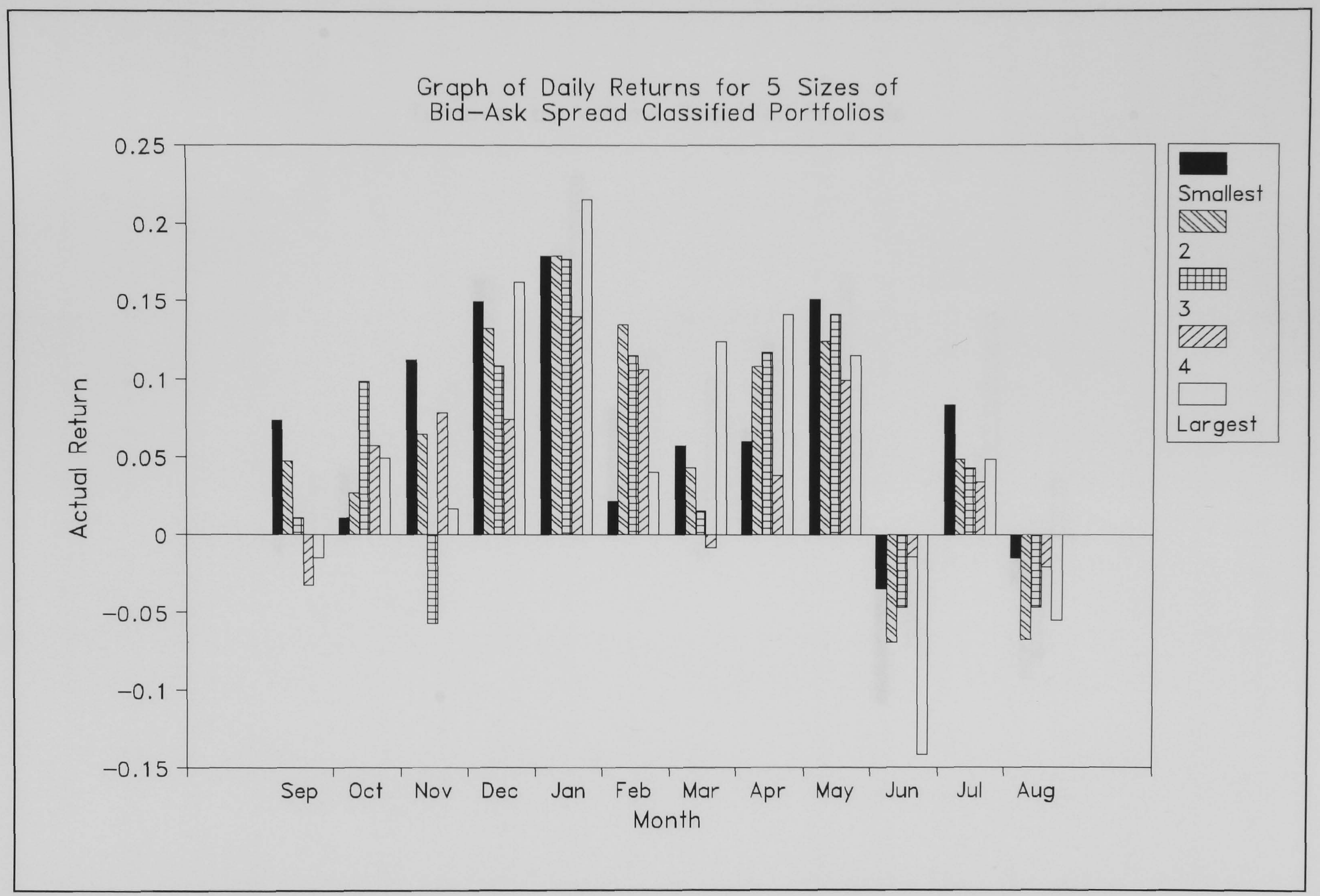
[28] Here however, both small market value *and* small priced portfolios experience higher returns than their larger counterparts.

Figure 3.1: Graphs of Monthly Returns Calculated using Daily Data Across the Differing Portfolio Sizes and Classifications

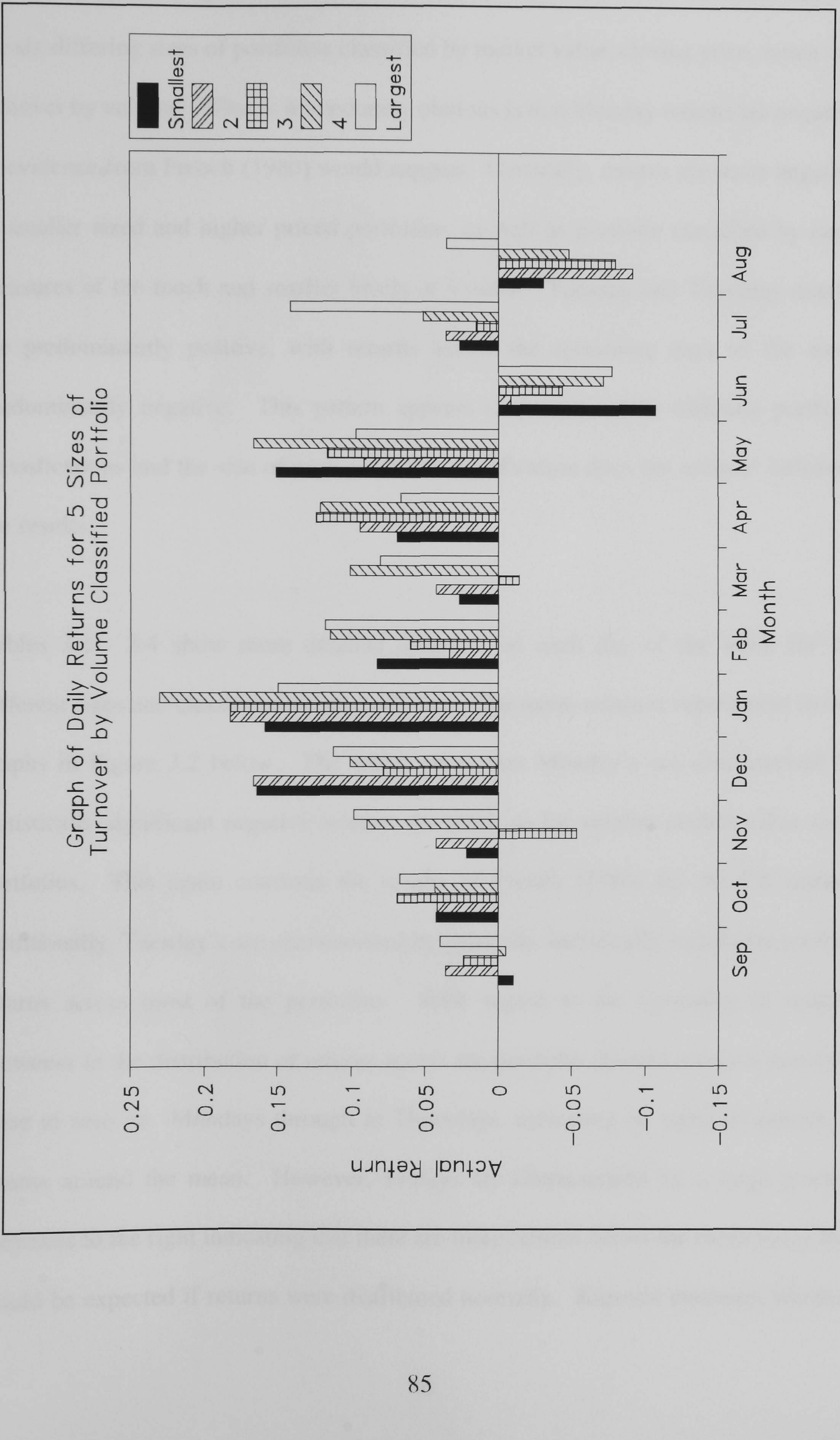




Graph of Daily Returns for 5 Sizes of
Transaction Price Classified Portfolios
Smallest
2
3
4
Largest
Actual Return
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Month



Graph of Daily Returns for 5 Sizes of
Bid-Ask Spread Classified Portfolios
Actual Return
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Month
Smallest
2
3
4
Largest



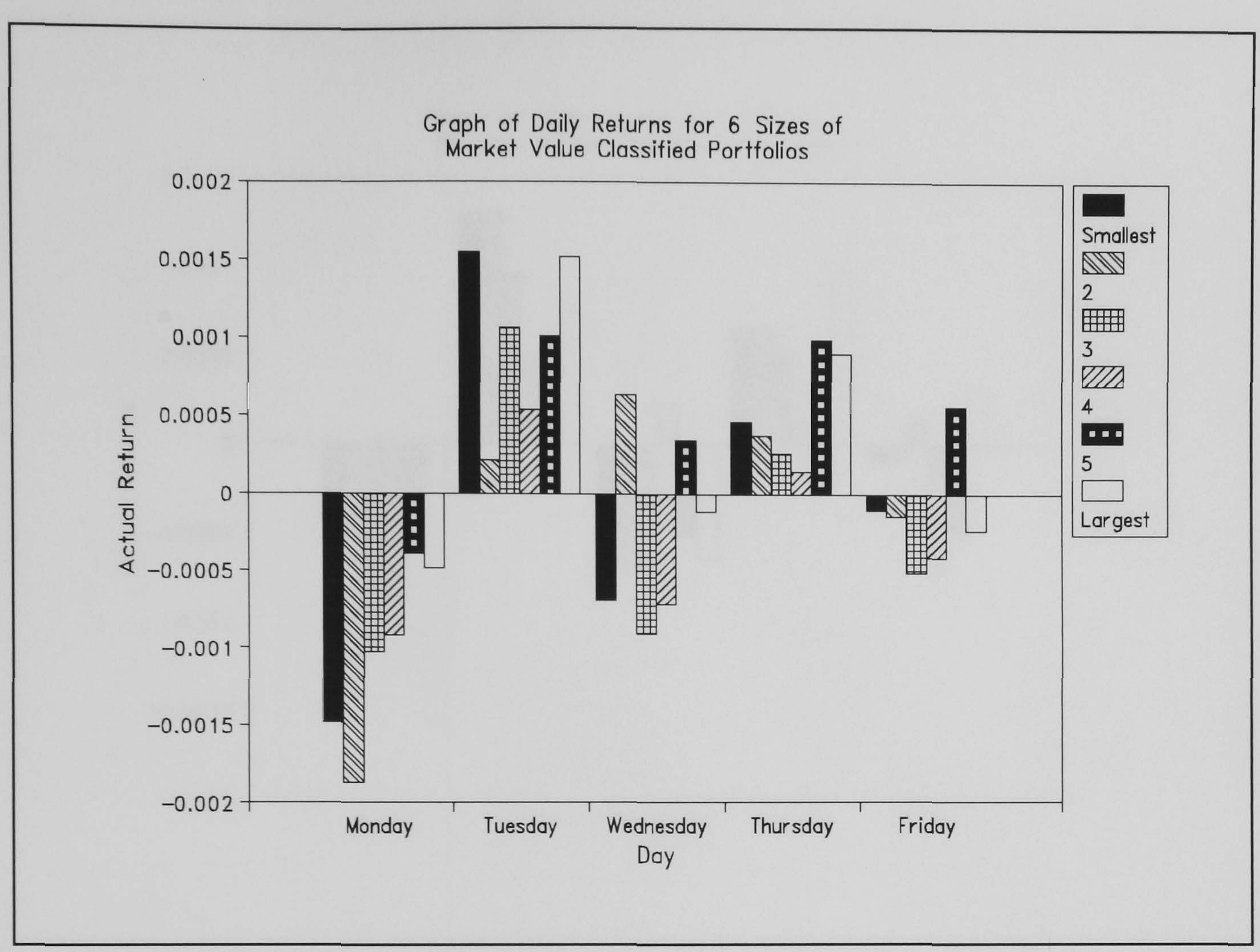
Graph of Daily Returns for 5 Sizes of Turnover by Volume Classified Portfolio
Smallest
2
3
4
Largest
Actual Return
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Month

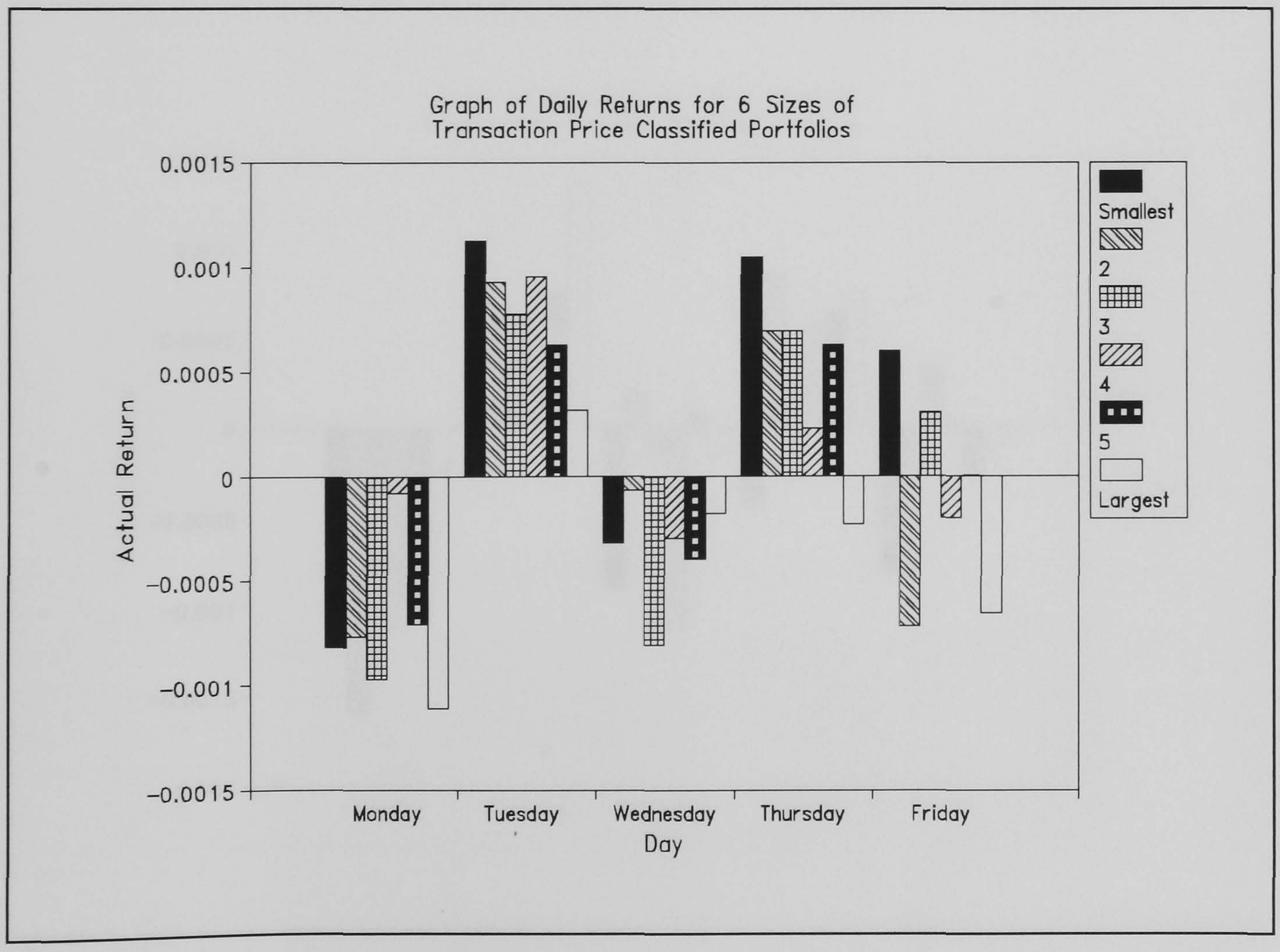
(b) *Day of the Week Seasonality*

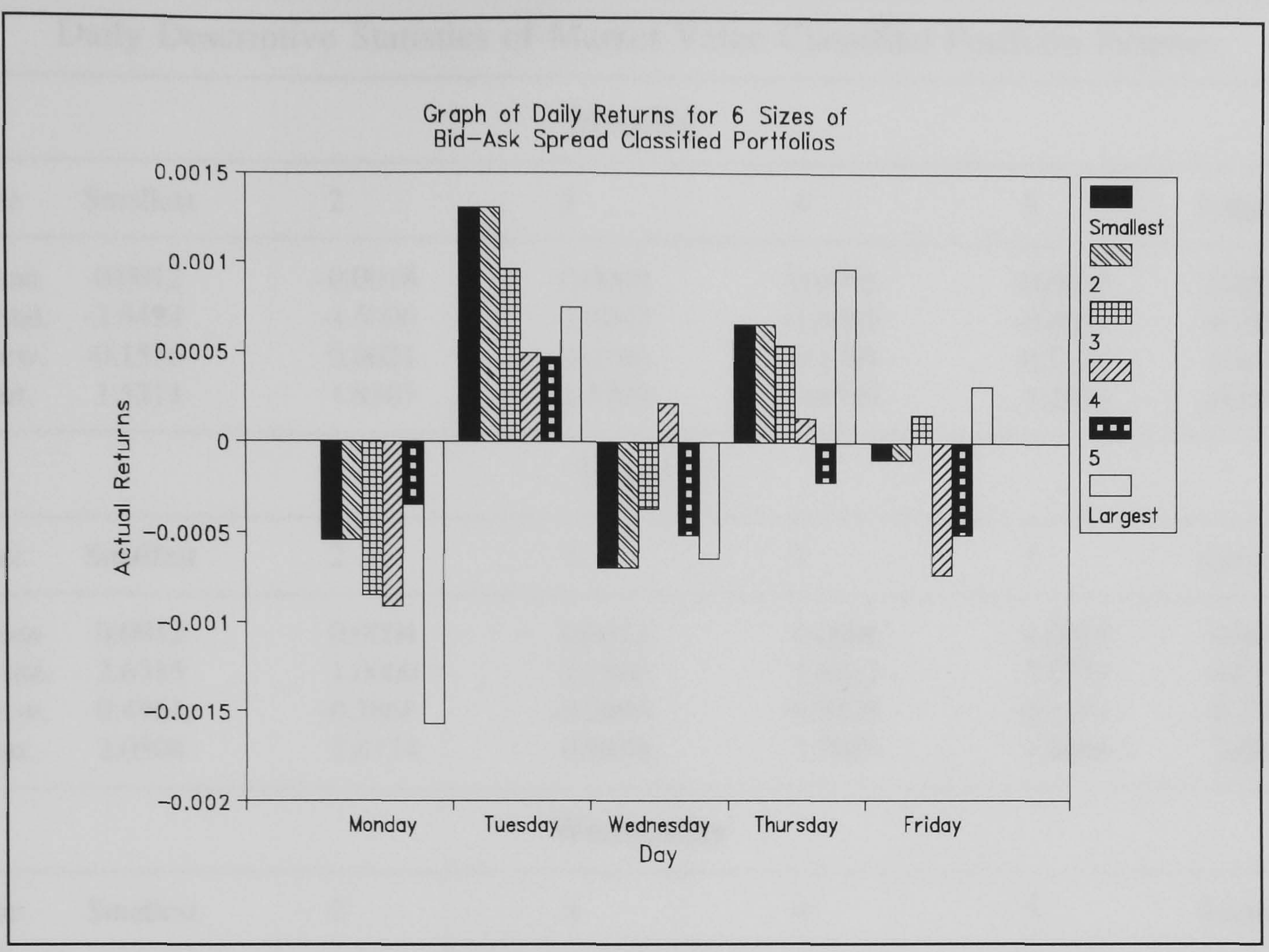
The four graphs in Figure 3.2 below, show the average daily actual return for each of the six differing sizes of portfolios classified by market value, closing price, touch and turnover by volume. What is immediately obvious is that Monday returns are negative as evidence from French (1980) would suggest. Generally, returns are more negative in smaller sized and higher priced portfolios, as well as portfolio classified by large measures of the touch and smaller levels of volume. Tuesday and Thursday returns are predominantly positive, with returns across the remaining days of the week predominantly negative. This pattern appears consistent across differing portfolio classifications and the size of each portfolio classification does not seem to influence the results.

Tables 3.1 - 3.4 show more detailed statistics on each day of the week for the different sizes and classifications of portfolios. The mean return is represented in the graphs in Figure 3.2 below. The tables show that Monday's are characterised by statistically significant negative returns, the more so for smaller market value sized portfolios. This again confirms the results of French (1980) for the US market. Additionally, Tuesday's are characterised by generally statistically significant positive returns across most of the portfolios. With regard to the normality of returns, skewness in the distribution of returns across the portfolio classifications is generally close to zero on Mondays through to Thursdays, indicating an equal proportion of returns around the mean. However, Fridays are characterised by a large positive skewness to the right indicating that there are more returns below the mean value than would be expected if returns were distributed normally. Kurtosis measures whether

Figure 3.2: Graphs of Daily Returns Across Portfolio Sizes and Classifications






Graph of Daily Returns for 6 Sizes of
Bid-Ask Spread Classified Portfolios
0.0015
0.001
0.0005
0
-0.0005
-0.001
-0.0015
-0.002
Actual Returns
Monday
Tuesday
Wednesday
Thursday
Friday
Day
Smallest
2
3
4
5
Largest

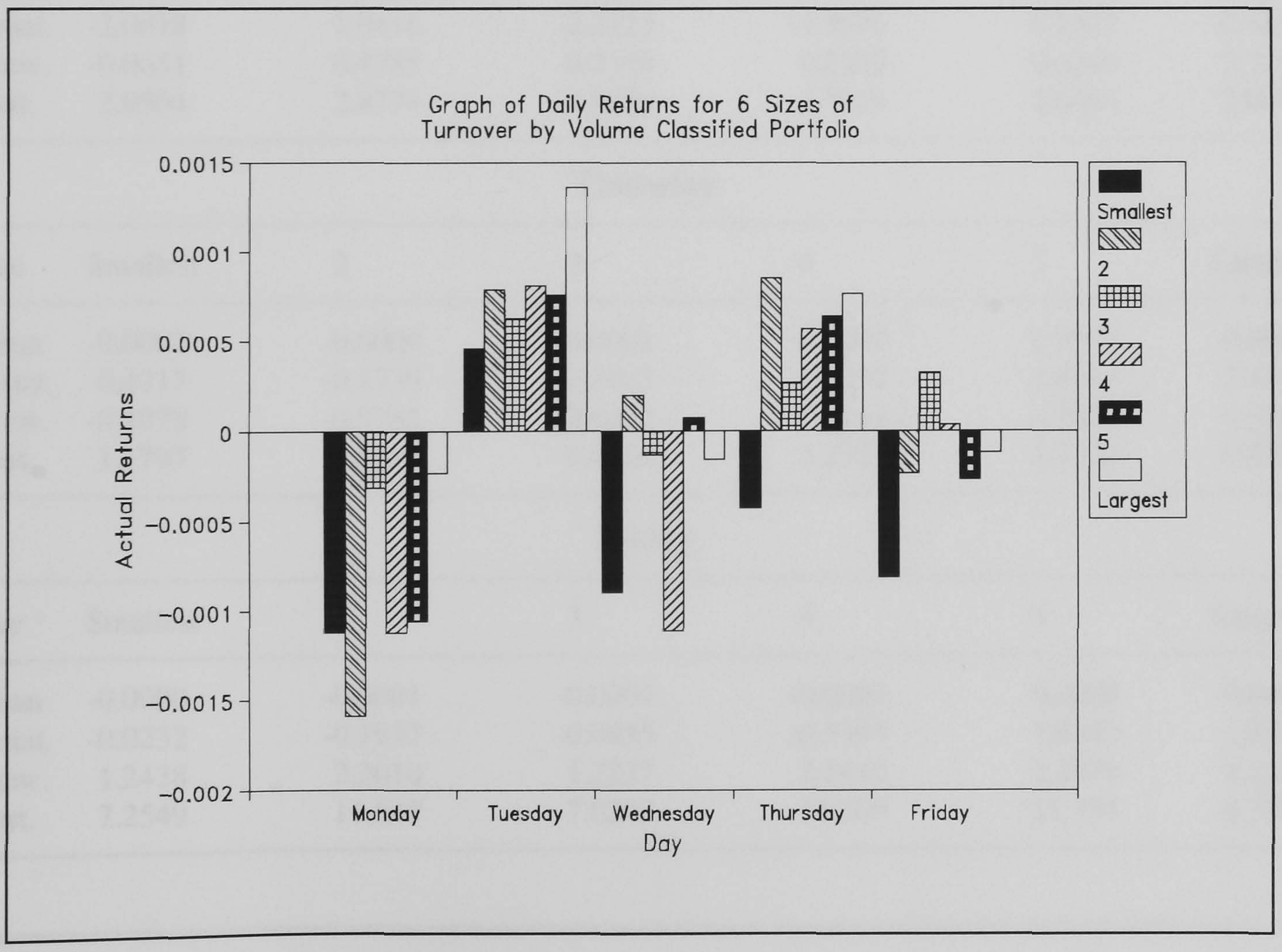

Graph of Daily Returns for 6 Sizes of
Turnover by Volume Classified Portfolio
0.0015
0.001
0.0005
0
-0.0005
-0.001
-0.0015
-0.002
Actual Returns
Monday
Tuesday
Wednesday
Thursday
Friday
Day
Smallest
2
3
4
5
Largest

Table 3.1

Daily Descriptive Statistics of Market Value Classified Portfolio Returns

Monday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0012	-0.0018	-0.0009	-0.0008	-0.0002	-0.0001
T-stat.	-2.5424	-4.5000	-1.8907	-1.6667	-0.4854	-0.2404
Skew.	-0.1556	0.0021	0.0786	0.1789	0.1201	0.0008
Kurt.	1.5211	1.8367	1.5209	0.8510	1.2571	-0.1840

Tuesday

Size	Smallest	2	3	4	5	Largest
Mean	0.0012	0.0004	0.0011	0.0006	0.0010	0.0016
T-stat.	2.6315	1.0000	2.7500	1.4113	2.7777	4.2105
Skew.	-0.4961	-0.7866	-0.2896	-0.0105	-0.3193	-0.2398
Kurt.	2.0504	2.8774	0.9858	1.7029	1.6466	2.0026

Wednesday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0008	0.0004	-0.0008	-0.0007	0.0001	-0.0002
T-stat.	-2.0618	1.0416	-2.2222	-1.7676	0.2907	-0.5814
Skew.	-0.0651	0.4785	0.2359	0.2309	0.6240	0.7295
Kurt.	2.0504	2.8774	0.9858	1.7029	1.6466	2.0026

Thursday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0002	-0.0000	-0.0001	-0.0002	0.0007	0.0004
T-stat.	-0.4717	-0.1739	-0.2427	-0.4237	1.8041	1.1111
Skew.	-0.1078	-0.9785	0.0972	0.1144	0.1927	0.5489
Kurt.	1.1797	6.5689	0.4168	1.2722	1.1403	0.5722

Friday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0000	-0.0001	-0.0004	-0.0003	0.0008	-0.0004
T-stat.	-0.0232	-0.1937	-0.0855	-0.5395	1.8340	-1.0526
Skew.	1.2438	2.2010	1.2237	2.1412	2.1079	1.2387
Kurt.	7.2549	11.647	7.0203	11.309	11.334	4.7467

Table 3.2

Daily Descriptive Statistics of Closing Price Classified Portfolio Returns

Monday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0009	-0.0008	-0.0011	-0.0002	-0.0008	-0.0012
T-stat.	-1.7578	-1.7094	-2.5229	-0.4504	-2.0618	-3.0000
Skew.	-0.0678	0.2295	0.1261	0.4928	-0.3696	-0.1851
Kurt.	0.5693	1.3462	0.7198	2.7999	0.6018	2.3102

Tuesday

Size	Smallest	2	3	4	5	Largest
Mean	0.0013	0.0011	0.0012	0.0011	0.0009	0.0003
T-stat.	2.9279	2.6190	3.0000	2.7227	2.4456	0.8064
Skew.	-0.4050	-0.4849	-0.1209	-0.2156	-0.9254	-0.4192
Kurt.	2.4550	1.4718	1.0684	1.9768	3.4204	1.1222

Wednesday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0004	-0.0000	-0.0009	-0.0002	0.0005	0.0000
T-stat.	-0.9345	-0.0206	-2.1844	-0.5813	1.7233	0.2616
Skew.	-0.0120	0.4406	0.5867	0.4149	0.4664	0.4757
Kurt.	-0.2836	-0.0388	0.7685	0.2514	-0.3029	0.6076

Thursday

Size	Smallest	2	3	4	5	Largest
Mean	0.0006	0.0001	0.0005	-0.0003	0.0003	-0.0007
T-stat.	1.3761	0.2315	1.1161	-0.7575	0.7812	1.7500
Skew.	0.1428	0.1912	-0.0393	-0.2450	0.0428	-0.0148
Kurt.	1.1919	0.3149	2.7724	1.5760	0.7696	0.7409

Friday

Size	Smallest	2	3	4	5	Largest
Mean	0.0005	-0.0006	0.0004	-0.0001	-0.0001	-0.0006
T-stat.	1.0000	1.2000	0.6944	-0.2101	-0.2577	-1.5306
Skew.	1.7026	1.4232	2.7329	1.8011	1.4972	0.9439
Kurt.	9.6152	5.4923	15.112	9.6189	8.3667	4.7359

Table 3.3

Daily Descriptive Statistics for Touch Classified Portfolio Returns

Monday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0005	-0.0008	-0.0009	-0.0011	-0.0003	-0.0016
T-stat.	-13.889	-1.9608	-2.1028	-2.5700	-0.6410	-3.1008
Skew.	-0.2806	-0.2381	-0.2011	-0.0279	0.2741	0.1066
Kurt.	0.6644	0.3417	1.5307	1.7525	1.2988	1.5288

Tuesday

Size	Smallest	2	3	4	5	Largest
Mean	0.0014	0.0010	0.0005	0.0010	0.0007	0.0009
T-stat.	3.6842	2.4752	1.3889	2.6042	1.6509	1.9396
Skew.	-0.4875	-0.9225	-0.2002	-0.2788	-0.0146	-0.5009
Kurt.	2.9165	3.0718	1.0378	1.4430	0.8620	1.8385

Wednesday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0007	-0.0005	0.0001	-0.0000	-0.0005	-0.0007
T-stat.	-2.0833	-1.5243	0.3086	-0.2343	-1.3298	-1.4831
Skew.	0.6984	0.5487	0.3792	0.1544	0.5151	0.0028
Kurt.	-0.1816	-0.3384	-0.1139	0.1421	0.4194	0.0064

Thursday

Size	Smallest	2	3	4	5	Largest
Mean	0.0004	0.0002	-0.0003	0.0001	-0.0006	0.0004
T-stat.	0.9856	2.4562	-3.7500	2.4781	-2.3221	2.2116
Skew.	-0.5660	-0.2920	0.0888	-0.0054	0.1049	0.3228
Kurt.	4.2529	1.7678	0.6879	0.5473	1.5011	1.4473

Friday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0000	0.0000	-0.0007	-0.0001	-0.0005	0.0002
T-stat.	-0.1667	0.0786	-1.5625	-0.2137	-0.9469	0.3846
Skew.	1.2087	1.4577	1.8054	1.7408	1.8439	1.0889
Kurt.	4.9404	8.1932	10.872	9.4146	4.9374	4.7359

Table 3.4

Daily Descriptive Statistics of Turnover by Volume Classified Portfolio Returns

Monday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0011	-0.0016	-0.0003	-0.0011	-0.0010	-0.0002
T-stat.	-2.7227	-3.9603	-0.6410	-2.2177	-2.1367	-0.4762
Skew.	-0.3824	-0.1417	0.1652	0.2587	-0.0409	-0.0791
Kurt.	2.7821	1.8493	1.0581	1.2955	0.4919	0.1782

Tuesday

Size	Smallest	2	3	4	5	Largest
Mean	0.0004	0.0008	0.0009	0.0009	0.0009	0.0014
T-stat.	1.1364	2.0833	2.2058	2.0454	2.0270	3.6458
Skew.	-0.3945	-0.6859	-0.4159	-0.4817	-0.1666	-0.3008
Kurt.	1.2932	2.3417	2.3064	1.5351	0.8718	3.4326

Wednesday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0008	-0.0001	0.0002	-0.0010	-0.0000	-0.0004
T-stat.	-2.6315	-0.3012	0.4987	-2.5510	-0.2250	-1.0869
Skew.	0.3436	0.5304	0.4202	-0.0488	0.4076	0.3770
Kurt.	0.1935	0.5562	0.0531	0.3178	0.0669	-0.3278

Thursday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0009	0.0004	-0.0001	0.0000	0.0003	0.0004
T-stat.	-2.3438	1.0416	-0.2137	0.1939	0.6756	1.0989
Skew.	-0.2018	0.0165	-0.3311	-0.2474	-0.0692	0.5758
Kurt.	1.2434	0.2032	4.0052	0.9544	2.1482	0.9385

Friday

Size	Smallest	2	3	4	5	Largest
Mean	-0.0008	0.0003	0.0003	0.0002	-0.0003	-0.0001
T-stat.	-2.0833	0.6637	0.5633	0.3731	-0.6048	-0.2427
Skew.	0.5721	1.8221	1.9947	1.9589	1.6219	1.0727
Kurt.	3.6219	10.485	10.227	10.917	6.8619	5.2861

the returns distribution has fat tails i.e. returns are not distributed with highest frequency around the mean. The results for all the portfolios show that kurtosis is quite high especially on Fridays. Overall, these results indicate that seasonal effects occur specifically on Mondays and Tuesdays in portfolio returns despite the influence of portfolio classification.

3.5. CONCLUSIONS

This chapter describes how portfolios are constructed with at least 5 years of daily data that are re-ordered periodically in order to avoid data-snooping biases highlighted recently by Lo & MacKinlay (1990c). By using four differing classifications we are able to examine the likely economic effects that each will impose on portfolio returns.

The market value classification enables the examination of a firm size effect [see Banz (1981) who found that smaller firm sized portfolios experienced higher than average risk adjusted returns] and closing price tests for a low-price effect [see Bhardwaj & Brooks (1992) who use price-sorted portfolios to test for US turn of the year effects]. The touch perhaps measures risk or illiquidity and may be inversely related to returns and turnover by volume measures information flows [see Merton (1987)].

The above descriptive statistics show the extent to which size and classification of a portfolio influences seasonal returns. Indeed, in support of much of the calendar anomalies literature, negative Monday effects are more prominent across small firm sized portfolios and small volume classified portfolios, as well as large touch sized portfolios.

Additionally, the results show that portfolio classification type does not influence day of the week return patterns per se. However, high returns are found in January, more for low priced portfolios and for the larger market value, touch and volume classifications. In subsequent chapters, we aim to use these portfolios to test for robustness in stock market anomalies on the LSE, in the light of evidence on security mispricing due to the touch and nonsynchronous trading.

4. TURN OF THE YEAR AND MONTHLY EFFECTS: THE INFLUENCE OF THE BID-ASK SPREAD

4.1. INTRODUCTION

The previous chapter described how portfolios were constructed and showed that generally, when using seasonal descriptive statistics, only portfolio size and *not* classification influences returns. This chapter uses these portfolios to examine, in the first instance, monthly and intra-monthly seasonal returns on the LSE. However, because investors' seasonal buying and selling behaviour is reflected in the touch, tests are also undertaken to see whether the touch can explain this seasonal behaviour in portfolio returns.

One prominent seasonal is the so-called January effect, which has been extensively researched in the US. Rozeff & Kinney (1976) were one of the first to find evidence of this monthly share price seasonality on the NYSE between 1904-1974. Some studies, especially in the US[29], argue that this calendar anomaly is attributed to investors' portfolio 'window dressing' involving portfolio re-balancing. This involves the selling of stocks before the calendar year end, which under the tax-selling hypothesis may be to limit any tax liability, and the subsequent buying back of 'cheap' stocks in the New Year.

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[29] See for example Ritter & Chopra (1989).

Investor behaviour hence may be consistent with a tax-loss selling hypothesis. The UK however, has a different tax and calendar year end, and as a result both a 'true' January calendar anomaly as well as a tax effect in April may exist. Therefore, due to the nature of the UK tax system, with its April 5th tax year end, analysis is undertaken to establish the prominence of a tax and/or January seasonality.

Since the evidence above implies that investors buy and sell around calendar turning points, more recent evidence has centred on a bid-ask spread explanation for seasonality - see for example, Keim (1989), Clark, McConnell & Singh (1992) and Bhardwaj & Brooks (1992) in the US. In order to test for the robustness of seasonality in the UK, the influence of the touch is considered. Equally weighted portfolios, re-ordered periodically, are used using 5 years of daily data. Daily dummy variable regression models were estimated using five different sizes of four classifications of portfolios in order to investigate a January effect, a tax-loss effect in March and April and the existence of other monthly seasonal patterns. In light of the evidence by Ariel (1987) highlighting differing investor buying and selling behaviour around the turn of the month, intra-monthly seasonality is investigated using the first, middle and last 5 days of each month.

The results establish the existence of a positive December effect (probably due to investors pre-empting positive January returns) as well as a January effect in the UK, but no tax effect. Furthermore, removing the effects of the touch, a measure of illiquidity causes these seasonal returns to disappear. Indeed, in further tests I investigate whether seasonal returns are driven by seasonality in the touch or whether the touch is determined by seasonal returns. The results show that the touch is seasonal rather than portfolio returns.

The remainder of this chapter is organised as follows: section 4.2 examines the theoretical and empirical explanations for January seasonality, including the small firm, risk, tax and spread effects. Section 4.3 describes the data used in this chapter, with section 4.4 reviewing the methodological issues used to establish seasonality and its explanations. Section 4.5 shows the empirical results with section 4.6 concluding.

4.2. TURN OF THE YEAR AND MONTHLY EFFECTS: THEORETICAL AND EMPIRICAL EXPLANATIONS

Tests for seasonality in stock returns were brought to the fore in 1976 by Rozeff and Kinney. They examined monthly rates of return on the NYSE over a 70 year period and found that average monthly returns in January were seven times higher than the average return in other months. Rozeff and Kinney also found that risk premiums estimated from a two parameter capital asset pricing model (CAPM), were higher in January compared to the other months.

Although Rozeff and Kinney did not try to explain seasonality, there are a number of hypotheses that may do so. One obvious one, cited above, is that seasonality may be a function of risk. In other words, high risk premiums in January are compensated for by high seasonal returns. Also, because December coincides with the end of the

US tax year, there may be a tax-selling explanation for seasonal returns around the turn of the year. However, of more immediate interest is Keim's (1983) finding that the average risk-adjusted return is large for small firms in January, when compared to the rest of the year.

4.2.1. *Small Firm Effect*

Earlier literature in the US on the firm size effect, reviewed by Schwert (1983), hypothesised various explanations for such a phenomenon. Banz (1981) suggests a negative association between firm size and stock returns even when controlling for risk using CAPM. Reinganum (1981) found a size effect after controlling for a price/earnings (P/E) effect. Later, Chan, Chen & Hsieh (1985) suggest that the bottom 5% of the NYSE companies (i.e. the smallest firms) had returns 12% higher than the top 5% of firms (i.e the largest firms). By risk adjusting these security returns using a multi-factor pricing equation, similar in concept to the arbitrage pricing theory (APT), the difference in returns narrowed to 2%. This latter result implies that the size effect is consistent with the risk-return trade-off and is therefore not an anomaly. In a similar study, Jegadeesh (1992) in the US found that even with a beta risk adjustment the size effect remained, but deemed other risk factors as a likely cause of this effect.

However, it was Keim's (1983) observation of seasonality in small firms that invoked a plethora of hypotheses as to why seasonality only seemed to occur in such firms. Keim found that a large part of risk adjusted returns of small firms occurred in the first week of January. More recently, Leong & Zaima (1991) using NYSE-AMEX stocks found evidence of a small firm effect. However, when Over-the-Counter (OTC) stocks are included in the analysis, this effect disappears. Nevertheless, examination of returns in January for small firms, reveals that they are large and positive in all the US markets considered, more so for the OTC stocks. Reinganum (1983) also confirmed that small firms exhibit large returns at the beginning of January, but showed that such seasonal returns were determined by investors' tax-loss selling. When these small firms were previous 'winners', i.e. in the previous year had experienced high price gains, their returns were lower on the first few days in January.

The "winner" and "loser" hypothesis was given most prominence by DeBondt & Thaler (1985, 1987) who analysed overreaction in the US markets. Their initial results suggest that firms that recently had a poor share performance and were prior losers, had a larger overreaction effect, when compared to prior winners. Most of this overreaction effect however, was realized in January. Overreaction of this nature seems much larger than the selling pressure exerted at the end of the previous year and so weakens any tax-loss selling explanation for such seasonality.

Later, DeBondt and Thaler in their 1987 study examined the seasonality question more closely. However, by their own admission they seemed unable to explain the January effect, indeed they commented on page 579: "Many puzzles remain, especially regarding the seasonality in excess returns. We have no satisfactory explanation for the January effect, rational or otherwise."

Despite this, DeBondt and Thaler's analysis of the winner and loser portfolio problem did reveal some interesting results. Losers' excess returns, especially in January, were negatively related to long- and short term past performance. Winner portfolios' excess returns in January were negatively related to excess returns from the prior December, perhaps due to tax effects. Additionally, they showed that the loser-winner effect is not related to CAPM beta risk measurements or a small firm effect, but rather to overreaction.

Zarowin (1990), using 50+ years of US data, replicated DeBondt and Thaler's work and found that neither risk nor seasonality alone can account for the results. In fact, losers outperform winners on a risk-adjusted basis over all months. When size is controlled for, losers outperform winners only in January. The paper shows that the tendency for losers to outperform winners is not due entirely to investor overreaction, but that losers are smaller sized firms than winners. When losers are compared to winners of equal size, returns are constant, and in periods when winners are smaller than losers, winners outperform losers.

Despite this attempt to show that an overreaction hypothesis explains January seasonality, especially for small firms, there is other evidence to explain seasonality. As we have already implied, the small firm effect theorised by Banz (1981) may coincide with some form of risk compensation. Indeed as is shown below, there is evidence to suggest that seasonality can also be explained by such a risk premium.

4.2.2. *Risk Premium Explanations for Seasonality*

So far the evidence suggests that small firms have higher risk-adjusted returns than larger firms, but not necessarily in January. In contradiction to this, Tinic & West (1984) show that the risk premiums using CAPM appeared very large in January when compared to other months. January seemed to be the only month that had a statistically significant positive risk-return relationship.

However, Rogalski & Tinic (1986) show that when using a CAPM framework that systematic and residual risk is higher in January for small firms. Rogalski and Tinic imply that returns need to be eight to nine times higher in January if they are to compensate for this increased risk. Clearly, there is a risk-return trade-off explanation for the January effect. Further work by Gultekin & Gultekin (1987), using a factor analysis approach in an APT framework, suggests that seasonality occurs in the risk premia. Also, the results suggest that the APT model can explain the risk premia of stock returns only in January, since when January is excluded from the data, the risk-return relationship breaks down.

Overall, this US evidence seems to support the hypothesis that January returns seasonality can be explained by seasonality in the risk premium. In recent studies however, more sophisticated tests have been undertaken to examine this relationship. Seyhun (1993) in the US, tests the hypothesis that January seasonality can be explained by omitted risk factors. To this end they use a stochastic dominance approach to test for this seasonal behaviour. Using stochastic dominance (SD) theory enables a test for the hypothesis that expected utility maximisers prefer small stocks in January. The SD approach has the advantage over asset pricing models in that it makes no assumption about the model of expected security returns, and has fewer assumptions about investors' utility functions.

Seyhun however, cites problems with the SD approach when used empirically. Here, realised returns might mis-estimate the dominance results since they do not provide consistent estimates of negative outliers in the population distribution of stock returns. Despite these problems, tests for SD in small firms on the NYSE suggest that SD is prominent in the first-order and so implies that omitted risk factors are not likely to explain the January seasonal.

In the UK, Demos, Sentana & Shah (1993) examine the risk-return structure on the LSE. Using a dynamic APT model they examine the conditional factor structure in January. By estimating all months of the year simultaneously, they ensure that the market factor is constant year round. Their results suggest, in contradiction to US evidence, that while January has a unique risk-return relationship, there is a positive and statistically significant relationship between systematic risk and returns in other months. Additionally, the APT shows that this January effect is not consistent across all assets.

Similarly, Clare, Psaradakis & Thomas (1994), examine the risk-return relationship for the UK stock market. In the first instance they find that the FTA All Share Index, which includes small as well as larger stocks, displays a significant deterministic pattern corresponding to seasonal behaviour in January. Additionally using five classifications of market value sorted portfolios, they confirm a small firm effect in January. Tests of the risk-return relationship using a generalised autoregressive heteroscedasticity in mean (GARCH-M) model, which measures volatility in the market, confirms that this proxy for risk does not provide a full explanation for seasonal returns.

While the results on risk explanations for January seasonal effects are mixed, especially in the UK, there are further non-asset pricing model explanations for seasonality in the market. Clearly, the establishment of the link between the small firm effect and seasonality opens up the possibility that selling by investors before calendar turning points, causing stock price falls could for example be due to tax-loss selling. Additionally, seasonality may coincide with the portfolio re-balancing hypothesis or even so-called portfolio 'window dressing,' all of which are explained below.

4.2.3. *The Tax-loss Selling Hypothesis*

Much of the evidence for the January seasonal anomaly has originated from the US where the tax year end coincides with the end of the calendar year. This evidence suggests that investors who are rational will, in order to maximise annual profits (or minimise losses), sell some of the constituent shares of their portfolios. This trading will occur in December for stocks that have had the greatest capital losses over the year and so are smaller in size. The result of this selling causes price falls in the first instance, however subsequently investors buy back these now smaller stocks in January (when prices generally look cheap). One can therefore hypothesise in the light of this evidence, that on average, returns will be lower in December and higher at the beginning of January[30].

One of the first to suggest that a tax-selling influence may contribute to seasonality was Givoly & Ovadia (1983), who examined NYSE monthly data. They found lower prices in December due to tax-loss selling, but found that returns rose in January especially in smaller firms. They perceived that the more precise the identification of tax-loss sellers, the stronger would be the tax explanation for US January seasonality.

Furthermore, Reinganum (1983) analysed the NYSE and AMEX markets over the period 1962-1980, and found a January effect with abnormally high returns especially in the first few trading days of the month. This appeared consistent with a tax-loss selling hypothesis. However, as we have said, tax-loss selling cannot explain the entire January seasonal since prior winners (i.e. small firms), are least likely to be sold for tax-loss purposes, as well as exhibit high January average returns.

In their international study of stock market seasonality, Gultekin & Gultekin (1983) find that the UK experiences a large April tax effect in addition to large returns in January. For all the other countries considered, apart from Australia, the tax year end coincides with the calendar year end. January returns are subsequently higher than for other months, but are not firm size dependent.

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[30] This seasonal behaviour may occur since investors might re-balance their portfolios in order to give the impression of good investment performance.

In contradiction to the all the studies mentioned above, Chan (1986), using CRSP file data between 1962-1983, suggested that optimal tax-loss selling does not predict that price pressure is associated with long-term losses. The January effect was found for both long and short-term losses and did not confirm or reject the existence of tax-motivated trading at the end of the year.

While a tax-loss hypothesis may be conducive with seasonality, in their recent study, Ritter & Chopra (1989) showed that, when using NYSE monthly returns between 1935 and 1986, January had negative market returns and small firm returns were positive, more so the higher the beta. This is consistent with a portfolio re-balancing hypothesis that implies investors sell stocks at the end of the year and buy back riskier stocks in January. This behaviour may be consistent with investors clearing their books in order to give an indication of their yearly investment performance, rather than with any tax motivated selling. Also as we have shown the tax-loss selling hypothesis and firm size effect appear to be connected to the extent that seasonals could be affected by the bid-ask spread.

4.2.4. *The January Seasonal - Bid-Ask Spread Explanations*

In accordance with the hypothesis above, Stoll & Whaley (1983) suggest that a firm size effect can be at least partially explained by the bid-ask spread in the US. This relationship however, may be more fundamental than that. Firstly, we can hypothesise that because smaller sized securities have a fewer number of shares in circulation they have less volume of trade in the market, and following Garbade (1982) and Demsetz (1968), there is therefore less public information about them. In the UK the touch may influence calendar anomalies as a result of mis-calculated returns caused by this buying and selling behaviour.

By assuming such an explanation, much of the evidence for seasonals may therefore be explainable through the microstructure in prices. For example, Bhardwaj & Brooks (1992), show that the January effect is primarily a low-share price effect and less so a market value effect[31]. Indeed, in the 1977-1986 period on the AMEX and NYSE markets, excess January returns were lower on low-price stocks than on high-price stocks. Since some informed traders have large before transaction costs, excess January returns on low-price stocks may be explained by higher transaction costs and the touch. This implies that the January anomaly is not likely to be exploitable by investors.

Contradictory evidence to these two studies is provided by Lamoureux & Sanger (1989). They found using the US NASDAQ index over the 1973-1985 period that quoted spreads are highly negatively correlated with firm size, but are not seasonal. Additionally, evidence against this seasonality-spread hypothesis has also centred on noise and tax-induced trading explanations. Firstly, Clark, McConnell & Singh (1992) using end of month bid-ask spread for 540 NYSE stocks in a cross-section over the period 1982-1987, refute the significance of a correlation between changes in spreads, at the turn of the year, and January stock returns; this seasonal anomaly may be due to "noise" in prices. In their recent US and Canadian study, Griffith & White (1993),

[31] This conjecture is examined later in this chapter when we use transaction price classified portfolios in tests for monthly and intra-monthly seasonality.

use intra-day data to examine tax-induced trading. While sell and buy trades occur at the bid in December and at the ask in January, respectively, this transaction behaviour is associated with a taxation hypothesis rather than any turn of the year effects.

4.2.5. *The Hypothesis of Monthly Seasonality on the LSE: An Overview*

What is evident from the conjecture and evidence above, despite the influence of bid-ask spread in the US and the touch in the UK, is that monthly seasonality on the LSE may be quite probable. Investors' actions at the turn of the calendar year and other monthly periods may mean that returns follow systematic trading patterns. Such actions may result in two scenarios. Firstly, turn of the year effects may occur because investors open a new 'investment book' and hence 'window dress' portfolios, especially at the start of a calendar year, in January and the tax year, in April. Secondly, as a consequence of these actions security prices and returns will fall due to selling before calendar turning points, and rise, due to the subsequent buying back of these (now small sized) stocks after the turning point.

In a further, more detailed analysis of returns, this time in intra-monthly periods, Ariel (1987) examined mean returns for US portfolios. Returns appeared seasonal only for days immediately before and during the first half of calendar months, and indistinguishable from zero for days during the last half of the month. This "intra-monthly effect" appeared independent of the January effect. In the UK, Cadsby & Ratner (1992) suggest that a turn of the month effect occurs on the last and first three days of the month. Such results justify a further intra-monthly investigation in UK.

Such seasonal behaviour may be more prevalent in smaller firms which at the end of the previous calendar period are more likely to have been over sold. However, due to the higher level risk and hence larger touch associated with smaller companies, investors who purchase small sized equities may appear to achieve higher than average returns. However, true abnormal returns may be much lower due to the influence of the touch.

This chapter aims to test the hypothesis that January and other monthly calendar effects do occur, but that their occurrence is explainable by the touch in security returns. Such returns may be overstated compared to actual returns especially on the days surround a calendar turning point. Therefore, a further hypothesis in the light of a partial microstructure explanation for longer run calendar seasonals, is that seasonal trading patterns, shown by movements in the touch may explain portfolio returns rather than seasonal returns explaining the touch.

4.3. METHODOLOGICAL ISSUES IN TESTING FOR DETERMINISTIC SEASONALITY

4.3.1. *Modelling Monthly and Intra-Monthly Seasonal Returns*

The descriptive statistics of portfolio returns shown in chapter 3, as well as the evidence above, point to the fact that monthly seasonality may be prominent on the LSE. However, a more formal method of examining seasonality is to fit a regression equation to the data described in section 3.3.1. Estimated coefficients under an OLS framework will show the influence seasonality has on returns, relative to the average return. Following the literature on daily and weekly calendar anomalies[32] dummy variable regression analysis may be more appropriate than standard OLS, since seasonality in the data may cause the assumptions underlying OLS[33] to be biased. Dummy variable analysis enables the effects of seasonality to be captured by the coefficients of the explanatory variables. The use of dummy variables, shown in (4.1), allows the intercept parameter to change through the year and enable us to distinguish between differing daily returns across the month.

$$D_i = \begin{cases} 0 \text{ if } i = 1,\ldots,T_1 \\ 1 \text{ if } i = T_1 + 1,\ldots,T \end{cases} \tag{4.1}$$

Here i is the number of daily returns and D_i is a dummy variable that varies across the month.

Given this, the following dummy variable regression in equation (4.2) can be used to model the effects of monthly seasonality on portfolio returns

$$R_{pt} = \delta_0 R_{p,t-1} + \sum_{i=1}^{12} \alpha_i D_i + \varepsilon_t \tag{4.2}$$

where R_{pt} are the returns on portfolio p in time t and $R_{p,t-1}$ are lagged portfolio returns. D_i is the dummy variable which takes the value of 1 in month i and zero otherwise.

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[32] See Board & Sutcliffe (1988) as an example.

[33] These are the assumptions we make about the residuals or measurement errors estimated from the least-squares estimators. The desirable properties of the residuals include mean zero; $\mu=0$, common variance; $Var(\mu)=\sigma^2$, independence; μ_i and μ_j are independent and independence of x_j the independent variable; that is x_j and μ_i are independent. Also, the errors are assumed to be normally distributed. See Maddala (1977), pp 74-103. Also, even with the use of dummy variable analysis these assumptions may still be violated.

When i=1 it is a January, and when i=2 it is a February and so on until i=12, when it is a December. A constant term is not needed since the monthly dummy variables already impose an intercept term. ε_t is the error or residual term where $\varepsilon_t \sim N(0,\sigma^2)$.

Under the assumption that monthly seasonality is prevalent on the LSE and following the observations of Ariel (1987) in the US, and Cadsby & Ratner (1992) in the UK, further investigation can be undertaken to determine what is driving monthly seasonality. Consequently, in order to test these observations, a dummy variable regression similar to the one in (4.2) can be estimated where each month is divided into intra-monthly periods, in this case into three 5 day periods. The first period is at the beginning of each month, the second is in the middle of each month and the third is at the end of each month. By examining intra-month seasonality, evidence may be gained as to whether returns fluctuate or are constant throughout the month. Intra-monthly effects can be modelled in the form of (4.3) below

$$R_{pt} = \alpha_0 + \delta_0 R_{p,t-1} + \sum_{i=1}^{12} \alpha_i D1_i + \sum_{i=1}^{12} \alpha_i D2_i + \sum_{i=1}^{12} \alpha_i D3_i + \varepsilon_t \qquad (4.3)$$

where D1 is a dummy variable that takes the value 1 on the first 5 days of month i and zero otherwise. D2 is a dummy variable that takes the value 1 on the middle 5 days of month i, zero otherwise and D3 is a dummy variable that takes the value 1 on the last 5 days of month i and zero otherwise. α_0 is a constant variable. Again when i = 1 it is a January, and when i = 2 a February and so on until i = 12, when it is a December. The other variables are as given previously. Specifying an intra-monthly model enables investors' specific buying and selling patterns in the few days around the turn of calendar periods to be more readily investigated.

4.3.2. *The Influence of the Touch on Monthly and Intra-Monthly Seasonals*

As we have already suggested, explanations for calendar anomalies include the influence of the touch. Seasonality hence may occur due to mispricing in returns around calendar turning points. This may be because periodic buying and selling of portfolios, for example at the end of a month, may cause the touch to widen and may explain seasonal returns.

As has been indicated, touch explanations for seasonal returns may be more prominent in smaller sized portfolios which are subject to more mispricing and inefficiency. Following US evidence on the spread from Roll (1984), mispricing in UK portfolios returns may increase the larger the touch. This implies that the touch may influence returns, especially in small firms at calendar turning points. Hence, because of the nature of the relationship between returns and the touch these parameters may 'interact'[34].

In order to account for this likely interaction, a dummy variable representing the touch on each day of the month can be included into the regression equation. This is the method used to test for the influence of the microstructure in monthly returns and is shown in (4.4) as follows

$$R_{pt} = \delta_0 R_{p,t-1} + \sum_{i=1}^{12} \alpha_i D_i + \sum_{i=1}^{12} \beta_i SP_p D_i + \varepsilon_t \qquad (4.4)$$

where SP_p is the daily touch for portfolio p and the other variables are as given

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[34] Judge, Hill, Griffiths, Lutkepohl & Lee (1988) show on page 426, that two variables interact when regressed together if their relationship causes the slope parameter of the model, as well as the intercept term, to change.

previously.

Intra-monthly seasonality can also be estimated in a similar way. The investment behaviour of investors will perhaps be more prominent in intra-monthly periods and therefore so will movements in the touch. Therefore, regressing interactive spread dummy variables simultaneously with their corresponding return dummies, initiates a test for a touch explanation of intra-monthly seasonality shown in (4.5).

$$
\begin{aligned}
R_{pt} = \alpha_0 + \delta_0 R_{p,t-1} &+ \sum_{i=1}^{12} \alpha_i D1_i + \sum_{i=1}^{12} \beta_i SP_p D1_i \\
&+ \sum_{i=1}^{12} \alpha_i D2_i + \sum_{i=1}^{12} \beta_i SP_p D2_i \\
&+ \sum_{i=1}^{12} \alpha_i D3_i + \sum_{i=1}^{12} \beta_i SP_p D3_i + \varepsilon_t
\end{aligned}
\tag{4.5}
$$

Here the variable SP_pD1_i represents the touch for portfolio p times a dummy variable that takes the value 1 on the first 5 days of month i and zero otherwise, SP_pD2_i is the touch for portfolio p times a dummy variable that takes the value 1 on the middle 5 days of month i and zero otherwise, SP_pD3_i is the touch for portfolio p times a dummy variable that takes the value 1 on the last 5 days of month i and zero otherwise. The other variables are given as previously.

The preceding section hypothesises the touch as a possible cause of monthly and intra-monthly seasonality in returns. However, the question remains as to what causes these seasonal effects. For example, does the level of the seasonal touch determine the size of portfolio returns or vice versa. This is the subject of the next section.

4.3.3. *Seasonal Touch Behaviour and Monthly and Intra-Monthly Returns*

Due to the nature of the relationship between the microstructure and returns, again the question of what causes these touch and return seasonal effects can be posed. One explanation is that the touch can be hypothesised as a possible cause of monthly and intra-monthly seasonality in returns. While the interaction between the touch and portfolio returns may show whether the touch influences seasonal return behaviour on the LSE, it does not give an explanation for this seasonality.

Since investors transacting behaviour is reflected in the touch, there is a possibility that portfolio returns could be driven by seasonality in the touch. For monthly seasonality this possibility can be tested using the regression given in (4.6) below

$$R_{pt} = \delta_0 R_{p,t-1} + \sum_{i=1}^{12} \alpha_i SP_p D_i + \varepsilon_t \tag{4.6}$$

and for intra-monthly seasonality

$$R_{pt} = \delta_0 R_{p,t-1} + \sum_{i=1}^{12} \alpha_i SP_p D1_i + \sum_{i=1}^{12} \alpha_i SP_p D2_i + \sum_{i=1}^{12} \alpha_i SP_p D3_i + \varepsilon_t \tag{4.7}$$

Additionally, there is a likelihood that the seasonal behaviour of investors is reflected in the returns rather than the touch. This is because buy and sell orders may determine the magnitude of seasonal returns. Therefore the following equation can be used to model the effects of the touch on monthly seasonality in returns

$$SP_{pt} = \sum_{i=1}^{12} \alpha_i R_p D_i + \varepsilon_t \tag{4.8}$$

where SP_{pt} is the daily touch of portfolio p in time t, R_p are returns on portfolio p. The other variables are given as previously.

For intra-monthly seasonal the following equation can be tested

$$SP_{pt} = \alpha_0 + \sum_{i=1}^{12} \alpha_i R_p D1_i + \sum_{i=1}^{12} \alpha_i R_p D2_i + \sum_{i=1}^{12} \alpha_i R_p D3_i + \varepsilon_t \qquad (4.9)$$

Here R_pD1_i represents a dummy variable times the returns on portfolio p in the first 5 days of month i. $R_{pt}D2_i$ is a dummy variable times the returns on portfolio p in the middle 5 days of month i. $R_{pt}D3_i$ is a dummy variable times the returns on portfolio p in the last 5 days of month i. The results from testing for monthly and intra-monthly seasonality as well as any seasonal spread explanations are shown below.

4.4. EMPIRICAL RESULTS

4.4.1. *Monthly Seasonality Results*

Table 4.1 below shows the monthly dummy variable regression results for portfolio returns estimated using the regression in equation (4.2). Firstly, lagged returns for each portfolio are highly significant (at the 1% level) and determine between 2.76% and 17.99% of current daily returns. Also lagged returns appear negatively related with firm size and turnover by volume classified portfolios. Also, all the portfolio classifications are characterised by occasionally significant (at the 10% level) January dummy variable coefficient labelled D_1 and December dummy variable labelled D_{12}.

The largest market value portfolio, has a significant May (D_5) and September (D_9) dummy variable. The latter variable is significant across the other classifications of portfolios apart from the volume classification which has a significant October (D_{10})

dummy variable, in the largest portfolio. Due to the volatile nature of daily data and the effects of investors periodically reappraising the constituents of their portfolios, a dummy variable, DUM is used to counter the effects of non-normality in the data caused by return outliers. The variable DUM corresponds to observation numbers 286, 288, 489, 532, 534, 598. The dates and effects that caused these outliers are explained below.

Observation numbers 286 and 288 correspond to October 17th and 19th 1989 respectively. These dates correspond to volatility in the market but no specific events. Observation number 489 corresponds to 7th August 1990 which marks the start of the Iraqi invasion of Kuwait and volatility and uncertainty in the world's financial and commodity markets. The observation numbers 532 and 534 correspond to the 5th and 9th October 1990. At this time rumours regarding the intentions of the Iraqis in the Gulf caused volatility in the market. Observation number 598 occurred on the 15th of January 1991 and coincided with the start of the air attack on Kuwait by the Allied forces. The markets reacted quite appreciably to this since the air strikes signalled the start of the war in the Gulf.

What is immediately obvious from the seasonal variables is that their coefficients are small (around 0.0015), if fairly significant across portfolios. These variables are quite constant across firm and portfolio size, as well as throughout the year. Overall, seasonality appears to be quite inconsistent across differing sizes of portfolios and therefore any conclusions about the strength of turn of the year seasonality appear weak. Additionally, there is no tax-selling seasonality at the end of March or stock

Table 4.1

Monthly Dummy Variable OLS Regression Model Results of Daily Returns Dependent upon Lagged Returns and Seasonal Dummy Variables for Equally Weighted Portfolios.

Market Value Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1719*** (0.0248)	0.1129*** (0.0240)	0.0876*** (0.0243)	0.0964*** (0.0255)	0.0369*** (0.0266)
D_1)		0.0014* (0.0009)		0.0013* (0.0008)	0.0018** (0.0008)
D_5					0.0017** (0.0009)
D_{12}	0.0016* (0.0009)				0.0015* (0.0008)
DUM	0.1011*** (0.0057)	0.1016*** (0.0047)	0.0978*** (0.0048)	0.1007*** (0.0062)	0.0998*** (0.0078)
	$R^2 = 0.227$ $\eta_1(1,1255) = 1.330$ $\eta_2(1,1255) = 0.001$ $\xi_3(2) = 8.609$ $\eta_4(1,1257) = 3.985$	$R^2 = 0.282$ $\eta_1(1,1255) = 6.153$ $\eta_2(1,1255) = 0.009$ $\xi_3(2) = 3.224$ $\eta_4(1,1257) = 4.689$	$R^2 = 0.255$ $\eta_1(1,1256) = 2.755$ $\eta_2(1,1256) = 1.519$ $\xi_3(2) = 3.479$ $\eta_4(1,1257) = 3.950$	$R^2 = 0.178$ $\eta_1(1,1255) = 0.524$ $\eta_2(1,1255) = 0.026$ $\xi_3(2) = 0.593$ $\eta_4(1,1257) = 2.605$	$R^2 = 0.116$ $\eta_1(1,1253) = 0.412$ $\eta_2(1,1253) = 0.187$ $\xi_3(2) = 3.642$ $\eta_4(1,1257) = 3.578$

Closing Price Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0825*** (0.0243)	0.0683*** (0.0258)	0.0846*** (0.0243)	0.1160*** (0.0257)	0.1578*** (0.0247)
D_1	0.0013* (0.0009)		0.0017* (0.0009)	0.0014* (0.0008)	
D_9		-0.0015* (0.0009)	-0.0018** (0.0009)		
D_{12}				0.0015* (0.0008)	
DUM	0.1014*** (0.0049)	0.1016*** (0.0066)	0.1019*** (0.0049)	0.1020*** (0.0066)	0.1009*** (0.0054)
	$R^2 = 0.258$ $\eta_1(1,1255) = 0.006$ $\eta_2(1,1255) = 0.074$ $\xi_3(2) = 0.957$ $\eta_4(1,1257) = 10.36$	$R^2 = 0.162$ $\eta_1(1,1255) = 0.259$ $\eta_2(1,1255) = 0.031$ $\xi_3(2) = 9.071$ $\eta_4(1,1257) = 2.656$	$R^2 = 0.261$ $\eta_1(1,1254) = 2.239$ $\eta_2(1,1254) = 0.077$ $\xi_3(2) = 9.318$ $\eta_4(1,1257) = 3.835$	$R^2 = 0.177$ $\eta_1(1,1254) = 1.457$ $\eta_2(1,1254) = 0.002$ $\xi_3(2) = 9.981$ $\eta_4(1,1257) = 2.393$	$R^2 = 0.231$ $\eta_1(1,1256) = 0.000$ $\eta_2(1,1256) = 0.067$ $\xi_3(2) = 16.27$ $\eta_4(1,1257) = 3.868$

Touch Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0475* (0.0252)	0.1289*** (0.0249)	0.1021*** (0.0250)	0.1246*** (0.0239)	0.1097*** (0.0254)
D_1	0.0015** (0.0008)		0.0015* (0.0008)		
D_9			-0.0014* (0.0009)		
D_{12}	0.0014* (0.0008)				
DUM	0.1017*** (0.0057)	0.1011*** (0.0055)	0.1019*** (0.0057)	0.1067*** (0.0047)	0.1097*** (0.0062)
	$R^2 = 0.204$	$R^2 = 0.217$	$R^2 = 0.214$	$R^2 = 0.275$	$R^2 = 0.184$
	$\eta_1(1,1254) = 0.292$	$\eta_1(1,1256) = 0.000$	$\eta_1(1,1254) = 0.265$	$\eta_1(1,1256) = 0.006$	$\eta_1(1,1256) = 0.414$
	$\eta_2(1,1254) = 0.021$	$\eta_2(1,1256) = 0.010$	$\eta_2(1,1254) = 0.181$	$\eta_2(1,1256) = 0.001$	$\eta_2(1,1256) = 0.014$
	$\xi_3(2) = 4.931$	$\xi_3(2) = 2.644$	$\xi_3(2) = 3.617$	$\xi_3(2) = 8.242$	$\xi_3(2) = 2.197$
	$\eta_4(1,1257) = 4.737$	$\eta_4(1,1257) = 3.386$	$\eta_4(1,1257) = 3.755$	$\eta_4(1,1257) = 5.420$	$\eta_4(1,1257) = 4.641$

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1799*** (0.0239)	0.0988*** (0.0245)	0.1082*** (0.0237)	0.0961*** (0.0249)	0.0276 (0.0255)
D_1		0.0015* (0.0008)		0.0015* (0.0009)	
D_{10}					0.0015* (0.0008)
D_{12}	0.0013* (0.0008)	0.0015* (0.0008)			
DUM	0.1011*** (0.0048)	0.1013*** (0.0051)	0.1012*** (0.0045)	0.0961*** (0.0249)	0.1021*** (0.0060)
	$R^2 = 0.281$	$R^2 = 0.247$	$R^2 = 0.292$	$R^2 = 0.216$	$R^2 = 0.181$
	$\eta_1(1,1255) = 0.002$	$\eta_1(1,1254) = 0.183$	$\eta_1(1,1256) = 0.051$	$\eta_1(1,1255) = 0.262$	$\eta_1(1,1255) = 0.023$
	$\eta_2(1,1255) = 0.076$	$\eta_2(1,1254) = 0.029$	$\eta_2(1,1256) = 0.010$	$\eta_2(1,1255) = 0.014$	$\eta_2(1,1255) = 0.002$
	$\xi_3(2) = 8.319$	$\xi_3(2) = 0.446$	$\xi_3(2) = 0.937$	$\xi_3(2) = 0.021$	$\xi_3(2) = 1.437$
	$\eta_4(1,1257) = 3.951$	$\eta_4(1,1257) = 5.498$	$\eta_4(1,1257) = 7.098$	$\eta_4(1,1257) = 4.832$	$\eta_4(1,1257) = 7.013$

Notes: Figures in parentheses are standard errors. R^2 is the adjusted R^2. ***, **, * t-statistic significant at 1%, 5% and 10% level.
η_1 is an F(,.,) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(,.,) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(,.,) distributed test for heteroscedasticity under the null of homoscedasticity.

purchases at the beginning of April. Hence, returns are more readily explained by lagged returns than by monthly seasonal factors in the market. Finally, the diagnostic tests overall confirm that the seasonal models are well specified.

As mentioned previously, monthly seasonality in returns may be at least partially explained by the percentage touch. Therefore, following our hypothesis of an 'interaction' between the touch and seasonal returns, the results in Table 4.2 are re-estimated with the effects of the touch removed. What is immediately striking about these results is that nearly all the previously significant seasonal dummy variables become insignificant when the effects of the touch are accounted for. In fact, after the effects of the touch have been removed, monthly seasonals remain on only seven occasions, and even then they are not highly significant.

Therefore, overall the results point to a microstructure explanation of monthly seasonality in the portfolio returns series across portfolio size and classification. Additionally lagged returns are still highly significant and explain the same proportion of daily returns. The diagnostic tests are again passed. The results that follow adopt a similar approach for tests of intra-monthly portfolio returns.

4.4.2. Intra-Monthly Seasonality Results

While the results in section 4.4.1 above show that monthly seasonality may be a function of the microstructure in prices, analysis of intra-monthly returns may reveal more about investor behaviour. In order to test this intra-monthly hypothesis of investor transacting behaviour the regressions in (4.3) and (4.4) are estimated.

Table 4.2

Monthly Dummy Variable OLS Regression Models Results of Returns Dependent upon Lagged Returns and Seasonal Dummy Variables for Equally Weighted Portfolios with Touch Effects Removed.

Market Value Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1719*** (0.0248)	0.1122*** (0.0240)	0.0876*** (0.0243)	0.0964*** (0.0255)	0.0363 (0.0266)
D_1		0.0029 (0.0024)		-0.0006 (0.0027)	0.0026 (0.0027)
D_5					0.0007 (0.0025)
D_{12}	0.0024 (0.0021)				0.0052* (0.0027)
DUM	0.1011*** (0.0057)	0.1016*** (0.0047)	0.0978*** (0.0048)	0.1007*** (0.0062)	0.0998*** (0.0078)
	$R^2 = 0.226$ $\eta_1(1,1254) = 1.263$ $\eta_2(1,1254) = 0.001$ $\xi_3(2) = 8.532$ $\eta_4(1,1257) = 3.984$	$R^2 = 0.281$ $\eta_1(1,1254) = 5.826$ $\eta_2(1,1254) = 0.010$ $\xi_3(2) = 3.488$ $\eta_4(1,1257) = 4.677$	$R^2 = 0.255$ $\eta_1(1,1256) = 2.755$ $\eta_2(1,1256) = 1.519$ $\xi_3(2) = 3.479$ $\eta_4(1,1257) = 3.950$	$R^2 = 0.178$ $\eta_1(1,1254) = 0.632$ $\eta_2(1,1254) = 0.025$ $\xi_3(2) = 0.543$ $\eta_4(1,1257) = 2.605$	$R^2 = 0.116$ $\eta_1(1,1250) = 0.382$ $\eta_2(1,1250) = 0.184$ $\xi_3(2) = 3.669$ $\eta_4(1,1257) = 3.549$

Closing Price Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0813*** (0.0243)	0.0692*** (0.0258)	0.0839*** (0.0243)	0.1154*** (0.0257)	0.1579*** (0.0247)
D_1	0.0044** (0.0022)		0.0014 (0.0025)	0.0033 (0.0024)	
D_9		-0.0046* (0.0025)	-0.0003 (0.0021)		
D_{12}				0.0029 (0.0025)	
DUM	0.1017*** (0.0049)	0.1006*** (0.0066)	0.1025*** (0.0050)	0.1020*** (0.0066)	0.1009*** (0.0054)
	$R^2 = 0.258$ $\eta_1(1,1254) = 0.014$ $\eta_2(1,1254) = 0.081$ $\xi_3(2) = 0.914$ $\eta_4(1,1257) = 10.23$	$R^2 = 0.162$ $\eta_1(1,1254) = 0.289$ $\eta_2(1,1254) = 0.016$ $\xi_3(2) = 8.675$ $\eta_4(1,1257) = 2.706$	$R^2 = 0.260$ $\eta_1(1,1252) = 2.116$ $\eta_2(1,1252) = 0.139$ $\xi_3(2) = 8.922$ $\eta_4(1,1257) = 3.683$	$R^2 = 0.176$ $\eta_1(1,1252) = 1.445$ $\eta_2(1,1252) = 0.029$ $\xi_3(2) = 10.61$ $\eta_4(1,1257) = 2.383$	$R^2 = 0.231$ $\eta_1(1,1256) = 0.002$ $\eta_2(1,1256) = 0.067$ $\xi_3(2) = 16.26$ $\eta_4(1,1257) = 3.868$

Table 4.2 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0473*	0.1289***	0.1002***	0.1245***	0.1097***
	(0.0252)	(0.0249)	(0.0250)	(0.0239)	(0.0254)
D_1	0.0026		0.0053**		
	(0.0024)		(0.0023)		
D_9			-0.0014		
			(0.0023)		
D_{12}	0.0024				
	(0.0026)				
DUM	0.1017***	0.1011***	0.1019***	0.1007***	0.1011***
	(0.0057)	(0.0055)	(0.0057)	(0.0047)	(0.0062)
	R^2 = 0.203	R^2 = 0.217	R^2 = 0.215	R^2 = 0.275	R^2 = 0.184
	$\eta_1(1,1252)$ = 0.296	$\eta_1(1,1256)$ = 0.002	$\eta_1(1,1252)$ = 0.123	$\eta_1(1,1256)$ = 0.006	$\eta_1(1,1256)$ = 0.414
	$\eta_2(1,1252)$ = 0.022	$\eta_2(1,1256)$ = 0.010	$\eta_2(1,1252)$ = 0.191	$\eta_2(1,1256)$ = 0.001	$\eta_2(1,1256)$ = 0.014
	$\xi_3(2)$ = 5.369	$\xi_3(2)$ = 2.644	$\xi_3(2)$ = 4.274	$\xi_3(2)$ = 8.242	$\xi_3(2)$ = 2.197
	$\eta_4(1,1257)$ = 4.716	$\eta_4(1,1257)$ = 3.386	$\eta_4(1,1257)$ = 3.696	$\eta_4(1,1257)$ = 5.420	$\eta_4(1,1257)$ = 4.641

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1799***	0.0977***	0.1082***	0.0957***	0.0276
	(0.0239)	(0.0245)	(0.0237)	(0.0249)	(0.0255)
D_1		0.0041*		0.0015*	
		(0.0024)		(0.0009)	
D_{10}					0.0043*
					(0.0023)
D_{12}	0.0019	0.0015			
	(0.0020)	(0.0023)			
DUM	0.1011***	0.1013***	0.1012***	0.0957***	0.1019***
	(0.0048)	(0.0051)	(0.0045)	(0.0249)	(0.0060)
	R^2 = 0.280	R^2 = 0.247	R^2 = 0.292	R^2 = 0.215	R^2 = 0.181
	$\eta_1(1,1254)$ = 0.039	$\eta_1(1,1252)$ = 0.099	$\eta_1(1,1256)$ = 0.051	$\eta_1(1,1254)$ = 0.189	$\eta_1(1,1254)$ = 0.083
	$\eta_2(1,1254)$ = 0.076	$\eta_2(1,1252)$ = 0.032	$\eta_2(1,1256)$ = 0.010	$\eta_2(1,1254)$ = 0.016	$\eta_2(1,1254)$ = 0.014
	$\xi_3(2)$ = 8.387	$\xi_3(2)$ = 0.576	$\xi_3(2)$ = 0.937	$\xi_3(2)$ = 0.036	$\xi_3(2)$ = 1.580
	$\eta_4(1,1257)$ = 3.947	$\eta_4(1,1257)$ = 5.442	$\eta_4(1,1257)$ = 7.098	$\eta_4(1,1257)$ = 4.809	$\eta_4(1,1257)$ = 6.976

Notes: Figures in parentheses are standard errors. R^2 is the adjusted R^2. ***, **, * t-statistic significant at 1%, 5% and 10% level.
η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

Table 4.3 below shows intra-monthly portfolio dummy variable regressions returns. Lagged returns (as consistent with the previous monthly regression results) are again highly significant (except for the largest market value and closing price classified portfolios). Again this implies that today's returns are dependent upon a proportion of yesterday's returns, in this case the proportion is between 1.67% and 17.25%.

Interestingly the results show the increased prominence of a statistically significant (at the 1% level) January dummy variable. The theory of seasonal investor behaviour implies that on average investors sell at the end of the previous calendar year and buy back cheap stock at the beginning of the new calendar year. However, the results indicate that the significant January dummy variable is $D3_1$, the variable representing the last 5 days of January. This suggests that investor buying in January occurs at the end of the month rather than at the beginning of the month.

Another prominent seasonal variable is $D3_{12}$ which is positive and corresponds to the last 5 days in December. However, even though this variable occurs frequently, it is only statistically significant at the 5% and 10% levels. An explanation for this significant positive seasonal variable is perhaps due to investors buying before the beginning of the new calendar year. Since investors may be rational, they could be anticipating the likely seasonal buying and selling behaviour in the market and clearly they would like to usurp any turn of the year effects.

Table 4.3

Intra-Monthly Dummy Variable OLS Regression Model Results of Daily Computed Returns Dependent upon Lagged Returns and Seasonal Dummy Variables for Differing Classifications of Equally Weighted Portfolios

Market Value Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1575*** (0.0248)	0.1064*** (0.0239)	0.0841*** (0.0243)	0.0865*** (0.0255)	0.0272 (0.0265)
$D3_1$	0.0051*** (0.0017)	0.0042*** (0.0018)		0.0042** (0.0018)	0.0064*** (0.0017)
$D1_3$	0.0044*** (0.0017)				
$D1_5$	0.0034** (0.0017)			0.0037** (0.018)	0.0037** (0.0017)
$D2_9$				-0.0036** (0.0018)	
$D2_{12}$	0.0046*** (0.0017)				
$D3_{12}$	0.0034** (0.0017)	0.0038** (0.0018)			0.0034** (0.0017)
CONSTANT	-0.0001 (0.0002)	0.0003 (0.0003)	0.0001 (0.0003)	0.0004 (0.0003)	0.0004 (0.0002)
DUM	0.1021*** (0.0057)	0.1016*** (0.0047)	0.0978*** (0.0048)	0.1052*** (0.0062)	0.0996*** (0.0077)
	$R^2 = 0.239$	$R^2 = 0.287$	$R^2 = 0.258$	$R^2 = 0.186$	$R^2 = 0.128$
	$\eta_1(1,1250) = 2.091$	$\eta_1(1,1252) = 4.609$	$\eta_1(1,1253) = 1.981$	$\eta_1(1,1252) = 0.332$	$\eta_1(1,1252) = 0.063$
	$\eta_2(1,1250) = 0.002$	$\eta_2(1,1252) = 0.000$	$\eta_2(1,1253) = 1.494$	$\eta_2(1,1252) = 0.012$	$\eta_2(1,1252) = 0.104$
	$\xi_3(2) = 8.794$	$\xi_3(2) = 1.841$	$\xi_3(2) = 2.938$	$\xi_3(2) = 0.690$	$\xi_3(2) = 3.297$
	$\eta_4(1,1257) = 4.149$	$\eta_4(1,1257) = 4.857$	$\eta_4(1,1257) = 4.033$	$\eta_4(1,1257) = 2.627$	$\eta_4(1,1257) = 3.693$

Table 4.3 cont.

Closing Price Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0781*** (0.0243)	0.0615*** (0.0258)	0.0787*** (0.0243)	0.1125*** (0.0257)	0.1481 (0.0247)
$D3_1$	0.0041** (0.0018)	0.0051*** (0.0019)	0.0058*** (0.0018)	0.0042*** (0.0017)	0.0045*** (0.0016)
$D1_5$					0.0037** (0.0016)
$D3_{12}$		0.0041** (0.0019)	0.0035* (0.0018)	0.0032* (0.0017)	
CONSTANT	0.0004 (0.0003)	0.0002 (0.0003)	0.0001 (0.0003)	0.0003 (0.0002)	0.0003 (0.0002)
DUM	0.1012*** (0.0049)	0.1006*** (0.0066)	0.1009*** (0.0049)	0.1005*** (0.0050)	0.1009*** (0.0054)
	$R^2 = 0.263$ $\eta_1(1,1254) = 0.001$ $\eta_2(1,1254) = 0.008$ $\xi_3(2) = 1.082$ $\eta_4(1,1257) = 10.47$	$R^2 = 0.167$ $\eta_1(1,1253) = 0.174$ $\eta_2(1,1253) = 0.005$ $\xi_3(2) = 6.282$ $\eta_4(1,1257) = 2.671$	$R^2 = 0.264$ $\eta_1(1,1253) = 2.229$ $\eta_2(1,1253) = 0.000$ $\xi_3(2) = 10.73$ $\eta_4(1,1257) = 3.838$	$R^2 = 0.184$ $\eta_1(1,1253) = 1.067$ $\eta_2(1,1253) = 0.002$ $\xi_3(2) = 10.37$ $\eta_4(1,1257) = 2.406$	$R^2 = 0.239$ $\eta_1(1,1253) = 0.065$ $\eta_2(1,1253) = 0.009$ $\xi_3(2) = 12.16$ $\eta_4(1,1257) = 3.962$

Table 4.3 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0379 (0.0252)	0.1211*** (0.0249)	0.0969*** (0.0251)	0.1189*** (0.0239)	0.1008*** (0.0254)
$D3_1$	0.0055*** (0.0017)	0.0050*** (0.0018)	0.0039** (0.0018)	0.0053*** (0.0017)	0.00396** (0.0019)
$D1_5$	0.0045*** (0.0017)		0.0040** (0.0018)		
$D3_5$					-0.0042** (0.0019)
$D3_{12}$		0.0038** (0.0018)			
CONSTANT	0.0003 (0.0002)	0.0003 (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)	0.0005 (0.0003)
DUM	0.1012*** (0.0049)	0.1010*** (0.0055)	0.1009*** (0.0057)	0.1006*** (0.0047)	0.1012*** (0.0061)
	$R^2 = 0.212$ $\eta_1(1,1253) = 0.072$ $\eta_2(1,1253) = 0.024$ $\xi_3(2) = 5.111$ $\eta_4(1,1257) = 4.702$	$R^2 = 0.225$ $\eta_1(1,1253) = 0.069$ $\eta_2(1,1253) = 0.005$ $\xi_3(2) = 1.293$ $\eta_4(1,1257) = 3.506$	$R^2 = 0.217$ $\eta_1(1,1253) = 0.303$ $\eta_2(1,1253) = 0.068$ $\xi_3(2) = 4.416$ $\eta_4(1,1257) = 3.681$	$R^2 = 0.280$ $\eta_1(1,1254) = 0.007$ $\eta_2(1,1254) = 0.019$ $\xi_3(2) = 6.828$ $\eta_4(1,1257) = 5.409$	$R^2 = 0.191$ $\eta_1(1,1253) = 0.644$ $\eta_2(1,1253) = 0.006$ $\xi_3(2) = 1.734$ $\eta_4(1,1257) = 4.644$

Table 4.3 cont.

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1725***	0.0962***	0.1042***	0.0917***	0.0167*
	(0.0239)	(0.0245)	(0.0237)	(0.0249)	(0.0253)
$D3_1$	0.0032**	0.0044***	0.0043***	0.0048***	0.0056***
	(0.0016)	(0.0017)	(0.0018)	(0.0019)	(0.0016)
$D1_5$	0.0036**				
	(0.0016)				
$D2_{12}$	0.0034**				
	(0.0016)				
CONSTANT	0.0002	0.0004	0.0000	0.0004	0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)
DUM	0.1008***	0.1013***	0.1012***	0.1006***	0.1012***
	(0.0048)	(0.0051)	(0.0045)	(0.0055)	(0.0060)
	$R^2 = 0.286$	$R^2 = 0.249$	$R^2 = 0.293$	$R^2 = 0.219$	$R^2 = 0.192$
	$\eta_1(1,1252) = 0.001$	$\eta_1(1,1254) = 0.102$	$\eta_1(1,1254) = 0.085$	$\eta_1(1,1254) = 0.184$	$\eta_1(1,1253) = 0.029$
	$\eta_2(1,1252) = 0.015$	$\eta_2(1,1254) = 0.000$	$\eta_2(1,1254) = 0.007$	$\eta_2(1,1254) = 0.002$	$\eta_2(1,1253) = 0.019$
	$\xi_3(2) = 8.463$	$\xi_3(2) = 0.381$	$\xi_3(2) = 0.930$	$\xi_3(2) = 0.002$	$\xi_3(2) = 1.911$
	$\eta_4(1,1257) = 4.090$	$\eta_4(1,1257) = 5.427$	$\eta_4(1,1257) = 7.131$	$\eta_4(1,1257) = 4.823$	$\eta_4(1,1257) = 6.465$

Notes:
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** t-statistic significant at the 1% level
** t-statistic significant at the 5% level
* t-statistic significant at the 10% level
η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

Additionally, the results show that there are other significant variables common to the portfolio return series including significant intra-monthly September, December, March, May and June seasonals. These variables appear infrequently and so carry little economic meaning. Again DUM corrects for the outliers described above in section 4.4.1. As the previous results for monthly effects imply, an explanation for the intra-monthly seasonality documented in Table 4.3 may lie with the influence the microstructure. Hence, in order to test this proposition a regression of the form in equation (4.4) is estimated to investigate whether intra-monthly seasonality can be explained by the microstructure in securities.

Table 4.4 shows the results of estimating intra-monthly dummy variable with the effects of the touch are removed. The results indicate that lagged returns are again highly significant and are very similar in values to those documented previously. Only market value, touch and volume classified portfolios of size 5, and the size 1 portfolio classified by the touch have insignificant $R_{p,t-1}$ variables, implying that stale prices are common to portfolios even with the effects of the microstructure are removed.

Even though analysis on an intra-monthly basis reveals more significant seasonal variables, again (as is consistent with the monthly results in Table 4.2) most of these variables become insignificant when the effects of the touch are removed. This suggests that intra-monthly seasonality can be on the whole explained by the microstructure in returns. The question therefore remains as to what is driving portfolio return seasonality: seasonality in returns or seasonality in the touch?

Table 4.4

Intra-Monthly Dummy Variable OLS Regression Model Results of Daily Computed Returns Dependent upon Lagged Returns and Seasonal Dummy Variables for Equally Weighted Portfolios with Touch Effects Removed

	Market Value Portfolio Classification				
Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1568***	0.1026***	0.0812***	0.0859***	0.0259
	(0.0249)	(0.0239)	(0.0243)	(0.0255)	(0.0265)
$D3_1$	0.0049*	0.0032		0.0017	0.0061**
	(0.0027)	(0.0029)		(0.0029)	(0.0028)
$D1_3$	0.0026		0.0001		
	(0.0028)		(0.0031)		
$D1_5$	0.0025			0.0031	0.0025
	(0.0028)			(0.0029)	(0.0028)
$D1_8$		0.0012			
		(0.0028)			
$D2_9$				-0.0037	
				(0.0029)	
$D2_{12}$	0.0064***				
	(0.0027)				
$D3_{12}$	0.0010	0.0001	-0.0017		0.0020
	(0.0027)	(0.0029)	(0.0031)		(0.0028)
CONSTANT	-0.0002	0.0003	0.0005	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
DUM	0.1012***	0.1016***	0.0979***	0.1015***	0.0996***
	(0.0056)	(0.0046)	(0.0047)	(0.0062)	(0.0077)
	$R^2 = 0.237$	$R^2 = 0.290$	$R^2 = 0.261$	$R^2 = 0.186$	$R^2 = 0.127$
	$\eta_1(1,1245) = 2.213$	$\eta_1(1,1249) = 4.716$	$\eta_1(1,1251) = 2.192$	$\eta_1(1,1249) = 0.641$	$\eta_1(1,1249) = 0.152$
	$\eta_2(1,1245) = 0.002$	$\eta_2(1,1249) = 0.005$	$\eta_2(1,1251) = 1.549$	$\eta_2(1,1249) = 0.012$	$\eta_2(1,1249) = 0.111$
	$\xi_3(2) = 9.464$	$\xi_3(2) = 1.859$	$\xi_3(2) = 2.968$	$\xi_3(2) = 0.653$	$\xi_3(2) = 3.231$
	$\eta_4(1,1257) = 4.098$	$\eta_4(1,1257) = 4.865$	$\eta_4(1,1257) = 3.944$	$\eta_4(1,1257) = 2.625$	$\eta_4(1,1257) = 3.671$

Table 4.4 cont.

Closing Price Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0782***	0.0586**	0.0796***	0.1137***	0.1465***
	(0.0243)	(0.0259)	(0.0243)	(0.0258)	(0.0254)
$D3_1$	0.0044*	0.0034	0.0055*	0.0037	0.0041
	(0.0027)	(0.0028)	(0.0029)	(0.0028)	(0.0029)
$D1_5$	0.0034		0.0032		
	(0.0027)		(0.0029)		
$D3_6$					-0.0014
					(0.0030)
$D3_{12}$		-0.0003			
		(0.0029)			
CONSTANT	0.0003	0.0003	0.0002	0.0002	0.0005
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
DUM	0.1016***	0.1010***	0.1009***	0.1006***	0.1012***
	(0.0057)	(0.0055)	(0.0057)	(0.0047)	(0.0061)
	$R^2 = 0.211$	$R^2 = 0.225$	$R^2 = 0.216$	$R^2 = 0.280$	$R^2 = 0.190$
	$\eta_1(1,1251) = 0.168$	$\eta_1(1,1251) = 0.017$	$\eta_1(1,1253) = 0.243$	$\eta_1(1,1253) = 0.000$	$\eta_1(1,1251) = 0.702$
	$\eta_2(1,1251) = 0.003$	$\eta_2(1,1251) = 0.004$	$\eta_2(1,1253) = 0.064$	$\eta_2(1,1253) = 0.019$	$\eta_2(1,1251) = 0.006$
	$\xi_3(2) = 4.991$	$\xi_3(2) = 1.041$	$\xi_3(2) = 4.458$	$\xi_3(2) = 6.562$	$\xi_3(2) = 1.777$
	$\eta_4(1,1257) = 4.689$	$\eta_4(1,1257) = 3.488$	$\eta_4(1,1257) = 3.672$	$\eta_4(1,1257) = 5.411$	$\eta_4(1,1257) = 4.635$

Table 4.4 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0371 (0.0252)	0.1188*** (0.0249)	0.0996*** (0.0251)	0.1179*** (0.0239)	0.0992*** (0.0247)
$D3_1$	0.0053* (0.0028)	0.0055* (0.0032)	0.0049* (0.0029)	0.0034 (0.0027)	0.0025 (0.0025)
$D1_5$					0.0024 (0.0025)
$D3_{12}$		-0.0011 (0.0032)			
CONSTANT	0.0004 (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)	0.0004 (0.0002)	0.0002 (0.0002)
DUM	0.1014*** (0.0049)	0.1007*** (0.0065)	0.1008*** (0.0049)	0.1018*** (0.0066)	0.1009*** (0.0054)
	$R^2 = 0.261$ $\eta_1(1,1253) = 0.003$ $\eta_2(1,1253) = 0.008$ $\xi_3(2) = 1.080$ $\eta_4(1,1257) = 10.42$	$R^2 = 0.168$ $\eta_1(1,1251) = 0.136$ $\eta_2(1,1251) = 0.006$ $\xi_3(2) = 5.998$ $\eta_4(1,1257) = 2.604$	$R^2 = 0.263$ $\eta_1(1,1253) = 2.697$ $\eta_2(1,1253) = 0.008$ $\xi_3(2) = 11.47$ $\eta_4(1,1257) = 3.824$	$R^2 = 0.178$ $\eta_1(1,1253) = 1.501$ $\eta_2(1,1253) = 0.004$ $\xi_3(2) = 10.85$ $\eta_4(1,1257) = 2.379$	$R^2 = 0.239$ $\eta_1(1,1251) = 0.001$ $\eta_2(1,1251) = 0.009$ $\xi_3(2) = 12.01$ $\eta_4(1,1257) = 3.928$

Table 4.4 cont.

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1733***	0.0962***	0.1042***	0.0916***	0.0162
	(0.0239)	(0.0245)	(0.0237)	(0.0249)	(0.0255)
$D3_1$	0.0022	0.0039	0.0049*	0.0039	0.0052*
	(0.0024)	(0.0027)	(0.0029)	(0.0031)	(0.0027)
$D1_5$	0.0026				
	(0.0026)				
$D2_{12}$	0.0059**				
	(0.0026)				
CONSTANT	0.0002	0.0004	0.0007	0.0004	0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)
DUM	0.1008***	0.1013***	0.1012***	0.1007***	0.1012***
	(0.0048)	(0.0051)	(0.0046)	(0.0055)	(0.0060)
	R^2 = 0.285	R^2 = 0.249	R^2 = 0.293	R^2 = 0.219	R^2 = 0.191
	$\eta_1(1,1249)$ = 0.004	$\eta_1(1,1253)$ = 0.131	$\eta_1(1,1253)$ = 0.106	$\eta_1(1,1253)$ = 0.255	$\eta_1(1,1251)$ = 0.014
	$\eta_2(1,1249)$ = 0.015	$\eta_2(1,1253)$ = 0.000	$\eta_2(1,1253)$ = 0.007	$\eta_2(1,1253)$ = 0.002	$\eta_2(1,1251)$ = 0.022
	$\xi_3(2)$ = 8.879	$\xi_3(2)$ = 0.365	$\xi_3(2)$ = 0.922	$\xi_3(2)$ = 0.004	$\xi_3(2)$ = 1.919
	$\eta_4(1,1257)$ = 4.082	$\eta_4(1,1257)$ = 5.436	$\eta_4(1,1257)$ = 7.114	$\eta_4(1,1257)$ = 4.832	$\eta_4(1,1257)$ = 6.392

Notes:
Figures in parentheses are standard errors. R^2 is the adjusted R^2.
*** t-statistic significant at the 1% level
** t-statistic significant at the 5% level
* t-statistic significant at the 10% level
η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

Due to the prominence of intra-monthly seasonality shown in the Table 4.3, we test this question by examining both intra-monthly touch and returns behaviour.

4.4.3. *Test Results of Seasonal Touch Behaviour and Intra-Monthly Returns*

Table 4.5 shows the results of tests for intra-monthly touch seasonality examined using equation (4.7) for the seasonal variables that are significant in Table 4.3. Again, DUM corrects for outliers in the data caused by the events highlighted in section 4.4.1. The results indicate that lagged returns are statistically significant for all but the largest portfolios, and are similar in value to previous results[35]. Additionally, intra-monthly variables corresponding to the touch are prominent for the last 5 days in January across most of the portfolios (SP_pD3_1). The last 5 days of December (SP_pD3_{12}) experience touch seasonality, but mainly in the smallest sized portfolios (1,2 and 3), and for all types of portfolio apart from the volume classifications. Other seasonal variables occur infrequently across the portfolios.

So far these results suggest that it is seasonality in the microstructure that is driving returns seasonality at the end of the calendar month in December and January. However, from the results in Table 4.6 when the independent variable becomes the touch and the dependent variables are seasonal return variables, portfolio return seasonality disappears. Therefore seasonality reflects investors transacting behaviour at the end of December and January which is reflected directly in the touch rather than in portfolio returns, which are hence *not* seasonal.

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[35] However, due to the inverse relationship between the 'touch' and firm size, it is the smallest sized portfolio classified by the 'touch', that has insignificant lagged returns.

Table 4.5

Intra-Monthly Dummy Variable OLS Regression Model Results of Daily Computed Returns Dependent upon Lagged Returns and Seasonal Touch Dummy Variables for Differing Classifications of Equally Weighted Portfolios

Market Value Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1579*** (0.0249)	0.1074*** (0.0239)	0.0841*** (0.0243)	0.0875*** (0.0255)	0.0264 (0.0266)
SP_pD3_1	0.2218** (0.0960)	0.3136** (0.1480)		0.4714*** (0.1907)	0.7781*** (0.2584)
SP_pD1_3	0.2882** (0.1188)				
SP_pD1_5	0.2133 (0.1232)			0.3629 (0.2062)	0.5467** (0.2688)
SP_pD2_9				-0.2936*** (0.1892)	
SP_pD2_{12}	0.1448 (0.0965)				
SP_pD3_{12}	0.2068** (0.0933)	0.3642*** (0.1339)			0.4687 (0.2348)
CONSTANT	-0.0001 (0.0002)	0.0002 (0.0003)	0.0001 (0.0003)	0.0004 (0.0003)	0.0004 (0.0002)
DUM	0.1012*** (0.0057)	0.1016*** (0.0047)	0.0978*** (0.0048)	0.1010*** (0.0062)	0.0996*** (0.0077)
	$R^2 = 0.234$ $\eta_1(1,1250) = 1.572$ $\eta_2(1,1250) = 0.000$ $\xi_3(2) = 9.459$ $\eta_4(1,1257) = 3.999$	$R^2 = 0.287$ $\eta_1(1,1252) = 5.398$ $\eta_2(1,1252) = 0.000$ $\xi_3(2) = 2.435$ $\eta_4(1,1257) = 4.767$	$R^2 = 0.258$ $\eta_1(1,1253) = 1.981$ $\eta_2(1,1253) = 1.494$ $\xi_3(2) = 2.938$ $\eta_4(1,1257) = 4.033$	$R^2 = 0.185$ $\eta_1(1,1252) = 0.641$ $\eta_2(1,1252) = 0.055$ $\xi_3(2) = 0.756$ $\eta_4(1,1257) = 2.603$	$R^2 = 0.125$ $\eta_1(1,1252) = 0.385$ $\eta_2(1,1252) = 0.093$ $\xi_3(2) = 3.090$ $\eta_4(1,1257) = 3.651$

Table 4.5 cont.

Closing Price Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0796*** (0.0243)	0.0602** (0.0258)	0.0785*** (0.0243)	0.1116*** (0.0257)	0.1468 (0.0247)
SP_pD3_1	0.1706 (0.1220)	0.3328** (0.1717)	0.4666*** (0.1719)	0.3475** (0.1614)	0.3942*** (0.1404)
SP_pD1_5					0.3593** (0.1655)
SP_pD3_{12}		0.4526*** (0.1597)	0.3468* (0.1513)	0.3544** (0.1542)	
CONSTANT	0.0005 (0.0003)	0.0002 (0.0003)	0.0001 (0.0003)	0.0003 (0.0002)	0.0003 (0.0002)
DUM	0.1009*** (0.0049)	0.1007*** (0.0066)	0.1009*** (0.0049)	0.1019*** (0.0066)	0.1009*** (0.0054)
	$R^2 = 0.259$ $\eta_1(1,1254) = 0.019$ $\eta_2(1,1254) = 0.003$ $\xi_3(2) = 0.981$ $\eta_4(1,1257) = 10.43$	$R^2 = 0.168$ $\eta_1(1,1253) = 0.358$ $\eta_2(1,1253) = 0.005$ $\xi_3(2) = 6.168$ $\eta_4(1,1257) = 2.602$	$R^2 = 0.264$ $\eta_1(1,1253) = 2.411$ $\eta_2(1,1253) = 0.000$ $\xi_3(2) = 10.79$ $\eta_4(1,1257) = 3.836$	$R^2 = 0.181$ $\eta_1(1,1253) = 1.617$ $\eta_2(1,1253) = 0.002$ $\xi_3(2) = 10.42$ $\eta_4(1,1257) = 2.400$	$R^2 = 0.239$ $\eta_1(1,1253) = 0.005$ $\eta_2(1,1253) = 0.006$ $\xi_3(2) = 12.75$ $\eta_4(1,1257) = 3.869$

Table 4.5 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.0386 (0.0252)	0.1189*** (0.0249)	0.0979*** (0.0251)	0.1183*** (0.0240)	0.1009*** (0.0254)
SP_pD3_1	0.6266*** (0.2166)	0.4549*** (0.1768)	0.1840 (0.1551)	0.3767*** (0.1388)	0.1884 (0.1160)
SP_pD1_5	0.5193*** (0.2160)		0.3344 (0.1743)		
SP_pD3_6					-0.3247*** (0.1296)
SP_pD3_{12}		0.4152*** (0.1531)			
CONSTANT	0.0003 (0.0002)	0.0003 (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)	0.0005 (0.0003)
DUM	0.1016*** (0.0057)	0.1010*** (0.0055)	0.1009*** (0.0057)	0.1006*** (0.0047)	0.1012*** (0.0061)
	$R^2 = 0.210$ $\eta_1(1,1253) = 0.358$ $\eta_2(1,1253) = 0.001$ $\xi_3(2) = 4.985$ $\eta_4(1,1257) = 4.638$	$R^2 = 0.225$ $\eta_1(1,1253) = 0.001$ $\eta_2(1,1253) = 0.001$ $\xi_3(2) = 1.198$ $\eta_4(1,1257) = 3.475$	$R^2 = 0.214$ $\eta_1(1,1253) = 0.471$ $\eta_2(1,1253) = 0.057$ $\xi_3(2) = 4.809$ $\eta_4(1,1257) = 3.660$	$R^2 = 0.279$ $\eta_1(1,1254) = 0.007$ $\eta_2(1,1254) = 0.023$ $\xi_3(2) = 5.379$ $\eta_4(1,1257) = 5.409$	$R^2 = 0.191$ $\eta_1(1,1253) = 0.498$ $\eta_2(1,1253) = 0.008$ $\xi_3(2) = 1.681$ $\eta_4(1,1257) = 4.621$

Table 4.5 cont.

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	Largest
$R_{p,t-1}$	0.1726*** (0.0240)	0.0975*** (0.0245)	0.1055*** (0.0237)	0.0927*** (0.0249)	0.0152 (0.0255)
SP_pD3_1	0.2238 (0.1238)	0.2921*** (0.1345)	0.2912*** (0.1759)	0.2806** (0.1325)	0.6015*** (0.2201)
SP_pD1_5	0.2817** (0.1400)				
SP_pD2_{12}	0.0922 (0.1159)				
CONSTANT	0.0002 (0.0002)	0.0004 (0.0002)	0.0001 (0.0003)	0.0004 (0.0003)	0.0005 (0.0002)
DUM	0.1009*** (0.0048)	0.1013*** (0.0051)	0.1012*** (0.0045)	0.1006*** (0.0055)	0.1010*** (0.0060)
	$R^2 = 0.283$	$R^2 = 0.249$	$R^2 = 0.292$	$R^2 = 0.219$	$R^2 = 0.189$
	$\eta_1(1,1252) = 0.003$	$\eta_1(1,1254) = 0.258$	$\eta_1(1,1254) = 0.043$	$\eta_1(1,1254) = 0.413$	$\eta_1(1,1253) = 0.006$
	$\eta_2(1,1252) = 0.011$	$\eta_2(1,1254) = 0.000$	$\eta_2(1,1254) = 0.005$	$\eta_2(1,1254) = 0.001$	$\eta_2(1,1253) = 0.020$
	$\xi_3(2) = 8.395$	$\xi_3(2) = 0.394$	$\xi_3(2) = 1.062$	$\xi_3(2) = 0.001$	$\xi_3(2) = 1.962$
	$\eta_4(1,1257) = 4.034$	$\eta_4(1,1257) = 5.418$	$\eta_4(1,1257) = 7.101$	$\eta_4(1,1257) = 4.815$	$\eta_4(1,1257) = 6.490$

Notes:
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** t-statistic significant at the 1% level
** t-statistic significant at the 5% level
* t-statistic significant at the 10% level
η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

Table 4.6

Intra-Monthly Dummy Variable OLS Regression Model Results of the Daily Computed Touch Dependent upon Seasonal Return Dummy Variables for Differing Classifications of Equally Weighted Portfolios

Market Value Portfolio Classification

Size	Smallest	2	3	4	Largest
R_pD3_1	0.0084	-0.0578		0.0025	0.0004
	(0.0856)	(0.0579)		(0.0277)	(0.0201)
R_pD1_3	-0.1157				
	(0.0966)				
R_pD1_5	0.0181			-0.0142	-0.0011
	(0.1029)			(0.0327)	(0.0248)
R_pD2_9				0.0288	
				(0.0194)	
R_pD2_{12}	0.2138**				
	(0.1010)				
R_pD3_{12}	0.0695	0.0255			0.0235
	(0.1061)	(0.0559)			(0.0221)
CONSTANT	0.0155***	0.0128***	0.0116***	0.0092***	0.0065***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0000)

Closing Price Portfolio Classification

Size	Smallest	2	3	4	Largest
R_pD3_1	-0.0228	-0.0279	-0.0058	0.0152	0.0177
	(0.0689)	(0.0444)	(0.0452)	(0.0414)	(0.0500)
R_pD1_5					0.0323
					(0.0647)
R_pD3_{12}		0.0474	0.0575	0.0409	
		(0.0462)	(0.0489)	(0.0458)	
CONSTANT	0.0134***	0.0117***	0.0108***	0.0098***	0.0099***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Table 4.6 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	Largest
R_pD3_1	-0.0174 (0.0319)	-0.0165 (0.0501)	-0.0346 (0.0517)	-0.0299 (0.0519)	-0.0159 (0.0558)
R_pD1_5	0.0319 (0.0376)		-0.0018 (0.0675)		
R_pD1_6					-0.0889 (0.0696)
R_pD3_{12}		0.0466 (0.0475)			
CONSTANT	0.0077*** (0.0001)	0.0100*** (0.0001)	0.0109*** (0.0001)	0.0122*** (0.0001)	0.0148*** (0.0001)

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	Largest
R_pD3_1	0.0002 (0.0007)	0.0069 (0.0464)	-0.0649 (0.0555)	0.0249 (0.0553)	-0.0271 (0.0247)
R_pD1_5	-0.0089 (0.0828)				
R_pD2_{12}	0.0876 (0.0806)				
CONSTANT	0.0123*** (0.0001)	0.0112*** (0.0001)	0.0117*** (0.0001)	0.0126*** (0.0001)	0.0077*** (0.0001)

Notes:
Figures in parentheses are standard errors.
*** t-statistic significant at the 1% level
** t-statistic significant at the 5% level

4.6. CONCLUSIONS

Evidence from the US suggests that seasonality in the form of the so-called January effect is prominent in securities and index returns series. Explanations for this predictable effect have centred on a firm size effect [Keim (1983], risk premium explanations [Rogalski & Tinic (1986)], a tax-effect [Givoly & Ovadia (1983)], a so-called portfolio re-balancing hypothesis [Ritter & Chopra (1989)], and the influence of the bid-ask spread in returns [Keim (1989) and Bhardwaj & Brooks (1992)].

Consequently, the US January effect may be determined by investors' buying and selling behaviour around the turn of the calendar year. Investors may be adjusting portfolios, cashing in profits and closing investment books at this time. Additionally, they also may simultaneously be transacting in securities in order to minimise their tax liability.

While this evidence examines seasonality in the US, calendar anomalies in the UK may occur in a slightly different fashion. Whereas in the US, the tax and calendar year end coincide, the UK has its tax year end at the beginning of April. However, because of this differing tax year end, a UK tax-effect may occur separately from a January effect. In order to test these two specific effects as well as monthly effects in general, differing sizes and periodically re-ordered classifications of portfolios were constructed using 6 years of daily data.

To examine the seasonality question, dummy variable regressions were estimated. The results indicate that monthly seasonality in January and December is present, though not prominent in portfolio returns. These positive significant seasonals occur irregularly across differing sizes and classifications of portfolios. Despite this, in January investors on average buy securities. Significant positive December seasonals imply that investors are trying to usurp any US led tax-loss selling or portfolio re-balancing at the end of the calendar year by buying securities in December. This contradicts the hypothesis of investors selling securities at the end of the calendar year in order to close investment books and then buy back cheap, small sized securities in January, thereby inducing positive returns in the New Year.

Due to the far from conclusive monthly seasonal effects, further analysis of the seasonality question was undertaken by examining investors' buying and selling behaviour in greater detail around calendar turning points. Following the observations of Ariel (1987) shorter frequency intra-monthly seasonality was examined. The results suggest that seasonality is fairly prominent at the end of December, and in contradiction to much of the evidence, very prominent at the end of January. This seems to verify investor behaviour found for the monthly data. However, in January investors seem to buy at the end of the month rather than just after the turn of the year.

In addition, there seem to be no significant variable corresponding to a tax effect around the end of March or the beginning of April. This suggests that the January effect is a true calendar anomaly rather than a UK tax motivated seasonal. However, due to the international nature of the UK stock market, and because it operates for part of the day in the same time zone as the US markets, the January effect may occur as a result of a US led January effect, even though the intra-monthly anomaly seems to occur at the end of January.

The results highlighted thus far, and to a greater extent in the earlier financial literature on seasonality, fails to recognise the influence that the microstructure has on returns. The microstructure in prices may intuitively help to explain calendar anomalies since the touch more readily reflects investors' transaction behaviour in the market around calendar turning points. The results confirm this hypothesis, since when the effects of the touch are removed, monthly and intra-monthly seasonality is no longer prevalent on the UK stock exchange.

Furthermore, seasonality in the market appears to be explained by seasonality in the touch rather than seasonality in portfolio returns. This implies that calendar anomalies occur due to mispricing in securities. Buying and selling by investors, while causing movements in returns, may also cause changes in the size of the touch. This microstructure explanation may be the cause of monthly as well as intra-monthly seasonality on the UK stock market.

5. DAY OF THE WEEK AND SETTLEMENT EFFECTS ON THE LSE: THE INFLUENCE OF THE BID-ASK SPREAD

5.1. INTRODUCTION

Similar to the longer run seasonalities examined in the previous chapter, short run calendar anomalies in security returns have attracted the increasing attention of researchers in financial economics. One such anomaly is the so-called weekend effect. French (1980) and Rogalski (1984) in the US, amongst others, found positive security returns on a Friday and negative returns on a Monday. Furthermore, Keim & Stambaugh (1984) found that the weekend effect exists across differing sized portfolios on the two main US stock markets. Also, they found that returns rise during the week and that Friday returns are strongly correlated with firm size[36].

Much of the evidence above suggests that the weekend is characterised by a non-trading effect which may occur due to investors closing their books on a Friday, and selling securities to avoid any risk associated with the non-trading period of the weekend. This effect may occur due to the inability of investors to act upon the release of information until the start of business on a Monday.

[36] This weekend effect occurs even when using prices devoid of biases associated with the bid-ask spread which could be as large as any daily return.

For the UK, Jaffe & Westerfield (1985), Board & Sutcliffe (1988) and Condoyanni, O'Hanlon & Ward (1987) found that the weekend effect may be influenced by the settlement system or two-week 'account' system operating in the LSE[37]. Under the settlement system rules, investors buying on the first day of the account (a Monday), pay for their securities on the middle Monday of the subsequent settlement period exactly 21 days later[38]. However, transactions made on the last day of the account period (a Friday), again will settle on the middle Monday of the subsequent settlement period, in this case only 10 days later.

Therefore, returns may be higher, on average, on the first Monday of each account period since investors will enjoy an extra 11-day 'interest free holiday' when compared to investors transacting at the end of the settlement period.[39] Similarly, one would expect that the account settling up day (the middle Monday) will be characterised by negative returns due to investors settling up their previous account by selling in the market in order to pay for their transactions.

Additionally, due to the ensuing non-trading weekend period returns at the end of a week may be characterised by uncertainty and so subject to more noise [see Black (1986)]. Such mispricing in security returns (due to noise) may be dependent on the

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[37] Additionally, Choy & O'Hanlon (1989) and Theobald & Price (1984) attribute a settlement effect to institutional influences operating in the market where larger traded securities are more likely to experience this type of calendar anomaly.

[38] The system is generally characterised by 24 dealing periods per year of which 20 are two weeks long and 4 are three weeks long.

[39] Theobald & Price (1984) were one of the first to document this hypothesis.

influence of microstructure on prices since the bid-ask spread may be more volatile than underlying prices. Indeed, more recent evidence from Keim (1989) and Porter (1992) in the US suggests that the weekend effect may be a function of the magnitude of the bid-ask spread. Therefore, short run calendar anomalies like longer run calendar anomalies in the UK may be explained by the touch in returns.

Using different sized equally weighted portfolios constructed from 5 years of daily data, a test for the existence of short run calendar anomalies on the LSE is undertaken. In contradiction to many US studies, the results suggest when using OLS dummy variable analysis, that a day of the week effect is *not* prominent on the LSE. Tests for a settlement effect additionally analyse returns on the Fridays before settlement Mondays and the Fridays before 'account' Mondays. Interestingly, the results confirm a settlement effect, as well as a seasonal Friday effect.[40]

Consistent with the investigation into monthly and turn of the year seasonality, day of the week and settlement effects are examined when the effects of the microstructure are removed. Returns devoid of the influence of the touch do not experience any significant daily or settlement seasonality. As shown previously, in order to determine what is driving the seasonal returns process, seasonality is estimated in both the touch and returns. The results suggest that seasonality is prominent in the touch rather than portfolio returns. The remainder of this chapter is organised as follows: section 5.2 reviews issues on day of the week and settlement effects, section 5.3 examines models of daily seasonality and section 5.4 describes the data. Section 5.5 reviews the

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[40] This is on the last Friday of the settlement period.

empirical results with section 5.6 concluding.

5.2. ISSUES ON DAY OF THE WEEK AND SETTLEMENT EFFECTS

5.2.1. *Day of the Week and Settlement Effect Explanations of Portfolio Returns*

The day of the week effect has been a well documented area in tests for predictable security returns. French (1980) was one of the first to examine the weekend effect by examining Standard and Poor's composite portfolios between 1953 and 1977 in the US. The criteria here was to judge whether stocks are traded continuously, in calendar time, when Monday returns will be different from Friday, or alternatively whether returns are generated in trading time (i.e. between opening time on Monday and closing time on Friday). The former scenario implies that the mean Monday return (comprising Saturday, Sunday and Monday returns) will be three times the mean return of other days, and the latter that the daily returns distribution will be constant.

The results from the French study were inconsistent with both these hypotheses in that Monday returns were negative and lower than the average return for the other days of the week. Interestingly, transaction costs eliminated any profitable opportunities if investors bought on a Monday and sold on a Friday. Further investigations by Keim & Stambaugh (1984) found negative Monday returns across differing sized portfolios on the NYSE and AMEX markets. The results suggested that returns also rise during the week and across portfolios, with smaller portfolios having higher returns. Friday returns are therefore strongly correlated with firm size. Keim and

Stambaugh confirm the weekend effect even when using prices devoid of the biases associated with the microstructure which could be as large as any daily return.

Intra-day analysis by Rogalski (1984), using the Dow Jones Industrial Average Index between 1974 and 1984, indicates that returns are negative from the close on Friday to the opening on Monday, suggesting a non-trading weekend effect. Monday open to close returns seem similar to returns on other days of the week, and close to close returns over the weekend are still consistent with French (1980), in that the negative returns due to the weekend effect outweigh the positive Monday returns.

Much of the evidence above suggests that the weekend is characterised by a non-trading effect. Typically one could hypothesise that investors close their books on a Friday by selling securities to avoid any risk associated with a non-trading period. This is due to the inability of being able to act upon the release of information until the Monday opening. One explanation for a negative weekend effect may reflect the greater likelihood of companies releasing 'bad' news during this time. Penman (1987) supports such a hypothesis in his analysis of the timing of fundamental (earnings) news and seasonalities.

In the UK, the issue of the weekend effect and daily seasonality is further complicated by the fixed trading system used by the Stock Exchange until very recently. Indeed, the LSE is characterised by a unique two week[41] 'account' system so that the weekend effect documented above may be influenced by a so-called settlement effect.

[41] Additionally, there are four account periods per year that are 3 weeks long.

Jaffe & Westerfield (1985) analysing the LSE, confirm previous weekend effects of high average Friday returns and negative average Monday returns. However, they also confirm the settlement hypothesis by showing that returns on account Mondays are positive while returns on non-account Mondays are negative. The difference between these returns of about 0.5% is, claim the authors, justified by the interest rates or opportunity cost of delayed pay-off from buying an equity at the end of an account period[42].

Under the settlement system rules, investors buying on the first day of the account (a Monday), will pay for their securities on the middle Monday of the subsequent settlement period exactly 21 days later. However, transactions made on the last day of the settlement period (a Friday), will have to be settled on the next but one Monday, 10 days later. Therefore, returns may be higher (on average) on the first Monday of each account period since investors will enjoy an extra 11 day interest free holiday when compared to investors transacting at the end of the settlement period. Similarly, one would expect that the account settling up day (the middle Monday) will be characterised by negative returns due to investors settling up their previous accounts by selling in the market. Condoyanni, O'Hanlon & Ward (1987) and Choy & O'Hanlon (1989) confirm this settlement hypothesis by finding that the first day of the LSE settlement period, is characterised by positive returns where as the middle

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[42] This confirms Theobald & Price (1984), who document positive 'account' Monday returns corresponding to an 'interest effect' and additionally an ex-dividend effect which typically occurs on this day. The ex-dividend effect however, will be negative and therefore reduce these positive returns. Such settlement effects were stronger for larger traded stocks than thinly traded ones, pointing to a positive size effect in settlement period returns.

Monday of the two week period (the settlement date of the previous account) has negative returns. Indeed Board & Sutcliffe (1988) suggest the settlement effect as an explanation of a UK day of the week effect.

However, in contradiction to Keim and Stambaugh's 1984 US observations, Choy & O'Hanlon (1989) in the UK, find that the day of the week effect is stronger in larger traded securities. They suggest that such a size effect can be explained by institutional investing[43] in the market. This is whereby large traded securities which are members of narrow indices such as the FT-30 and FT-SE 100 index are more likely to experience a stronger day of the week effect due to systematic computerised trading. Such periodic trading may, as we shall see influence the size of the touch.

5.2.2. *Bid-Ask Spread Explanations for Daily Seasonality*

The evidence above suggests that a day of the week is prominent in both the UK and US stock markets. It is these systematic trading patterns around calendar turning points that has encouraged the search for other explanations of daily seasonality. Again consistent with the turn of the year literature examining the influence of microstructure on prices has recently become popular.

One typical study is by Keim (1989) who examines returns on each day of the week using transaction returns and mid-spread returns in the US. The difference between these two return values is the bid-ask bias, which was found to be negative on a Monday and positive and rising throughout the rest of the week. Clearly, this may

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[43] See Theobald & Price (1984).

contribute to the day of the week effect in returns. Fortin (1990) takes the seasonality issue further by examining the relationship between increasing returns during the week [starting with negative Monday returns] and the bid-ask spread in the US markets. The analysis suggests that during the week the spread remains constant while returns rise, contradicting Keim's (1989) study. Additionally, the spread was found to be a linearly increasing function of returns, with the smallest stocks having the largest spread and returns.

With the availability of more and more high frequency data, intra-day analysis of day of the week effects has become increasingly popular. Porter (1992), examining US stocks, showed that closing prices are closer to the ask price on Friday than on other days of the weeks. When using portfolios classified by price, the results indicate that higher priced portfolios have a higher probability that the closing transaction is at the ask price regardless of the day of the week. Porter concludes that up to 20% of the weekend effect in the US can be explained by bid-ask price behaviour.

Further explanations for a so-called day of the week effect have centred on the effects of security size (measured by market value) on returns. Differing sized portfolios should, due to the influence of differing spread sizes and perhaps more price volatility, exhibit differing seasonal returns behaviour. Clearly, the influence of the microstructure, as well as firm size on day of the week effects should hence be investigated.

5.3. MODELLING DAILY SEASONALITY

5.3.1. *Day of the Week Effects*

Differing returns behaviour across the week may occur due to the perceived change in risk and investor behaviour. In addition, the influence of the institutionalised settlement system on the LSE may help to explain this behaviour. In the first instance, this returns behaviour across the week on the LSE can be investigated using regression analysis. Following the literature on daily calendar anomalies[44] as well the methodology used to test for monthly effects in chapter 4, dummy variable regression analysis seems more appropriate since it enables the effects of daily seasonality to be captured more readily by the explanatory variables. Using 5 dummy variables corresponding to each day of the week, OLS regression can capture the day of the week effects as shown below

$$R_{p,t} = \alpha_0 R_{p,t-1} + \sum_{i=1}^{5} \beta_i D_i + \varepsilon_t \qquad (5.1)$$

where $R_{p,t}$ is the total return of the sample period on portfolio p, and $R_{p,t-1}$ are lagged portfolio returns. D_i is a dummy variable which takes the value 1 on a Monday (i=1), Tuesday (i=2), Wednesday (i=3), Thursday (i=4) and Friday (i=5), or zero otherwise. ε_t is a white noise error term. A constant term is not needed since the daily dummy variables already impose an intercept term.

One problem with this specification of the model is that it may mask the effects of other market seasonal influences, such as the LSE institutionalised settlement effects.

[44] See Board & Sutcliffe (1988) as an example.

While the influence of the settlement period is an important factor when considering the actions of investors on Mondays, there are other significant days during the week which may prove important in the analysis of seasonal effects on the LSE.

As hypothesised above, due to the expectation of information arriving during the weekend, when the market is closed, investors on a Friday may perceive equities more risky and reduce their exposure by subsequently selling. Additionally, due to settlement system rules the ensuing account Monday could influence investors who may sell on average in order to settle up outstanding accounts with the Stock Exchange. Returns on settlement Mondays are positive and higher than on other days due to the longer interest free period enjoyed by purchasers of equities on this day.

In order to allow for the possibility of seasonal effects related to settlement procedures (5.1) can be modified to yield an equation of the form in (5.2) below

$$R_{p,t} = \alpha_0 R_{p,t-1} + \beta_0 M_1 + \beta_1 M_2 + \sum_{i=2}^{4} \beta_i D_i + \beta_5 F_1 + \beta_6 F_2 + \varepsilon_t \qquad (5.2)$$

where $R_{p,t}$, $R_{p,t-1}$ and β_i are as before in (5.1). M_1 is a dummy that takes the value 1 on settlement Mondays, M_2 is a dummy that takes the value 1 on account Mondays, zero otherwise. D_i is a dummy variables that takes the value 1 on a Tuesday (i=2), Wednesday (i=3) or Thursday (i=4) and zero otherwise. F_1 is a dummy that takes the value 1 on Fridays before settlement Mondays, and F_2 is a dummy that takes the value 1 on Fridays before account Mondays, zero otherwise. This model then allows for the distinction to be made between day of the week anomalies and anomalies due to the settlement system. Given the evidence on monthly effects, we can hypothesise that these seasonal returns at the beginning and the end of the calendar week may be influenced by the touch.

5.3.2. *The Influence of the Touch on Seasonal Portfolio Returns*

Of equal interest here is the extent to which seasonality occurs due to the influence of the touch in portfolio returns. One such explanation is that seasonality may occur as a result of illiquidity in the market [Roll (1984)], or may reflect investors' transaction costs accruing to market makers when buy or sell orders are made. Consequently, 'true' returns are hidden since closing prices include this touch component.

Previous evidence [see section 5.2.2.] suggests that the nature of the relationship between returns and the touch implies that these parameters 'interact'. In order to account for this likely interaction between returns and the touch, the use of a dummy variable representing the touch on each day of the week can be included into equations (5.1) and (5.2), which consequently may change the slope and intercept terms in the regression relationship.

Thus, dummy variables representing returns can be specified simultaneously with interactive dummy variables representing the corresponding daily touch, in order to test for the microstructure effects present in seasonal returns. Thus we have, for day of the week effects,

$$R_{p,t} = \alpha_0 R_{p,t-1} + \sum_{i=1}^{5} \beta_i D_i + \sum_{i=1}^{5} \gamma_i SP_p D_i + \varepsilon_t \qquad (5.3)$$

where SP_pD_i is the daily touch on portfolio p and the other variables are given as previously, and for settlement effects equation (5.4) below

$$\begin{aligned} R_{p,t} = {} & \alpha_0 R_{p,t-1} + \beta_0 M_1 + \gamma_0 SP_p M_1 + \beta_1 M_2 + \gamma_1 SP_p M_2 \\ & + \sum_{i=2}^{4} \beta_i D_i + \sum_{i=2}^{4} \gamma_i SP_p D_i \qquad (5.4) \\ & + \beta_5 F_1 + \gamma_5 SP_p F_1 + \beta_6 F_2 + \gamma_6 SP_p F_2 + \varepsilon_t \end{aligned}$$

Here SP_pM_1 is an interactive spread variable times a dummy variable on settlement Mondays , SP_PM_2 is an interactive spread variable times a dummy variable on account Mondays, SP_pF_1 is an interactive spread variable times a dummy variable on Fridays before settlement Mondays, and SP_pF_2 is an interactive spread variable times a dummy variable on Fridays before account Mondays. The other variables are the same as previously given.

So far this chapter has addressed tests for a day of the week effect with specific reference to the two days surrounding the weekend: the Fridays and Mondays associated with the settlement system. Clearly, the advent of these trading regulations influences investors' behaviour. Allied to this fact is the changing risk levels, reflected in the touch, across the week which could under this scenario account for differing daily returns seasonality; this is the subject of section 5.3.3.

5.3.3. *Seasonal Touch Behaviour and Day of the Week Effects*

Due to the nature of the relationship between the microstructure and returns, the touch can be hypothesised as a possible cause of daily seasonality in returns and furthermore, as an explanation of the settlement effect. Again the question of what causes these microstructure and return seasonal effects is posed. While the interaction between the touch and portfolio returns may show whether the touch influences seasonal behaviour on the LSE, it does not give an explanation for this seasonality. However, since we know investor behaviour is reflected in the microstructure, there is a possibility that portfolio returns could be driven by seasonality in the touch. This hypothesis can be tested using (5.5) below

$$R_{p,t} = \alpha_0 R_{p,t-1} + \gamma_0 SP_p M_1 + \gamma_1 SP_p M_2 + \sum_{i=2}^{4} \gamma_i SP_p D_i + \gamma_5 SP_p F_1 + \gamma_6 SP_p F_2 + \varepsilon_t \quad (5.5)$$

where the variables are given as previously.

Additionally, there is a likelihood that seasonal returns could drive market makers' behaviour, which is reflected in the touch. This scenario can be tested as follows

$$SP_{p,t} = \alpha_0 + \beta_0 R_p M_1 + \beta_1 R_p M_2 + \sum_{i=2}^{4} \beta_i R_p D_i + \beta_5 R_p F_1 + \beta_6 R_p F_2 + \varepsilon_t \quad (5.6)$$

where R_pD_i are the portfolio returns times a dummy variable which takes the value 1 on Tuesday (i=2), Wednesday (i=3) or Thursday (i=4), zero otherwise. R_pM_1 and R_pM_2 are portfolio returns times a dummy variable which takes the value 1 on settlement Mondays and on account Mondays respectively, zero otherwise. R_pF_1 and R_pF_2 are portfolios returns times a dummy variable which takes the value 1 on the Fridays before settlement Mondays and on the Fridays before account Mondays, zero otherwise. The empirical results from estimating all the above models are shown in section 5.4. below.

5.4. EMPIRICAL RESULTS: TESTING FOR DAILY SEASONALITY

5.4.1. *Results of Tests for Day of the Week Effects*

Tables 5.1 and 5.2 show the regression results from specifying seasonal dummy variable models from the equations (5.1) and (5.2) respectively, defined in section 5.3.1. All the following analyses use the portfolios described in section 3.3.2. above. The results in this section examine the day of the week effect as well as the influence of the settlement system on daily returns.

Table 5.1 shows the results for a daily dummy variable regression representing each day of the week. For market value classified portfolios, lagged returns are statistically significant for the smallest portfolio only, and generally the variables of daily returns are insignificant. However, Friday returns are negative and significant for portfolios sized 3 and 4, as well as for the largest portfolio. This indicates that investors may well be selling on Fridays in anticipation of the ensuing non-trading period - the weekend. Across all the portfolios, the value of the coefficients appear small and do not experience an inverse relationship with portfolio size. DUM is a dummy variable that corrects for outliers and hence non-normality in the data corresponding to periods of volatility in the market. DUM corresponds to observation numbers 132, 177, 241, 246, 559 and 630. Observation number 132 corresponds to 7th August 1990 which was the time of the Iraqi invasion of Kuwait. Observation 177 corresponds to 9th October 1990 which corresponded to worries about the crisis in Kuwait. Observation number 241 and 246 coincide with the start and end of the fighting in the Gulf War respectively. Observation 559 corresponds to 10th April 1992 and the General Election

Table 5.1

OLS Regression Model Results of Returns Dependent upon Lagged Returns and Daily Dummy Variables Representing each Day of the Week for Equally Weighted Portfolios

Market Value Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1746***	0.0175	0.0611	0.0231	0.0411	0.0229
	(0.0365)	(0.0352)	(0.0379)	(0.0364)	(0.0364)	(0.0378)
D_1	-0.0006	-0.0018**	-0.0011	-0.0009	-0.0004	-0.0000
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
D_2	0.0017*	0.0014	0.0009	0.0008	0.0011	0.0015
	(0.0009)	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0008)
D_3	-0.0012	0.0004	-0.0011	-0.0009	-0.0002	-0.0005
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
D_4	0.0004	0.0007	0.0003	-0.0003	0.0009	0.0009
	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0008)	(0.0008)
D_5	-0.0011	-0.0014	-0.0019**	-0.0022**	-0.0009	-0.0016**
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
DUM	0.1003***	0.1023***	0.1054***	0.1076***	0.0987***	0.1025***
	(0.0097)	(0.0073)	(0.0123)	(0.0087)	(0.0085)	(0.0120)
	$R^2 = 0.166$	$R^2 = 0.237$	$R^2 = 0.111$	$R^2 = 0.175$	$R^2 = 0.170$	$R^2 = 0.102$
	$\eta_1(1,621) = 0.077$	$\eta_1(1,621) = 3.117$	$\eta_1(1,621) = 0.377$	$\eta_1(1,621) = 0.023$	$\eta_1(1,621) = 0.139$	$\eta_1(1,621) = 3.746$
	$\eta_2(1,621) = 0.039$	$\eta_2(1,621) = 0.050$	$\eta_2(1,621) = 0.008$	$\eta_2(1,621) = 0.007$	$\eta_2(1,621) = 0.210$	$\eta_2(1,621) = 0.007$
	$\xi_3(2) = 7.163$	$\xi_3(2) = 9.964$	$\xi_3(2) = 7.699$	$\xi_3(2) = 4.748$	$\xi_3(2) = 5.646$	$\xi_3(2) = 5.729$
	$\eta_4(1,627) = 1.336$	$\eta_4(1,627) = 1.709$	$\eta_4(1,627) = 0.996$	$\eta_4(1,627) = 1.439$	$\eta_4(1,627) = 1.501$	$\eta_4(1,627) = 1.846$

Table 5.1 cont.

Closing Price Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.0999***	0.0285	-0.0207	0.0846***	0.0642*	0.1223***
	(0.0372)	(0.0373)	(0.0349)	(0.0359)	(0.0369)	(0.0360)
D_1	-0.0010	-0.0010	-0.0012	-0.0005	-0.0007	-0.0006
	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
D_2	0.0016	0.0014	0.0008	0.0013	0.0013*	0.0010
	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0007)	(0.0007)
D_3	-0.0008	-0.0003	-0.0010	-0.0006	-0.0006	-0.0003
	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
D_4	0.0012	0.0005	0.0004	0.0006	0.0008	-0.0006
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
D_5	-0.0011	-0.0023***	-0.0013	-0.0019**	-0.0012	-0.0017**
	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0007)
DUM	0.0996***	0.1009***	0.1019***	0.1007***	0.1017***	0.1051***
	(0.0104)	(0.0105)	(0.0071)	(0.0084)	(0.0097)	(0.0090)
	$R^2 = 0.134$	$R^2 = 0.125$	$R^2 = 0.243$	$R^2 = 0.189$	$R^2 = 0.148$	$R^2 = 0.186$
	$\eta_1(1,621) = 1.468$	$\eta_1(1,621) = 0.287$	$\eta_1(1,621) = 1.429$	$\eta_1(1,621) = 0.828$	$\eta_1(1,621) = 0.055$	$\eta_1(1,621) = 0.640$
	$\eta_2(1,621) = 0.028$	$\eta_2(1,621) = 0.006$	$\eta_2(1,621) = 0.004$	$\eta_2(1,621) = 0.002$	$\eta_2(1,621) = 0.002$	$\eta_2(1,621) = 0.012$
	$\xi_3(2) = 5.374$	$\xi_3(2) = 1.799$	$\xi_3(2) = 8.038$	$\xi_3(2) = 4.738$	$\xi_3(2) = 6.769$	$\xi_3(2) = 4.949$
	$\eta_4(1,627) = 1.198$	$\eta_4(1,627) = 1.642$	$\eta_4(1,627) = 1.720$	$\eta_4(1,627) = 1.738$	$\eta_4(1,627) = 1.624$	$\eta_4(1,627) = 2.925$

Table 5.1 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	-0.0053	0.0694**	0.0113	0.0565	0.1198***	0.0958***
	(0.0351)	(0.0351)	(0.0359)	(0.0358)	(0.0342)	(0.0356)
D_1	0.0001	-0.0001	-0.0008	-0.0010	-0.0001	-0.0011
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
D_2	0.0015**	0.0016	-0.0002	0.0012	0.0009	0.0015
	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
D_3	-0.0010	-0.0006	-0.0002	-0.0002	-0.0008	-0.0007
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0010)
D_4	0.0008	0.0009	0.0004	0.0008	-0.0004	0.0003
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0010)
D_5	-0.0015**	-0.0013	-0.0019**	-0.0015	-0.0016	-0.0014
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0010)
DUM	0.1018***	0.1011***	0.1005***	0.1011***	0.1001***	0.1022***
	(0.0073)	(0.0075)	(0.0081)	(0.0080)	(0.0067)	(0.0081)
	$R^2 = 0.236$	$R^2 = 0.228$	$R^2 = 0.197$	$R^2 = 0.201$	$R^2 = 0.269$	$R^2 = 0.207$
	$\eta_1(1,621) = 0.001$	$\eta_1(1,621) = 0.363$	$\eta_1(1,621) = 0.042$	$\eta_1(1,621) = 0.001$	$\eta_1(1,621) = 0.199$	$\eta_1(1,621) = 0.222$
	$\eta_2(1,621) = 0.011$	$\eta_2(1,621) = 0.001$	$\eta_2(1,621) = 0.0197$	$\eta_2(1,621) = 0.011$	$\eta_2(1,621) = 0.005$	$\eta_2(1,621) = 0.017$
	$\xi_3(2) = 4.012$	$\xi_3(2) = 2.202$	$\xi_3(2) = 0.759$	$\xi_3(2) = 4.239$	$\xi_3(2) = 2.499$	$\xi_3(2) = 0.058$
	$\eta_4(1,627) = 4.179$	$\eta_4(1,627) = 3.427$	$\eta_4(1,627) = 2.415$	$\eta_4(1,627) = 2.663$	$\eta_4(1,627) = 3.897$	$\eta_4(1,627) = 3.919$

Table 5.1 cont.

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1460***	0.0564	0.0119	0.0803**	0.0638	-0.0015
	(0.0352)	(0.0355)	(0.0334)	(0.0341)	(0.0351)	(0.0371)
D_1	-0.0004	-0.0009	0.0005	-0.0008	-0.0006	-0.0001
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)
D_2	-0.0010	-0.0001	0.0010	0.0014	-0.0013	0.0017
	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0008)
D_3	-0.0011	-0.0001	-0.0005	-0.0011	-0.0003	-0.0005
	(0.0007)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)
D_4	-0.0002	0.0006	-0.0004	0.0007	0.0005	0.0005
	(0.0007)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)
D_5	-0.0018	-0.0012	-0.0009	-0.0016	-0.0018	-0.0015
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)
DUM	0.1011***	0.0939***	0.1010***	0.1009***	0.1013***	0.0965***
	(0.0079)	(0.0073)	(0.0078)	(0.0066)	(0.0075)	(0.0094)
	$R^2 = 0.225$	$R^2 = 0.212$	$R^2 = 0.300$	$R^2 = 0.274$	$R^2 = 0.227$	$R^2 = 0.139$
	$\eta_1(1,621) = 0.024$	$\eta_1(1,621) = 0.322$	$\eta_1(1,621) = 0.377$	$\eta_1(1,621) = 0.314$	$\eta_1(1,621) = 0.059$	$\eta_1(1,621) = 1.027$
	$\eta_2(1,621) = 0.028$	$\eta_2(1,621) = 1.844$	$\eta_2(1,621) = 0.017$	$\eta_2(1,621) = 0.013$	$\eta_2(1,621) = 0.009$	$\eta_2(1,621) = 0.646$
	$\xi_3(2) = 3.707$	$\xi_3(2) = 1.844$	$\xi_3(2) = 1.486$	$\xi_3(2) = 0.123$	$\xi_3(2) = 5.923$	$\xi_3(2) = 2.024$
	$\eta_4(1,627) = 3.556$	$\eta_4(1,627) = 0.125$	$\eta_4(1,627) = 4.381$	$\eta_4(1,627) = 4.122$	$\eta_4(1,627) = 4.799$	$\eta_4(1,627) = 1.485$

Notes:

D_i are the dummy variables representing differing days of the week.
When i=1 it is a Monday, when i=2 a Tuesday and so on until i=5, a Friday.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
DUM is a dummy variable that captures unusually large outliers in the data
*** t-statistic significant at the 1% level
** t-statistic significant at the 5% level
η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

Victory by the Conservative Party in the UK. This dummy variable is highly significant in these and all the subsequent seasonal regression models in this chapter.

For the other classifications of portfolios the results follow a similar pattern to the market value classified portfolios. However, for a larger number of the portfolios, lagged returns are significant indicating that in some instances yesterday's returns influence today's returns. Overall however, the results indicate that a day of the week effect does not generally seem to be significant on the LSE. Apart from the turnover by volume portfolios however, negative Friday effects for around half the portfolios seem prominent. These negative returns imply that investors may be selling securities before the weekend non-trading period.

Due to the fact that a day of the week effect does not seem prominent on the LSE, other explanations for daily seasonality need to be investigated. Clearly, the rules governing the timing of transactions and the settling up of previous transactions on the market may cause institutionalised seasonality on the LSE. One obvious seasonal influence hence may be the settlement system operating on the market. This system may be a cause of daily seasonality, specifically on settlement and non-settlement Mondays. Following Theobald & Price (1984) and Board & Sutcliffe (1988) amongst others, the settlement (first) Monday of the two week account period generally should have positive returns, while the account day or middle Monday should have negative returns due to the 'interest hypothesis' examined in section 5.2.1. In addition, negative returns on the account day could be caused by investors liquidating their portfolios in order to settle up outstanding accounts with the Stock Exchange.

Table 5.2 shows the results of testing for settlement and non-settlement Mondays simultaneously with the other days of the week. Firstly, for size 1 and 3 of market value portfolios, daily lagged returns are positive as well as statistically significant. Lagged returns are also significant for at least 3 of the 6 sizes of closing price, touch and the volume classified portfolios. Settlement Monday returns (M_1) appear to be positive and significant for at least 4 sizes of each classification of portfolio.

Account Mondays (M_2) on the other hand have highly significant negative returns across all the sizes and classifications of portfolio. Also, generally returns across other days of the week are insignificant apart from on the settlement Fridays (F_1), which are highly significant across all the portfolios. The diagnostic tests are generally passed for all the portfolios. Allied to this are significant negative Friday returns on the last day of the settlement period i.e. the day before the new two week account period. This may indicate that investors are selling securities in order to balance their account books since this Friday is the last trading day before the next account day (the middle Monday of the following settlement period). In this scenario and under the assumption that investors hold long positions in the market, they may be selling, since this is the last opportunity to earn interest on open long positions.

These results suggest that on the LSE, daily seasonality can be explained by the influence of the settlement system operating in the market on Mondays and on the last Friday of the account period. The interest opportunity cost hypothesis seems to be supported by these results and the middle Monday account day seems to be partly determined by investors' systematic transacting behaviour.

Table 5.2

OLS Regression Model Results of Returns Dependent upon Lagged Returns and Daily Dummy Variables Representing the Fridays before a Settlement or Non-Settlement Monday, the Settlement and Non-Settlement Mondays and the Other Days of the Week for Equally Weighted Portfolios

	Market Value Portfolio Classification					
Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1777***	0.0299	0.0754**	0.0357	0.0566	0.0335
	(0.0363)	(0.0347)	(0.0374)	(0.0357)	(0.0358)	(0.0373)
M_1	0.0016	0.0013	0.0026**	0.0035***	0.0032***	0.0036***
	(0.0013)	(0.0012)	(0.0013)	(0.0014)	(0.0011)	(0.0011)
M_2	-0.0029***	-0.0055***	-0.0053***	-0.0057***	-0.0043***	-0.0038***
	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0011)	(0.0011)
D_2	0.0017**	0.0005	0.0009	0.0008	0.0012	0.0016**
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
D_3	-0.0012	0.0004	-0.0011	-0.0010	-0.0002	-0.0005
	(0.0009)	(0.0008)	(0.0009)	(0.0010)	(0.0008)	(0.0008)
D_4	0.0005	0.0006	0.0003	-0.0003	0.0009	0.0009
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
F_1	-0.0029**	-0.0041***	-0.0044***	-0.0047***	-0.0033***	-0.0036***
	(0.0014)	(0.0013)	(0.0014)	(0.0015)	(0.0012)	(0.0013)
F_2	-0.0003	0.0001	-0.0008	-0.0014	0.0002	-0.0007
	(0.0014)	(0.0013)	(0.0014)	(0.0014)	(0.0012)	(0.0012)
DUM	0.0991***	0.1019***	0.1056***	0.1021***	0.0988***	0.1012***
	(0.0097)	(0.0073)	(0.0122)	(0.0086)	(0.0085)	(0.0119)
	$R^2 = 0.175$	$R^2 = 0.263$	$R^2 = 0.142$	$R^2 = 0.209$	$R^2 = 0.203$	$R^2 = 0.133$
	$\eta_1(1,619) = 0.000$	$\eta_1(1,619) = 3.695$	$\eta_1(1,619) = 0.074$	$\eta_1(1,619) = 0.287$	$\eta_1(1,619) = 0.769$	$\eta_1(1,619) = 3.312$
	$\eta_2(1,619) = 0.054$	$\eta_2(1,619) = 0.158$	$\eta_2(1,619) = 0.205$	$\eta_2(1,619) = 0.010$	$\eta_2(1,619) = 0.124$	$\eta_2(1,619) = 0.001$
	$\xi_3(2) = 6.709$	$\xi_3(2) = 13.33$	$\xi_3(2) = 5.771$	$\xi_3(2) = 5.555$	$\xi_3(2) = 7.855$	$\xi_3(2) = 11.08$
	$\eta_4(1,627) = 1.384$	$\eta_4(1,627) = 1.474$	$\eta_4(1,627) = 0.715$	$\eta_4(1,627) = 1.297$	$\eta_4(1,627) = 1.609$	$\eta_4(1,627) = 1.691$

Table 5.2 cont.

Closing Price Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1140***	0.0372	-0.0057	0.0991***	0.0737**	0.1241***
	(0.0364)	(0.0369)	(0.0345)	(0.0355)	(0.0363)	(0.0358)
M_1	0.0039***	0.0024*	0.0024*	0.0029***	0.0025**	0.0012
	(0.0014)	(0.0014)	(0.0013)	(0.0012)	(0.0011)	(0.0011)
M_2	-0.0062***	-0.0048***	-0.0051***	-0.0042***	-0.0041***	-0.0029***
	(0.0014)	(0.0013)	(0.0013)	(0.0012)	(0.0011)	(0.0011)
D_2	0.0016	0.0014	0.0008	0.0013	0.0013	0.0010
	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0007)	(0.0007)
D_3	-0.0008	-0.0003	-0.0010	-0.0006	-0.0006	-0.0003
	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
D_4	0.0012	0.0005	0.0003	0.0005	0.0008	-0.0007
	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
F_1	-0.0036***	-0.0048***	-0.0042***	-0.0044***	-0.0033***	-0.0033***
	(0.0015)	(0.0015)	(0.0014)	(0.0013)	(0.0012)	(0.0012)
F_2	0.0002	-0.0015	0.0002	-0.0004	-0.0001	-0.0015
	(0.0015)	(0.0014)	(0.0013)	(0.0013)	(0.0011)	(0.0012)
DUM	0.0999***	0.1016***	0.1013***	0.1006***	0.10177***	0.1028***
	(0.0102)	(0.0104)	(0.0070)	(0.0083)	(0.0096)	(0.0090)
	$R^2 = 0.173$	$R^2 = 0.151$	$R^2 = 0.269$	$R^2 = 0.216$	$R^2 = 0.177$	$R^2 = 0.198$
	$\eta_1(1,619) = 1.161$	$\eta_1(1,619) = 0.503$	$\eta_1(1,619) = 1.594$	$\eta_1(1,619) = 0.923$	$\eta_1(1,619) = 0.040$	$\eta_1(1,619) = 0.701$
	$\eta_2(1,619) = 0.000$	$\eta_2(1,619) = 0.000$	$\eta_2(1,619) = 0.027$	$\eta_2(1,619) = 0.004$	$\eta_2(1,619) = 0.002$	$\eta_2(1,619) = 0.002$
	$\xi_3(2) = 6.137$	$\xi_3(2) = 2.455$	$\xi_3(2) = 11.30$	$\xi_3(2) = 6.247$	$\xi_3(2) = 6.258$	$\xi_3(2) = 5.663$
	$\eta_4(1,627) = 1.130$	$\eta_4(1,627) = 1.605$	$\eta_4(1,627) = 1.559$	$\eta_4(1,627) = 1.695$	$\eta_4(1,627) = 1.436$	$\eta_4(1,627) = 3.083$

Table 5.2 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.0027	0.0787**	0.0277	0.0711**	0.1282***	0.1045***
	(0.0347)	(0.0347)	(0.0355)	(0.0351)	(0.0336)	(0.0354)
M_1	0.0029***	0.0032***	0.0025**	0.0028***	0.0038***	0.0015
	(0.0011)	(0.0012)	(0.0011)	(0.0012)	(0.0012)	(0.0014)
M_2	-0.0028***	-0.0036***	-0.0041***	-0.0049***	-0.0041***	-0.0038***
	(0.0011)	(0.0011)	(0.0009)	(0.0012)	(0.0012)	(0.0014)
D_2	-0.0016**	0.0016**	0.0007	0.0012	0.0009	0.0015
	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
D_3	-0.0010	-0.0006	-0.0002	-0.0002	-0.0008	-0.0007
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0010)
D_4	0.0007	0.0009	0.0004	0.0007	-0.0005	0.0003
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)
F_1	-0.0028**	-0.0027**	-0.0042***	-0.0046***	-0.0035***	-0.0039***
	(0.0012)	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0015)
F_2	-0.0010	-0.0008***	-0.0006	0.0002	-0.0011	-0.0004
	(0.0011)	(0.0012)	(0.0011)	(0.0012)	(0.0013)	(0.0014)
DUM	0.1000***	0.0991***	0.0983***	0.0998***	0.0996***	0.1011***
	(0.0073)	(0.0074)	(0.0080)	(0.0079)	(0.0067)	(0.0081)
	$R^2 = 0.254$	$R^2 = 0.249$	$R^2 = 0.222$	$R^2 = 0.236$	$R^2 = 0.294$	$R^2 = 0.220$
	$\eta_1(1,619) = 0.008$	$\eta_1(1,619) = 0.457$	$\eta_1(1,619) = 0.507$	$\eta_1(1,619) = 0.032$	$\eta_1(1,619) = 0.369$	$\eta_1(1,619) = 0.118$
	$\eta_2(1,619) = 0.046$	$\eta_2(1,619) = 0.016$	$\eta_2(1,619) = 0.089$	$\eta_2(1,619) = 0.002$	$\eta_2(1,619) = 0.075$	$\eta_2(1,619) = 0.000$
	$\xi_3(2) = 6.418$	$\xi_3(2) = 4.068$	$\xi_3(2) = 2.077$	$\xi_3(2) = 6.212$	$\xi_3(2) = 2.415$	$\xi_3(2) = 0.263$
	$\eta_4(1,627) = 3.795$	$\eta_4(1,627) = 3.217$	$\eta_4(1,627) = 1.993$	$\eta_4(1,627) = 2.303$	$\eta_4(1,627) = 3.635$	$\eta_4(1,627) = 3.863$

Table 5.2 cont.

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1486***	0.0626	0.0241	0.0970***	0.0744**	0.0161
	(0.0350)	(0.0352)	(0.0332)	(0.0337)	(0.0348)	(0.0362)
M_1	0.0013	0.0016	0.0031**	0.0030**	0.0029**	0.0043***
	(0.0011)	(0.0011)	(0.0012)	(0.0013)	(0.0013)	(0.0012)
M_2	-0.0024**	-0.0036***	-0.0031***	-0.0046***	-0.0042***	-0.0044***
	(0.0010)	(0.0011)	(0.0012)	(0.0013)	(0.0013)	(0.0011)
D_2	0.0010	0.0012	0.0009	0.0015	0.0013	0.0017**
	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0008)
D_3	-0.0011	-0.0001	-0.0005	-0.0011	-0.0003	-0.0005
	(0.0007)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)
D_4	-0.0002	0.0006	-0.0004	0.0007	0.0005	0.0005
	(0.0007)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)
F_1	-0.0032***	-0.0029**	-0.0036***	-0.0049***	-0.0042***	-0.0043***
	(0.0012)	(0.0012)	(0.0014)	(0.0014)	(0.0014)	(0.0013)
F_2	-0.0014	-0.0008	-0.0003	0.0004	-0.0003	-0.0010
	(0.0011)	(0.0012)	(0.0013)	(0.0014)	(0.0013)	(0.0012)
DUM	0.0989***	0.0927***	0.1011***	0.0994***	0.0996***	0.0948***
	(0.0078)	(0.0073)	(0.0060)	(0.0065)	(0.0074)	(0.0093)
	$R^2 = 0.235$	$R^2 = 0.228$	$R^2 = 0.318$	$R^2 = 0.301$	$R^2 = 0.249$	$R^2 = 0.183$
	$\eta_1(1,619) = 0.011$	$\eta_1(1,619) = 0.290$	$\eta_1(1,619) = 0.461$	$\eta_1(1,619) = 0.147$	$\eta_1(1,619) = 0.031$	$\eta_1(1,619) = 1.964$
	$\eta_2(1,619) = 0.057$	$\eta_2(1,619) = 2.777$	$\eta_2(1,619) = 0.002$	$\eta_2(1,619) = 0.006$	$\eta_2(1,619) = 0.029$	$\eta_2(1,619) = 0.666$
	$\xi_3(2) = 4.831$	$\xi_3(2) = 2.318$	$\xi_3(2) = 3.247$	$\xi_3(2) = 0.059$	$\xi_3(2) = 7.440$	$\xi_3(2) = 4.709$
	$\eta_4(1,627) = 3.269$	$\eta_4(1,627) = 0.029$	$\eta_4(1,627) = 3.949$	$\eta_4(1,627) = 3.561$	$\eta_4(1,627) = 4.199$	$\eta_4(1,627) = 1.618$

Notes:
M_1 are dummy variables representing Settlement Mondays. M_2 are dummy variables representing Non-Settlement Mondays
D_2 are dummy variables representing Tuesdays. D_3 are dummy variables representing Wednesdays.
D_4 are dummy variables representing Thursdays.
F_1 are dummy variables representing the Fridays before Settlement Mondays
F_2 are dummy variables representing the Fridays before Non-Settlement Mondays
DUM is a dummy variable that captures unusually large outliers in the data
Figures in parentheses are standard errors. R^2 is the adjusted R^2.
*** t-statistic significant at the 1% level. ** t-statistic significant at the 5% level.
η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

5.4.2. *Results of Tests for the Influence of the Touch in Seasonal Returns*

As we have implied in section 5.3, seasonality in portfolio returns around calendar turning point opens up the possibility that the touch may influence returns. Table 5.3 below show the results from test for seasonal return patterns when excluding the effects of the touch. The analysis is based on the seasonal settlement results which are shown in Tables 5.2 .

Table 5.3 examines the significance of seasonality for settlement and non-settlement Mondays as well as on the other days of the week when the effects of the touch are removed. The results for the market value classified portfolios are as follows: (i) lagged returns are significant for portfolios size 1, 3 and 5; (ii) the previously documented positive settlement Monday (M_1) returns become insignificant and negative for 3 out of the 6 portfolio sizes; (iii) the negative returns previously documented for the account or middle Monday (M_2) of the settlement period are now only significant in the size 5 portfolio. Wednesday seasonality seems prominent in portfolios size 3 and 4 even with the effects of the touch removed.

For the other classifications of portfolios, the results indicate that lagged returns are highly significant in each portfolio for around 3 out of the 6 portfolios. Additionally, an account Monday effect (M_2), is significant for a few of the larger sized portfolios specifically sizes 3, 4 and 5. Again the diagnostic tests are again generally passed.

The results in Table 5.3 imply that the previous documented Monday settlement and non-settlement effects, as well as settlement Fridays effects, reported in section 5.4.1,

Table 5.3

OLS Regression Model Results of Returns Dependent upon Lagged Returns and Daily Dummy Variables Representing Settlement and Non-Settlement Mondays and the Fridays before a Settlement or Non-Settlement Monday and the Other Days of the Week for Equally Weighted Portfolios with the Effects of the Touch Removed

	Market Value Portfolio Classification					
Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1765***	0.0389	0.0829**	0.0342	0.0657	0.0373
	(0.0364)	(0.0353)	(0.0379)	(0.0358)	(0.0361)	(0.0377)
M_1	-0.0079	0.0026	0.0041	-0.0032	-0.0027	0.0024
	(0.0075)	(0.0070)	(0.0075)	(0.0092)	(0.0096)	(0.0069)
M_2	-0.0104	-0.0116	-0.0044	-0.0133	-0.0203***	-0.0039
	(0.0068)	(0.0061)	(0.0066)	(0.0073)	(0.0068)	(0.0064)
D_2	-0.0015	-0.0025	-0.0011	-0.0061	-0.0054	0.0039
	(0.0049)	(0.0048)	(0.0048)	(0.0068)	(0.0062)	(0.0058)
D_3	0.0040	-0.0030	0.0128***	0.0160**	-0.0007	-0.0018
	(0.0051)	(0.0047)	(0.0046)	(0.0071)	(0.0072)	(0.0055)
D_4	-0.0103**	0.0062	-0.0022	0.0042	0.0004	-0.0054
	(0.0052)	(0.0052)	(0.0051)	(0.0068)	(0.0067)	(0.0057)
F_1	-0.0019	-0.0050	0.0075	0.0157	-0.0056	-0.0050
	(0.0077)	(0.0071)	(0.0074)	(0.0103)	(0.0115)	(0.0083)
F_2	-0.0041	-0.0051	-0.0049	-0.0008	-0.0038	-0.0057
	(0.0060)	(0.0047)	(0.0054)	(0.0063)	(0.0055)	(0.0053)
DUM	0.0982***	0.1012***	0.1023***	0.1042***	0.1044***	0.0994***
	(0.0097)	(0.0074)	(0.0129)	(0.0088)	(0.0088)	(0.0121)
	$R^2 = 0.178$	$R^2 = 0.260$	$R^2 = 0.152$	$R^2 = 0.218$	$R^2 = 0.205$	$R^2 = 0.128$
	$\eta_1(1,612) = 0.000$	$\eta_1(1,612) = 1.785$	$\eta_1(1,612) = 0.137$	$\eta_1(1,612) = 0.485$	$\eta_1(1,612) = 2.629$	$\eta_1(1,612) = 3.835$
	$\eta_2(1,612) = 0.008$	$\eta_2(1,612) = 0.262$	$\eta_2(1,612) = 0.307$	$\eta_2(1,612) = 0.138$	$\eta_2(1,612) = 0.020$	$\eta_2(1,612) = 0.003$
	$\xi_3(2) = 6.819$	$\xi_3(2) = 14.22$	$\xi_3(2) = 6.866$	$\xi_3(2) = 4.745$	$\xi_3(2) = 5.941$	$\xi_3(2) = 8.918$
	$\eta_4(1,627) = 1.082$	$\eta_4(1,627) = 1.175$	$\eta_4(1,627) = 0.637$	$\eta_4(1,627) = 0.990$	$\eta_4(1,627) = 0.953$	$\eta_4(1,627) = 1.513$

Table 5.3 cont.

Closing Price Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1157***	0.0462	-0.0004	0.1045***	0.0755**	0.1287***
	(0.0365)	(0.0374)	(0.0345)	(0.0358)	(0.00366)	(0.0360)
M_1	-0.0021	0.0072	0.0071	0.0080	-0.0105	-0.0089
	(0.0064)	(0.0081)	(0.0052)	(0.0077)	(0.0085)	(0.0073)
M_2	-0.0091	-0.0122	-0.0129***	-0.0066	-0.0112	-0.0006
	(0.0059)	(0.0069)	(0.0047)	(0.0066)	(0.0061)	(0.0066)
D_2	-0.0062	-0.0072	0.0014	0.0005	-0.0026	0.0035
	(0.0042)	(0.0053)	(0.0036)	(0.0051)	(0.0056)	(0.0044)
D_3	0.0069	0.0089	-0.0024	-0.0060	0.0029	-0.0103
	(0.0045)	(0.0054)	(0.0033)	(0.0053)	(0.0055)	(0.0054)
D_4	-0.0017	-0.0021	-0.0007	-0.0018	0.0040	-0.0024
	(0.0044)	(0.0054)	(0.0034)	(0.0056)	(0.0056)	(0.0048)
F_1	0.0120	0.0030	-0.0099	-0.0144	0.0016	-0.0119
	(0.0071)	(0.0087)	(0.0054)	(0.0097)	(0.0094)	(0.0072)
F_2	-0.0012	-0.0029	-0.0070	-0.0037	-0.0083	-0.0057
	(0.0058)	(0.0060)	(0.0041)	(0.0055)	(0.0049)	(0.0049)
DUM	0.1008***	0.1037***	0.1003***	0.1012***	0.1018***	0.1001***
	(0.0104)	(0.0109)	(0.0071)	(0.0086)	(0.0097)	(0.0091)
	$R^2 = 0.181$	$R^2 = 0.154$	$R^2 = 0.272$	$R^2 = 0.214$	$R^2 = 0.179$	$R^2 = 0.200$
	$\eta_1(1,612) = 1.308$	$\eta_1(1,612) = 0.646$	$\eta_1(1,612) = 0.018$	$\eta_1(1,612) = 1.551$	$\eta_1(1,612) = 0.018$	$\eta_1(1,612) = 0.549$
	$\eta_2(1,612) = 0.006$	$\eta_2(1,612) = 0.004$	$\eta_2(1,612) = 0.297$	$\eta_2(1,612) = 0.010$	$\eta_2(1,612) = 0.008$	$\eta_2(1,612) = 0.047$
	$\xi_3(2) = 6.054$	$\xi_3(2) = 2.144$	$\xi_3(2) = 12.65$	$\xi_3(2) = 6.161$	$\xi_3(2) = 9.178$	$\xi_3(2) = 5.179$
	$\eta_4(1,627) = 1.062$	$\eta_4(1,627) = 1.364$	$\eta_4(1,627) = 1.318$	$\eta_4(1,627) = 1.607$	$\eta_4(1,627) = 0.997$	$\eta_4(1,627) = 2.960$

Table 5.3 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.0048 (0.0348)	0.0786** (0.0351)	0.0262 (0.0358)	0.0745** (0.0351)	0.1291*** (0.0339)	0.1168*** (0.0359)
M_1	-0.0048 (0.0052)	-0.0006 (0.0049)	0.0155 (0.0089)	-0.0065 (0.0077)	-0.0065 (0.0086)	-0.0027 (0.0069)
M_2	-0.0017 (0.0042)	-0.0090 (0.0041)	-0.0098*** (0.0053)	-0.0109** (0.0052)	-0.0126** (0.0058)	-0.0075 (0.0053)
D_2	-0.0004 (0.0035)	-0.0002 (0.0033)	0.0022 (0.0059)	-0.0055 (0.0054)	-0.0088 (0.0059)	0.0000 (0.0050)
D_3	0.0046 (0.0039)	-0.0034 (0.0033)	-0.0037 (0.0057)	0.0066 (0.0056)	0.0062 (0.0058)	-0.0061 (0.0051)
D_4	0.0012 (0.0031)	-0.0002 (0.0031)	-0.0060 (0.0046)	0.0056 (0.0044)	0.0046 (0.0047)	0.0087 (0.0046)
F_1	0.0026 (0.0056)	0.0022 (0.0048)	-0.0074 (0.0086)	-0.0096 (0.0097)	-0.0009 (0.0085)	-0.0113 (0.0072)
F_2	0.0044 (0.0058)	-0.0018 (0.0044)	-0.0080 (0.0083)	-0.0068 (0.0091)	0.0044 (0.0081)	-0.0006 (0.0077)
DUM	0.1002*** (0.0073)	0.0988*** (0.0076)	0.1006*** (0.0082)	0.0994*** (0.0086)	0.1022*** (0.0097)	0.1022*** (0.0082)
	$R^2 = 0.253$ $\eta_1(1,612) = 0.000$ $\eta_2(1,612) = 0.087$ $\xi_3(2) = 6.687$ $\eta_4(1,627) = 3.856$	$R^2 = 0.247$ $\eta_1(1,612) = 0.615$ $\eta_2(1,612) = 0.025$ $\xi_3(2) = 4.162$ $\eta_4(1,627) = 2.683$	$R^2 = 0.221$ $\eta_1(1,612) = 1.129$ $\eta_2(1,612) = 0.063$ $\xi_3(2) = 2.296$ $\eta_4(1,627) = 1.867$	$R^2 = 0.237$ $\eta_1(1,612) = 0.042$ $\eta_2(1,612) = 0.011$ $\xi_3(2) = 5.768$ $\eta_4(1,627) = 1.737$	$R^2 = 0.297$ $\eta_1(1,612) = 0.648$ $\eta_2(1,612) = 0.326$ $\xi_3(2) = 2.117$ $\eta_4(1,627) = 3.048$	$R^2 = 0.219$ $\eta_1(1,612) = 0.009$ $\eta_2(1,612) = 0.001$ $\xi_3(2) = 0.062$ $\eta_4(1,627) = 3.652$

Table 5.3 cont.

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1492***	0.0683	0.0277	0.1048***	0.0739**	0.0219
	(0.0354)	(0.0353)	(0.0334)	(0.0337)	(0.0349)	(0.0363)
M_1	-0.0092	-0.0129	0.0051	-0.0070	0.0010	0.0046
	(0.0078)	(0.0087)	(0.0044)	(0.0089)	(0.0077)	(0.0065)
M_2	-0.0071	-0.0079	-0.0104***	-0.0080	-0.0120**	-0.0068
	(0.0051)	(0.0052)	(0.0039)	(0.0059)	(0.0054)	(0.0047)
D_2	0.0015	-0.0015	-0.0011	-0.0153**	-0.0016	-0.0065
	(0.0045)	(0.0056)	(0.0032)	(0.0064)	(0.0050)	(0.0047)
D_3	-0.0038	-0.0088	0.0003	-0.0106	0.0116**	0.0084
	(0.0054)	(0.0057)	(0.0031)	(0.0063)	(0.0051)	(0.0046)
D_4	-0.0050	0.0042	0.0006	0.0092	0.0014	-0.0018
	(0.0042)	(0.0045)	(0.0030)	(0.0048)	(0.0043)	(0.0038)
F_1	-0.0108	-0.0086	-0.0070	0.0069	0.0055	0.0066
	(0.0077)	(0.0098)	(0.0048)	(0.0116)	(0.0080)	(0.0063)
F_2	0.0012	-0.0098	-0.0017	0.0091	0.0003	0.0068
	(0.0072)	(0.0084)	(0.0045)	(0.0117)	(0.0081)	(0.0069)
DUM	0.0987***	0.0922***	0.1004***	0.1007***	0.1006***	0.0963***
	(0.0079)	(0.0073)	(0.0061)	(0.0086)	(0.0075)	(0.0094)
	$R^2 = 0.233$	$R^2 = 0.229$	$R^2 = 0.316$	$R^2 = 0.310$	$R^2 = 0.253$	$R^2 = 0.189$
	$\eta_1(1,612) = 0.022$	$\eta_1(1,612) = 0.220$	$\eta_1(1,612) = 0.026$	$\eta_1(1,612) = 0.137$	$\eta_1(1,612) = 0.000$	$\eta_1(1,612) = 1.368$
	$\eta_2(1,612) = 0.004$	$\eta_2(1,612) = 2.379$	$\eta_2(1,612) = 0.015$	$\eta_2(1,612) = 0.042$	$\eta_2(1,612) = 0.078$	$\eta_2(1,612) = 1.173$
	$\xi_3(2) = 3.642$	$\xi_3(2) = 2.416$	$\xi_3(2) = 2.146$	$\xi_3(2) = 0.052$	$\xi_3(2) = 7.478$	$\xi_3(2) = 4.197$
	$\eta_4(1,627) = 3.205$	$\eta_4(1,627) = 0.033$	$\eta_4(1,627) = 3.579$	$\eta_4(1,627) = 3.569$	$\eta_4(1,627) = 3.818$	$\eta_4(1,627) = 1.077$

Notes:
M_1 are dummy variables representing Settlement Mondays. M_2 are dummy variables representing Non-Settlement Mondays
D_2 are dummy variables representing Tuesdays. D_3 are dummy variables representing Wednesdays.
D_4 are dummy variables representing Thursdays.
F_1 are dummy variables representing the Fridays before Settlement Mondays
F_2 are dummy variables representing the Fridays before Non-Settlement Mondays
Figures in parentheses are standard errors. R^2 is the adjusted R^2.
DUM is a dummy variable that captures unusually large outliers in the data
*** t-statistic significant at the 1% level. ** t-statistic significant at the 5% level
η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

generally become insignificant when the microstructure is accounted for in daily returns. Therefore predictable daily seasonal variables representing settlement effects seems to be explained away by the microstructure present in returns. Clearly, this seems to suggest that investor transacting behaviour represented by the touch accounts for return seasonality.

One interesting aspect of all the results so far in this chapter is that a size effect (examined using market value classified portfolios) and a small price effect (examined using closing price classified portfolios) does not seem to effect daily seasonality on the LSE. Indeed a settlement effect seems as likely in small size/price portfolios as it does in larger ones. Again following the intuition in chapter 4, we have no evidence thus far to suggest whether this seasonal behaviour is actually in the returns process or in the touch. This question will be answered in the next section by testing for seasonality in the touch as well as seasonality in returns.

5.4.3. *Results of Tests for Seasonality in the Touch.*

The previous analysis firstly confirms the existence of a settlement effect on the LSE and then finds that the microstructure can account for such daily seasonality in the market. However, there is no evidence to suggest whether seasonality is in the touch or returns. The results of tests for each explanation of daily seasonality are shown in Table 5.4 and 5.5 respectively. As is evident in Table 5.4, seasonality in the touch is prominent across most of the portfolios for the settlement Monday SP_pM_1, and highly significant across all the portfolios for account Mondays SP_PM_2 and on the last Friday of the two week account period, SP_pF_1. However, the results shown in Table

Table 5.4

OLS Regression Model Results of Returns Dependent upon Lagged Returns and Daily Touch Dummy Variables Representing Settlement and Non-Settlement Mondays and the Fridays before Settlement or Non-Settlement Monday for Equally Weighted Portfolios

	Market Value Portfolio Classification					
Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1740***	0.0261	0.0753**	0.0346	0.0543	0.0320
	(0.0364)	(0.0346)	(0.0374)	(0.0356)	(0.0358)	(0.0373)
SP_pM_1	0.0905	0.0951	0.2201**	0.3124***	0.3576	0.4509***
	(0.0646)	(0.0788)	(0.1006)	(0.1079)	(0.1209)	(0.1429)
SP_pM_2	-0.1240**	-0.3397***	-0.4095***	-0.4361***	-0.4025***	-0.4589***
	(0.0648)	(0.0061)	(0.1013)	(0.1094)	(0.1215)	(0.1433)
SP_pF_1	-0.1395**	-0.2557***	-0.3685***	-0.4045***	-0.3549***	-0.4433***
	(0.0719)	(0.0861)	(0.1104)	(0.1183)	(0.1368)	(0.1619)
SP_pF_2	-0.0057	0.0379	-0.0340	-0.1112	0.0517	-0.0568
	(0.0685)	(0.0837)	(0.1075)	(0.1171)	(0.1307)	(0.1589)
DUM	0.0984***	0.1004***	0.1031***	0.1004***	0.0966***	0.1008***
	(0.0097)	(0.0072)	(0.0123)	(0.0086)	(0.0084)	(0.0119)
	$R^2 = 0.170$	$R^2 = 0.262$	$R^2 = 0.144$	$R^2 = 0.212$	$R^2 = 0.199$	$R^2 = 0.129$
	$\eta_1(1,622) = 0.052$	$\eta_1(1,622) = 5.908$	$\eta_1(1,622) = 0.398$	$\eta_1(1,622) = 0.054$	$\eta_1(1,622) = 0.298$	$\eta_1(1,622) = 2.495$
	$\eta_2(1,622) = 0.096$	$\eta_2(1,622) = 0.169$	$\eta_2(1,622) = 0.055$	$\eta_2(1,622) = 0.005$	$\eta_2(1,622) = 0.198$	$\eta_2(1,622) = 0.023$
	$\xi_3(2) = 7.099$	$\xi_3(2) = 16.98$	$\xi_3(2) = 5.675$	$\xi_3(2) = 6.142$	$\xi_3(2) = 9.506$	$\xi_3(2) = 9.649$
	$\eta_4(1,627) = 1.359$	$\eta_4(1,627) = 1.449$	$\eta_4(1,627) = 0.874$	$\eta_4(1,627) = 1.385$	$\eta_4(1,627) = 1.446$	$\eta_4(1,627) = 1.505$

Table 5.4 cont.

Closing Price Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1136***	0.0333	-0.0101	0.0983***	0.0703	0.1229***
	(0.0365)	(0.0369)	(0.0346)	(0.0355)	(0.0364)	(0.0358)
SP_pM_1	0.2263***	0.1753	0.1697	0.2668***	0.2598***	0.1396
	(0.0757)	(0.0959)	(0.1005)	(0.1028)	(0.1018)	(0.0959)
SP_pM_2	-0.3264***	-0.3241***	-0.3402***	-0.3439***	-0.3660***	-0.2459***
	(0.0769)	(0.0972)	(0.1014)	(0.1029)	(0.1038)	(0.0929)
SP_pF_1	-0.2392***	-0.3599***	-0.2868***	-0.3495***	-0.3159***	-0.2489**
	(0.0861)	(0.1076)	(0.1091)	(0.1120)	(0.1137)	(0.1040)
SP_pF_2	0.0213	-0.0993	0.0868	-0.0145	0.0355	-0.1064
	(0.0811)	(0.1045)	(0.1091)	(0.1099)	(0.1093)	(0.1003)
DUM	0.0973***	0.0992***	0.1000***	0.0985***	0.1002***	0.1017***
	(0.0102)	(0.0105)	(0.0071)	(0.0083)	(0.0096)	(0.0091)
	$R^2 = 0.172$	$R^2 = 0.150$	$R^2 = 0.262$	$R^2 = 0.214$	$R^2 = 0.174$	$R^2 = 0.197$
	$\eta_1(1,622) = 0.754$	$\eta_1(1,622) = 0.099$	$\eta_1(1,622) = 3.350$	$\eta_1(1,622) = 0.507$	$\eta_1(1,622) = 0.169$	$\eta_1(1,622) = 0.437$
	$\eta_2(1,622) = 0.016$	$\eta_2(1,622) = 0.016$	$\eta_2(1,622) = 0.039$	$\eta_2(1,622) = 0.003$	$\eta_2(1,622) = 0.015$	$\eta_2(1,622) = 0.006$
	$\xi_3(2) = 7.572$	$\xi_3(2) = 2.400$	$\xi_3(2) = 9.178$	$\xi_3(2) = 8.063$	$\xi_3(2) = 6.726$	$\xi_3(2) = 6.193$
	$\eta_4(1,627) = 1.091$	$\eta_4(1,627) = 1.697$	$\eta_4(1,627) = 1.537$	$\eta_4(1,627) = 1.677$	$\eta_4(1,627) = 1.373$	$\eta_4(1,627) = 2.957$

Table 5.4 cont.

Touch Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	-0.0001 (0.0347)	0.0748** (0.0348)	0.0244 (0.0355)	0.0671 (0.0351)	0.1253*** (0.0336)	0.0986*** (0.0354)
SP_pM_1	0.1609*** (0.0549)	0.2151*** (0.0745)	0.1648** (0.0829)	0.2554** (0.1034)	0.3762*** (0.1172)	0.1976 (0.1726)
SP_pM_2	-0.1434*** (0.0561)	-0.1980*** (0.0753)	-0.2826*** (0.0851)	-0.3929*** (0.1048)	-0.3410*** (0.1166)	-0.4404*** (0.1749)
SP_pF_1	-0.1596*** (0.0625)	-0.1825** (0.0794)	-0.3103*** (0.0938)	-0.3929*** (0.1147)	-0.3310*** (0.1268)	-0.4452** (0.1913)
SP_pF_2	-0.0616 (0.0591)	-0.0460 (0.0774)	-0.0296 (0.0902)	0.0311 (0.1116)	-0.1202 (0.1233)	-0.0477 (0.1869)
DUM	0.0998*** (0.0072)	0.0987*** (0.0077)	0.0967*** (0.0080)	0.0982*** (0.0079)	0.0992*** (0.0067)	0.1006*** (0.0081)
	$R^2 = 0.252$	$R^2 = 0.243$	$R^2 = 0.220$	$R^2 = 0.232$	$R^2 = 0.293$	$R^2 = 0.217$
	$\eta_1(1,622) = 0.001$	$\eta_1(1,622) = 0.081$	$\eta_1(1,622) = 0.176$	$\eta_1(1,622) = 0.001$	$\eta_1(1,622) = 0.706$	$\eta_1(1,622) = 0.015$
	$\eta_2(1,622) = 0.198$	$\eta_2(1,622) = 0.054$	$\eta_2(1,622) = 0.113$	$\eta_2(1,622) = 0.007$	$\eta_2(1,622) = 0.063$	$\eta_2(1,622) = 0.002$
	$\xi_3(2) = 4.623$	$\xi_3(2) = 4.924$	$\xi_3(2) = 2.086$	$\xi_3(2) = 6.993$	$\xi_3(2) = 2.402$	$\xi_3(2) = 0.400$
	$\eta_4(1,627) = 4.000$	$\eta_4(1,627) = 3.148$	$\eta_4(1,627) = 2.107$	$\eta_4(1,627) = 2.492$	$\eta_4(1,627) = 3.793$	$\eta_4(1,627) = 3.926$

Table 5.4 cont.

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	5	Largest
$R_{p,t-1}$	0.1469***	0.0585	0.0200	0.0929***	0.0702**	0.0154
	(0.0350)	(0.0352)	(0.0332)	(0.0337)	(0.0347)	(0.0363)
SP_pM_1	0.1111	0.1399	0.1983**	0.2011**	0.2216**	0.4251***
	(0.0767)	(0.0857)	(0.0891)	(0.0844)	(0.0974)	(0.1188)
SP_pM_2	-0.1541**	-0.2619***	-0.1654	-0.2888***	-0.2832***	-0.4326***
	(0.0753)	(0.0875)	(0.0923)	(0.0864)	(0.0990)	(0.1209)
SP_pF_1	-0.2171***	-0.2143**	-0.2297**	-0.3237***	-0.3432***	-0.4884***
	(0.0835)	(0.0956)	(0.0989)	(0.0928)	(0.1095)	(0.1913)
SP_pF_2	-0.1062	-0.04679	0.0374	0.0177	-0.0198	-0.0087
	(0.0786)	(0.0914)	(0.0975)	(0.0904)	(0.1033)	(0.1300)
DUM	0.0987***	0.0922***	0.0997***	0.0985***	0.0990***	0.0933***
	(0.0079)	(0.0073)	(0.0061)	(0.0065)	(0.0074)	(0.0093)

$R^2 = 0.231$	$R^2 = 0.227$	$R^2 = 0.312$	$R^2 = 0.298$	$R^2 = 0.248$	$R^2 = 0.179$
$\eta_1(1,622) = 0.051$	$\eta_1(1,622) = 0.852$	$\eta_1(1,622) = 1.018$	$\eta_1(1,622) = 0.043$	$\eta_1(1,622) = 0.024$	$\eta_1(1,622) = 1.468$
$\eta_2(1,622) = 0.042$	$\eta_2(1,622) = 2.563$	$\eta_2(1,622) = 0.008$	$\eta_2(1,622) = 0.022$	$\eta_2(1,622) = 0.030$	$\eta_2(1,622) = 0.812$
$\xi_3(2) = 4.861$	$\xi_3(2) = 2.283$	$\xi_3(2) = 2.850$	$\xi_3(2) = 0.076$	$\xi_3(2) = 7.441$	$\xi_3(2) = 4.734$
$\eta_4(1,627) = 3.195$	$\eta_4(1,627) = 0.000$	$\eta_4(1,627) = 3.985$	$\eta_4(1,627) = 3.759$	$\eta_4(1,627) = 4.404$	$\eta_4(1,627) = 1.529$

Notes:
SP_pM_1 are dummy variables representing the Touch on Settlement Mondays
SP_pM_2 are dummy variables representing the Touch on Account Mondays
SP_pF_1 are dummy variables representing the Touch on Fridays before Settlement Mondays
SP_pF_2 are dummy variables representing the Touch on Fridays before Account Mondays
Figures in parentheses are standard errors.
DUM is a dummy variable that captures unusually large outliers in the data
R^2 is the adjusted R^2.
*** t-statistic significant at the 1% level
** t-statistic significant at the 5% level
η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(,.,) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

Table 5.5

OLS Regression Model Results of the Touch Dependent upon Daily Return Dummy Variables Representing Settlement and Non-Settlement Mondays and the Fridays before a Settlement or Non-Settlement Mondays for Equally Weighted Portfolios

Market Value Portfolio Classification

Size	Smallest	2	3	4	5	Largest
CONSTANT	0.0200*** (0.0001)	0.0152*** (0.0001)	0.0125*** (0.0001)	0.0122*** (0.0001)	0.0093*** (0.0001)	0.0079*** (0.0001)
R_pM_1	0.0683 (0.0533)	-0.0122 (0.0422)	0.0240 (0.0311)	0.0260 (0.0248)	0.0109 (0.0193)	0.0146 (0.0160)
R_pM_2	0.0186 (0.0434)	0.0356 (0.0309)	-0.0244 (0.0225)	-0.0225 (0.0173)	-0.0169 (0.0131)	-0.0053 (0.0064)
R_pF_1	0.0095 (0.0605)	-0.0288 (0.0514)	-0.0547 (0.0311)	-0.0599 (0.0274)	0.0001 (0.0178)	0.0211 (0.0187)
R_pF_2	0.0249 (0.0466)	0.0450 (0.0285)	0.0484 (0.0193)	-0.0014 (0.0176)	0.0192 (0.0101)	0.0033 (0.0117)
	$R^2 = 0.003$	$R^2 = 0.005$	$R^2 = 0.011$	$R^2 = 0.005$	$R^2 = 0.002$	$R^2 = 0.004$

Closing Price Portfolio Classification

Size	Smallest	2	3	4	5	Largest
CONSTANT	0.0176*** (0.0002)	0.0137*** (0.0001)	0.0122*** (0.0001)	0.0117*** (0.0001)	0.0105*** (0.0001)	0.0115*** (0.0001)
R_pM_1	0.0363 (0.0614)	0.0024 (0.0399)	-0.0409 (0.0462)	0.0134 (0.0256)	0.0390 (0.0201)	0.0351 (0.0246)
R_pM_2	-0.0129 (0.0457)	-0.0021 (0.0284)	0.0230 (0.0334)	-0.0172 (0.0215)	0.0079 (0.0144)	-0.0097 (0.0166)
R_pF_1	-0.0132 (0.0694)	-0.0145 (0.0397)	0.0297 (0.0494)	0.0037 (0.0283)	0.0127 (0.0214)	-0.0128 (0.0287)
R_pF_2	0.0042 (0.0482)	0.0153 (0.0297)	0.0311 (0.0308)	0.0113 (0.0146)	0.0266 (0.0143)	0.0328 (0.0166)
	$R^2 = 0.001$	$R^2 = 0.001$	$R^2 = 0.004$	$R^2 = 0.002$	$R^2 = 0.006$	$R^2 = 0.004$

Table 5.5 cont

Touch Portfolio Classification

Size	Smallest	2	3	4	5	Largest
CONSTANT	0.0192***	0.0151***	0.0134***	0.0113***	0.0105***	0.0078***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R_pM_1	0.1111	0.0451	-0.0299	0.0449	0.0227	0.0129
	(0.0634)	(0.0573)	(0.0288)	(0.0277)	(0.0207)	(0.0192)
R_pM_2	-0.0119	0.0743	-0.0333	-0.0254	-0.0183	-0.0022
	(0.0486)	(0.0427)	(0.0202)	(0.0181)	(0.0164)	(0.0137)
R_pF_1	-0.0488	-0.0879	0.0144	0.0080	-0.0077	0.0214
	(0.0656)	(0.0598)	(0.0276)	(0.0264)	(0.0233)	(0.0224)
R_pF_2	0.0072	0.0562	-0.0353	0.0396	0.0248	0.0134
	(0.0461)	(0.0383)	(0.0194)	(0.0176)	(0.0137)	(0.0139)
	R^2 = 0.006	R^2 = 0.006	R^2 = 0.002	R^2 = 0.009	R^2 = 0.003	R^2 = 0.004

Turnover by Volume Portfolio Classification

Size	Smallest	2	3	4	5	Largest
CONSTANT	0.0137***	0.0129***	0.0131***	0.0150***	0.0130***	0.0095***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R_pM_1	0.0637**	0.0549	-0.0139	0.0239	0.0076	0.0136
	(0.0313)	(0.0309)	(0.0456)	(0.0269)	(0.0340)	(0.0256)
R_pM_2	0.0206	-0.0190	0.0408	-0.0496	-0.0033	-0.0195
	(0.0231)	(0.0203)	(0.0387)	(0.0201)	(0.0222)	(0.0194)
R_pF_1	0.0288	0.0165	0.0328	-0.0363	-0.0288	-0.0434
	(0.0355)	(0.0311)	(0.0537)	(0.0287)	(0.0359)	(0.0274)
R_pF_2	0.0195	0.0286	0.0401	0.0117	0.0240	0.0067
	(0.0261)	(0.0182)	(0.0309)	(0.0178)	(0.0218)	(0.0204)
	R^2 = 0.003	R^2 = 0.004	R^2 = 0.005	R^2 = 0.007	R^2 = 0.003	R^2 = 0.006

Notes:
R_pM_1 are dummy variables representing Returns on Settlement Mondays
R_pM_2 are dummy variables representing Returns on Account Mondays
R_pF_1 are dummy variables representing Returns on the Fridays before Settlement Mondays
R_pF_2 are dummy variables representing Returns on the Fridays before Account Mondays
Figures in parentheses are standard errors. R^2 is the adjusted R^2.
*** t-statistic significant at the 1% level
** t-statistic significant at the 5% level

5.5 indicate that seasonality is not present in returns since when the touch is regressed on seasonal return variables there appears to be no statistically significant effect. Clearly, this re-affirms the results in Table 5.4, that the daily seasonal process is in the touch rather than portfolio returns.

These results provide proof that it is the microstructure, a measure of illiquidity in stock prices, around calendar turning points that causes seasonality in returns. Generally, the touch is a measure of investors' transacting behaviour in the market. Since the level of transactions reflects information about a security, market makers determine the risk attached to each security (as measured through the touch) by reacting to this investment behaviour. The touch size can be seen as a signal to the market reflecting the short run risk characteristic of a security, which around calendar turning points exhibits seasonal behaviour, still further.

5.5. CONCLUSIONS

Following evidence from the US[45], short run calendar anomalies such as the weekend effect have shown that security returns can be predictable during certain periods of the week. More specifically, this evidence suggests that Friday returns should on average be positive, while Monday returns should be negative. This so-called day of the week effect could arise due to the uncertainty caused by the non-trading period over the weekend. Investors would hence want to exit the market on a Friday (causing

[45] See French (1980) and Rogalski (1984).

negative returns) and re-enter the market on a Monday after the weekend (causing positive returns) to avoid this period of uncertainty.

More recently, evidence in the UK[46] suggests that short run calendar anomalies such as the weekend effect occur due to the influence of the fixed institutionalised settlement system that operated on the LSE up until very recently. Specifically, a weekly trading effect corresponding to predictable seasonal returns occurs on the first Monday and the account (middle) Monday of the two week settlement period. This previous evidence suggests that returns on the former Monday are positive, while returns on the latter Monday are negative due to the opportunity cost of the interest foregone from not buying on the first day of the settlement period and selling on the last.

Additionally, the influence of other anomalies such as the firm size effect and the microstructure in prices can help to explain this seasonal effect. Evidence from the US[47] has suggested that short run daily seasonality may at least be partially explained by the bid-ask spread. This is perhaps because investors' buying and selling behaviour influences the size of the bid-ask spread around seasonal turning points.

This chapter aims to test the proposition that a day of the week effect and a settlement effect are prominent on the LSE, and that these predictable calendar returns can be

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[46] See Theobald & Price (1984), Board & Sutcliffe (1988) and Choy & O'Hanlon (1989) for example.

[47] See Keim (1989) and Porter (1992).

accounted for by the effect of touch. Across the six sizes and four classifications of portfolios the initial results indicate that day of the week effects similar to those documented in the US are not prominent on the LSE.

However, analysis of the influence of the settlement system on calendar anomalies shows that the settlement (first) Monday of the two week settlement period is characterised by positive returns, while the middle or account Monday has negative returns. In addition the Fridays before settlement Mondays (i.e. the last day of the settlement period) has negative returns. This is consistent across all the sizes and classifications of portfolios and confirms the 'interest hypothesis' advocated by Theobald & Price (1984) amongst others. Overall, this evidence therefore seems to support seasonal effects on the LSE[48]. Finally, what is clear from the results is that the value of returns is not related to the size of each portfolio, so contradicting evidence of a firm size and price effect in returns.

Due to the theoretical and empirical relationship between returns and the microstructure, especially around calendar turning points, investigation is made into the influence the touch has on seasonal returns. For daily seasonality on the Mondays and Fridays associated with the settlement period, the previously significant seasonality is nullified when the effects of the touch are removed. In addition, this effect seems prominent in smaller sized as well as larger sized portfolios implying that the touch and settlement effects are not a function of firm size.

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[48] Lagged returns also proved generally significant indicating that daily returns may be predictable.

These results suggest that it is the microstructure that contributes to predictable settlement effects in returns on the LSE. In order to test this hypothesis, we test for seasonality in the touch and seasonality in the returns process. Interestingly, the results suggest that day of the week effects common to the LSE are determined by seasonality in the touch on settlement and account Mondays as well as on the last Friday of the two week settlement period.

The obvious implication from these and the previous chapter's results, is that seasonality in portfolio returns is not prominent on the LSE, and that any documented seasonal effects occur due to seasonality in the touch. This in turn reflects market maker and ultimately investors' behaviour around calendar turning points in the market. Therefore, profitable opportunities from timely transactions around short run calendar anomalies [after accounting for the touch] seem to be unavailable to investors transacting on the LSE.

6. PREDICTABILITY OF DAILY STOCK RETURNS ON THE LSE: A PRICE ADJUSTMENT APPROACH

6.1. INTRODUCTION

So far we have tested for long run and short run seasonality on the LSE. The results initially support the hypothesis of seasonality in the market across differing sizes and classifications of portfolios. However, market seasonality seems to depend upon the microstructure in returns, to the extent that the touch explains seasonal returns. What is more apparent from the results in the previous two chapters is that daily stock returns are more dependent upon predictable past returns rather than any seasonal parameters.

These results support much statistical evidence in the finance literature (especially from the US[49]) of security return predictability. Indeed, more recent empirical research[50] also suggests that returns from differing sized portfolios and market indices are predictable. One such study is by French & Roll (1986). They suggest that daily price variance is transitory and characterised by 'noise trading' by uniformed traders [Black (1986)]. Such pricing errors due to noise trading, especially in smaller firms, are eventually reversed as informed traders act on this divergence and

[49] See Fama (1991) for a review.

[50] See French & Roll (1986), Fama & French (1988) and Jegadeesh (1990) amongst others in the US, and MacDonald & Power (1992) in the UK.

bring prices back towards fundamentals.

Additionally, Fama & French (1988) following Summers (1986), support the theory that prices take divergent swings away from fundamentals in the long run and find that 3 to 5 year returns had strong negatively correlated returns. Such correlation reflects a slow mean-reverting component in security prices which appeared to be predictable for about 40% of the 3 to 5 year return variances in small sized portfolios. Jegadeesh (1990) again in the US finds, using monthly data, highly significant first-order serial correlation across all sizes of portfolios.

Explanations for this predictability have centred upon the influence of the bid-ask spread in returns. Indeed, Roll (1984) shows the direct link between predictiveness, measured by negative correlation, and the spread. Evidence from the UK study by MacDonald & Power (1992) confirm that positive autocorrelation caused by price divergence, is eradicated by the spread. Apart from the Jegadeesh (1990) study, firm size and the spread seems to influence the degree of return predictability. Conformation of this evidence is shown by Conrad, Kaul & Nimalendran (1991) in the US, who imply that between 11% and 24% of the variation in weekly returns can be explained by the bid-ask spread. Clearly, evidence from the studies highlighted above imply that return predictability is not as economically significant as its advocates imply it should be.

While the literature above (despite the influence of the spread) finds statistical evidence of return predictability, it gives no indication of the predictiveness of an investors' decision making process in the market. This chapter aims to redress this imbalance by using a model that mimics more closely investor behaviour. In the light of this, and given the assumption that current and future information in the market is uncertain, risk-averse investors will try and minimise the cost of the deviation of actual price from its underlying intrinsic value. The assumptions underlying this investor behaviour model are given as follows. Firstly, prices react to information in the market. Secondly, the 'value' of a security represents fundamental information (since this information is costly) and thirdly, noise trading in the market causes uncertainty. In the light of these assumptions the following hypothesis can be stated: risk-averse investors will not fully adjust prices on the receipt of fundamental information, so subsequently prices will only partially adjust to changes in value and hence follow a partial adjustment model (PAM) [Amihud & Mendelson (1987)].

This chapter extends Amihud and Mendelson's idea of partial price adjustment and provides a theoretical framework from which investors minimise the cost of price adjustment. An additional advantage of this framework is that it allows the more (empirically) rigorous Error Correction Mechanism (ECM) to be specified. The predictability question is hence examined using this more rigorous ECM framework and models various equally weighted portfolio series. Portfolios are constructed from market value, touch, and turnover by volume classifications formed from 5 years of daily data[51]. As we have already shown, the first classification, market value, enables the examination of a size effect in security returns. The second, the touch,

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[51] The transaction price classification was dropped since it replicated the results from testing for firm size using market value.

following Roll (1984), gives an indication of returns behaviour under differing liquidity levels and the third classification, turnover by volume, following Demsetz (1968) shows the effects of classifying by differing information levels.

The results suggest that daily security predictability is a negative function of firm size regardless of portfolio construction. Interestingly, many portfolio series have a significant lag 4 and 10 returns component which intuitively may correspond to a weekly effect and 11 day cycle in prices. Also, smaller size portfolios are characterised by a significant error correction component which may be indicative of an adjustment process in prices where investors correct for disequilibrium in intrinsic value.

Finally, return predictability seems more prominent when prices include a touch component i.e. when closing as opposed to bid prices are estimated. Clearly, despite the absence of a day of the week effect, daily return predictability for one and two week cycles seems prominent on the LSE. The chapter is organised as follows: section 6.2 reviews issues on return predictability, 6.3 the theoretical modelling issues, section 6.4, the data methodology, section 6.5, the empirical results with section 6.6 concluding.

6.2. ISSUES ON RETURN PREDICTABILITY

6.2.1. *Return Predictability, Overreaction and Noise*

Inefficiencies in the securities market can be caused by persistent noise, overreaction and volatility. Much of the volatility debate has centred around the Shiller (1981) and LeRoy & Porter (1981) papers which imply that stock prices are too volatile compared to underlying dividends. In the scenario of an efficiently priced stock, its intrinsic fundamental value should equal the present value of future dividends. It is the efficiency with which intrinsic value adjusts to new information that can lead to stock mispricing. Clearly the greater the mispricing the greater the likelihood that anomalies will exist and that returns are predictable.

As we have shown previously in the DeBondt & Thaler (1985, 1987) studies overreaction by investors initially to recent information may cause a temporary movement of prices away from fundamentals. This literature is directly related to the mean-reverting behaviour of stock prices found by Fama & French (1988) and Poterba & Summers (1988). Their emphasis is on a transitory component in stock returns that could be caused by a movement of prices away from a fundamental permanent component which is dependent on rational expectations of stock returns.

Indeed it seems that this previous work[52] only uses ex-post variables with lower frequency data and provides only weak evidence that the autocorrelations of returns are zero (i.e. returns are unpredictable). This latter point, arguably, according to

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[52] See Fama & French (1988) and Poterba & Summers (1988).

Campbell (1991) implies that if all autocorrelations are zero then ex-post stock returns are white noise and hence expected returns are constant. The point here is that small autocorrelations of ex-post returns can result even when expected returns are volatile and persistent; but more on this in chapter 7.

Explanations for these movements of prices away from fundamentals could be the result of noise trading[53]. An investor's a priori information set determines the type of trade that will occur. Under the assumption that underlying value and prices follow a geometric random walk, noise traders may trade on non-fundamental information that could carry little economic relevance[54]. Information traders however, who seek out more costly fundamental information will be able to trade on the back of noise traders who have caused prices to move away from their intrinsic underlying value and hence make profits. In this scenario there is the problem of noise in prices, i.e. knowing whether transactions are made using noise or fundamental information.

As we know from chapter 3, the larger the volume of trade the larger positions information traders will take up in the market. Clearly the size of these long and short positions depends on an investors risk preference; as a result positions taken are limited in size. Since it is difficult to tell non-fundamental from fundamental information, traders will not know the full extent of noise trading in the market. Indeed fundamentalists generate further noise (in some cases inadvertently) in order

[53] See Black (1986).

[54] See for example the evidence in Dubofsky (1991), showing increased volatility subsequent to stock splits.

to induce noise traders to push prices further away from their intrinsic value. Indeed, noise trading is a continual short run phenomenon and causes prices to move away from value. Large positions will be taken by information traders and as a result prices will revert back to fundamentals in the long run. This is consistent with the mean reversion representation of price movements.

Noise and hence the volatility of prices are also affected by the speed and type of information that traders use. With underlying intrinsic value being difficult to observe, any new information will affect the level of noise in prices. Indeed noise trading could be the result of so-called positive feedback trading, hypothesised by De Long, Shleifer, Summers & Waldmann (1990a)[55]. However, of potentially more interest is the influence that the bid-ask spread has on return predictability. Clearly, mispricing of underlying returns may occur, due to the size of the spread as well as intra-spread movements caused by investors transacting behaviour. Thus the spread may cause false inferences about the level of return predictability.

6.2.2. *The Influence of the Bid-Ask Spread on Return Predictability*

As has been shown, the difference between the bid (selling) and ask (buying) price facing investors can help to explain, for example, the anomalies highlighted above. Roll (1984) shows that overreaction and price reversals cause negative autocorrelation in stock returns which is the result of the bid-ask spread. Atkins & Dyl (1990), Lehmann (1990), Conrad, Kaul & Nimalendran (1991) and specifically Kaul &

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[55] Such trading is generally seen as usurping the buying and selling action of noise traders.

Nimalendran (1990) show that a large proportion of overreaction can be accounted for by the bid-ask spread. This is because the spread component in observed transaction prices causes prices to be pushed away from the underlying value of the stock. In fact, Kaul & Nimalendran (1990) show that up to 50% of overreaction in small firms and up to 23% of overreaction in larger firms can be explained by the effects of the quoted spread.

The Kaul and Nimalendran (1990) study also used variance ratio (VR) tests of daily to twelve weekly NASDAQ stock returns. The results indicate that spread errors caused substantial spurious volatility. The VR results show little evidence of market overreaction, however one week bid-bid returns show some price reversal which could be due to the effects of weekend non-trading which can induce negative autocorrelation. Hence, explanations for overreaction and mispricing compared to a given underlying value are clearly influenced by the bid-ask spread in returns.

Furthermore as we have seen, examination of the overreaction hypothesis using the winner and loser stocks phenomenon[56], by Atkins & Dyl (1990), found that overreaction is small especially when compared to the bid-ask spread effect. Indeed overreaction, especially to negative information (according to a number of studies) may be explained by movements between the ask and bid price. In fact, Conrad, Kaul & Nimalendran (1990) found that time-varying expected returns and bid-ask errors explained up to 24% of security returns variance and the majority of returns negative autocovariance, a common measure of overreaction. Whereas Zarowin (1990) found

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[56] See DeBondt & Thaler (1985, 1987).

that firm size and not overreaction explains loser returns, Lehmann (1990) found that price reversals are common on a weekly basis even after taking account of the bid-ask spread.

Finally, another source of security mispricing may be due to the influence of the dealing system operating in a market. The LSE operates as a dealership market[57] where orders for securities are executed by dealers at a preset quoted price given on the SEAQ (Stock Exchange Automatic Quotation) system. The dealers in the market quote the bid and ask prices they are willing to buy and sell at, up to a specified transaction size. Each dealer operates independently and so does not know until the information of a transaction is displayed on the system, who else, if anyone is buying or selling in the market. Both these two characteristics of the LSE mean that there are invariably many differing bid and ask prices and hence touch sizes quoted at anyone time, and without the knowledge of the market participants. This may contribute to noise in the market and the mispricing of securities compared to some underlying value.

Clearly, the evidence above points to a link between the bid-ask spread (or touch in the UK) and firm size. Some of the earlier evidence from Stoll & Whaley (1983), show that market value and share price vary inversely with risk-adjusted returns, but that higher transaction costs due to spread illiquidity and commission rates negate any size effects. Recent work by Jegadeesh (1992) however found, that the size effect remained even with a beta risk adjustment. Other risk factors were deemed as a likely

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[57] See Pagano & Röell (1991) for a discussion on dealership markets.

cause of this effect[58].

The following scenario may help to explain the link between firm size and the touch. Using the assumptions examined in chapter 3, that smaller firms have less volume of trade and therefore less information about them in the market[59], following Roll (1984) we can hypothesise that market makers are less informative about smaller firms since they perceive them as more risky. Consequently, they widen the difference between their buying (bid) and selling (ask) price to cover this risk. This can result in mispricing, overreaction and noise, which may contribute to larger expected returns. By intuition a wider touch implies more illiquidity in stock prices which increases their risk. Riskier stocks will discourage investors from transacting in them. This fall in the volume of trade of stocks will mean there is less information in the market. Hence we have returned full circle, since these are the characteristics of smaller stocks. Differing sized portfolios should therefore exhibit different returns behaviour and may help to explain and contribute to return predictability[60]. The following section hypothesises a test for return predictability using a model of investor price adjustment behaviour, using portfolio returns, prices and intrinsic value.

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[58] Additionally, we have shown that Leong & Zaima (1991) and Lamoureux & Sanger (1989) implied the size effect was a calendar anomaly.

[59] See Garbade (1982) and Demsetz (1968)

[60] Many of the studies on the size effect are subject to the constraints imposed by using asset pricing models such as the capital asset pricing model. Mis-specification of these models, may distort investigations into the size effect.

6.3. THE PRICE ADJUSTMENT PROCESS

6.3.1. *The Hypothesis of Price Adjustment*

Amihud & Mendelson (1987) in the US [hereafter A&M], hypothesise that observed stock prices, p_t, adjust efficiently (though noisily) to changes in underlying intrinsic value, v_t. The difference between price and value is attributable to 'noise' which may cause the 'pushing' of price away from value. Noise in turn can be attributed to two main sources. The first could be described as noise trading [see Black (1986)]. This is perhaps due to illiquidity in traders stock positions, the speed with which information arrives and inefficiencies in its use and assimilation. The second type of noise is to do with the influence of a trading mechanism on stock prices.

The LSE operates on a dealership basis where market makers continually quote prices they are willing to offer in a stock. One form of noise is the quote-revision of the price, i.e. a continually changing touch and/or price[61]. Others include discreteness in stock prices (Harris (1990)), the random arrival of buy and sell orders to the market and delays in price discovery[62]. In order to examine the contribution the touch makes to inefficiencies in the price adjustment process when there are changes in intrinsic value, both bid and closing price series are used[63]. Prices devoid of the

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[61] See Jang & Venkatesh (1991) who cite evidence from the US.

[62] A&M cite Mendelson (1987) and Cohen, Maier, Schwartz & Whitcomb (1986) respectively on these points.

[63] This is following Kaul & Nimalendran (1990) who found that market overreaction when measured by variance ratios (VR) was substantially reduced when bid-ask bounce was accounted for in the price series.

touch should adjust more efficiently.

Due to the fact that information has a cost and noise in the market implies risk, investors will only partially adjust price to changes in the underlying value of a stock. This price adjustment process can be captured in a myopic backward looking partial adjustment model (PAM) with noise, used by A&M and shown below

$$\Delta p_t = \alpha_0 + \beta_1 [v_t - p_{t-1}] + \varepsilon_t \qquad (6.1)$$

Here α_0 is a constant, β_1 is the adjustment coefficient, p_t and v_t are the log of price and intrinsic value respectively. Δp_t is logged returns and ε_t is an error term where $\sim N(0,\sigma_\varepsilon^2)$. The error term ε_t is due to noise trading and trading mechanism effects. The adjustment coefficient β_1 will reflect the efficiency of the adjustment of prices to changes in value. When $0<\beta_1<1$, there is a partial adjustment and in the unlikely scenario $\beta_1=0$, there are no price movements to changes in value. Clearly when $\beta_1>1$, traders overreact to new information about the value of the security, and when $\beta_1=1$, there is a full price adjustment.

When this latter adjustment occurs the PAM takes the following form

$$p_t = \alpha_0 + v_t + \varepsilon_t \qquad (6.2)$$

Investors, because they are risk averse and rational, aim to optimally adjust the price of a security when they receive fundamental information which affects the value of that security. This is the partial adjustment process without the existence of noise traders. Optimal adjustment involves minimising a so-called quadratic loss function (QLF). The QLF penalises deviations from equilibrium and rapid price adjustments made by investors. Following Pagan (1985), the myopic PAM theorised in equation (6.1) above arises when agents minimise a QLF that penalises deviations of actual price, p_t, from target value, v_t, and changes in the 'normal' growth rate, α_t. This is shown below as

$$QLF = \frac{1}{2}(p_t - v_t)^2 + \frac{\theta_1}{2}(\Delta p_t - \alpha_t)^2 \tag{6.3}$$

where θ_1, as well as θ_2 shown in (6.5) below, are the marginal cost of adjustment relative to the marginal cost of being away from equilibrium. By finding the optimal p_t that minimises the QLF, (6.1) above can be written as a strict version of the myopic PAM condition where

$$\Delta p_t = \beta_1 (v_t - p_{t-1}) \tag{6.4}$$

when α_0=0. However, Hendry & von Ungern Sternberg (1981) argue that variables can actually change from their normal growth rate and that this will not be too costly if the variable changes in the same direction as the equilibrium. As a result an additional term such as

$$- \theta_2 (p_t - p_{t-1})(v_t - v_{t-1}) \tag{6.5}$$

can be added to (6.3) to take account of this fact. Minimising the QLF in (6.3), augmented by (6.5) with respect to p_t, yields an ECM such as (6.6)

$$\Delta p_t = \alpha_0 + \gamma_1 \Delta v_t - \beta_1 (p_{t-1} - v_{t-1}) \tag{6.6}$$

which imposes proportionality between p_t and v_t in the long run, i.e. $p_t = v_t$, where $\gamma_1 = (1+\theta_2)/(1+\theta_1)$ and $\beta_1 = 1/(1+\theta_1)$. The advantage of specifying such an ECM model of price behaviour, is that it is an optimal decision rule and so is more representative of the actions of investors and it encompasses the PAM as a subset when $\gamma_1 = -\beta_1$.

6.3.2. *Extracting Intrinsic Value using the Kalman Filter*

Following (6.2) and assuming homogeneous restrictions on p_t and v_t, the following relationship can be shown to hold

$$p_t = \alpha_0 + v_t + \varepsilon_t \qquad (6.7)$$

where p_t is the observed market price of the security, v_t is initially an unobservable component of a securities price that represents fundamental information, and follows a random walk and ε_t is the noise or error term which fluctuates around this value.

The model in (6.7) shows how price is determined by the information updating process influencing intrinsic value. Equation (6.7) can be seen as an unobservable components model and intrinsic value, represented by v_t, can be extracted using the Kalman Filter. The Kalman Filter enables (6.7) to be written as a measurement equation, and the process of the unobservable component, v_t, as a series of transition equations in a state-space form as shown below[64]:

$$p_t = S_t v_t + \varepsilon_t \qquad \varepsilon_t \sim N(0,\sigma^2_\varepsilon) \qquad (6.8)$$

$$v_t = v_{t-1} + \beta_{t-1} + u_t \qquad u_t \sim N(0,\sigma^2_u) \qquad (6.9)$$

$$\beta_t = \beta_{t-1} + \zeta_t \qquad \zeta_t \sim N(0,\sigma^2_\zeta) \qquad (6.10)$$

The transition equations in (6.9) and (6.10) show that v_t and the global trend in v_t, evolve as a stochastic random walk process since information arrives stochastically,

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[64] Harvey (1982) examines the Kalman Filter as an application in time-series models. Harvey shows that the state space form in his words [page 4] ... "makes two fundamental contributions to classical time-series analysis." Firstly, the state-space models enables the prediction error of a dynamic model to be decomposed and secondly it enables signal extraction from a time-series model.

and, following the assumptions of Ross (1989), prices and their rate of change respond to new information. We estimate 6.8 - 6.10 to obtain an estimate of v_t.

6.4. DATA

The data set used in this chapter is the same as used in chapter 5. Returns are calculated from closing prices and bid prices. The touch variables for each portfolio are not used to show the influence of the microstructure in returns due to problems of multicollinearity which arise in the model with a large number of lags of the touch variable. Therefore bid prices are used to account for the influence of the touch. This is consistent with Kaul & Nimalendran (1991) who find that transaction prices over-estimate overreaction by up to 50% for small sized portfolios when compared to portfolios constructed using bid prices. Portfolios are again classified by market value, the touch and turnover by volume. Closing priced portfolios are omitted since they replicate the market value results. Thus the remaining classifications enable the robustness of return predictability across the differing classifications of portfolios to be tested. Test results of the predictability question are shown in section 6.5 below. Here a general multi-lag model is estimated which, in its restricted form can be represented as a partial adjustment model.

6.5. ESTIMATING PRICE ADJUSTMENT BEHAVIOUR AND ANOMALIES

Due to the use of high frequency data and the dynamic nature of investment decisions highlighted in previous sections, a returns series is more than likely to be represented by a multi-lag model than a single-lag model. In order to examine some of the theoretical and empirical issues discussed above, OLS regression techniques were used. Under the assumptions of Hendry & von Ungern-Sternberg (1981), a dynamic linear regression model with multiple lags of returns, price and intrinsic value was specified as shown below in (6.11)

$$\Delta p_t = \alpha_0 + \sum_{j=1}^{m} \alpha_j \Delta p_{t-j} + \sum_{i=1}^{m} \beta_i p_{t-i} + \sum_{i=1}^{m} \gamma_i v_{t-i} + \varepsilon_t \qquad (6.11)$$

where Δp_t, p_t and v_t are the logarithms of returns (including dividends), price and value respectively, in time t, and ε_t is an error term. In order to capture any weekly seasonality in the model lags of around ten were specified for each of the variables used in the regression.

6.5.1. *Unrestricted Models of Returns Behaviour*

The statistically significant results (at least at the 5% level) given in Tables 6.1 - 6.9 below, show unrestricted models of returns behaviour after estimating (6.11) above. Attaching economic meaning to the results from these models is obviously important. Thus, returns variables with a lag in period 4 may correspond to five day or weekly predictability and variables with a lag 10 similarly correspond to an 11 day cycle in prices. Similar lags in p_t and v_t show their influence on the dependent variable. Equal value but opposite signed coefficients of specific lags of p_t and v_t, which up hold the restriction that $p_t = v_t$, can be formulated as an error correction mechanism (ECM) component.

The ECM shows the daily adjustment process in prices when investors are correcting for disequilibrium in intrinsic value. Clearly, higher order ECM components, such at lag 4 may be correcting for the adjustment process for weekly predictability. The diagnostic specification of the results, in Appendix 2 shows that the residuals from all the models of return predictability are well specified, are of correct functional form, exhibit no serial correlation or non-normality and are homoscedastic.

6.5.2. *Results for Portfolios Classified by Market Value.*

Tables 6.1 - 6.3 show the statistically significant parameters of (6.11) for portfolios classified by different sizes of market value, which is the conventional way used to test the influence of firm size on portfolio returns. One of the most important observations from the results, is that as portfolio size increases from 1 to 6, generally the number of significant parameters reduces (especially those which carry most economic meaning, such as lagged returns). A set of dummy variables, DUM, corrects for large outliers and non-normality seen in the diagnostic tests of all the portfolio series. This is the same dummy variable used in chapter 5.

For all the bid and closing priced portfolio returns, R_t is dependent upon R_{t-10} (10 day lagged returns). R_{t-1} lags are prominent in the smallest size portfolios and in portfolio size 3. Additionally lag 4 of R_t is also prominent in portfolios size 1 and 2, indicating that predictable weekly prices are perhaps a function of firm size. In addition to the

Table 6.1

Unrestricted Regression Model of Returns Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by Market Value

Bid Price Data

Size	Smallest	2	3	4	5	Largest
R_{t-1}	0.131*** (0.036)		0.076** (0.037)			
R_{t-4}	0.102*** (0.036)	0.073** (0.034)				
R_{t-8}		0.084** (0.034)				
R_{t-10}	0.094*** (0.037)	0.079*** (0.035)	0.143*** (0.038)	0.153*** (0.036)	0.145*** (0.037)	0.098*** (0.038)
P_{t-1}	0.096*** (0.029)		0.051** (0.026)	0.042** (0.019)		
P_{t-4}					-0.055** (0.023)	
V_{t-1}	-0.098*** (0.029)		-0.052** (0.026)	-0.040** (0.020)		
V_{t-4}					0.055** (0.023)	
C	0.016 (0.011)	-0.000 (0.000)	-0.005 (0.020)	0.022 (0.015)	-0.003 (0.024)	0.000 (0.000)
DUM	0.044*** (0.004)	0.041*** (0.027)	0.040*** (0.004)	0.041*** (0.003)	0.034*** (0.003)	0.037*** (0.004)
	R^2 = 0.21	R^2 = 0.293	R^2 = 0.15	R^2 = 0.22	R^2 = 0.17	R_2 = 0.10

Notes:
C is a constant.
DUM is a dummy variable.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

Table 6.2

Unrestricted Regression Model of Returns Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by Market Value

Closing Price Data

Size	Smallest	2	3	4	5	Largest
R_{t-1}	0.142*** (0.036)		0.085** (0.037)			
R_{t-2}					0.136*** (0.045)	
R_{t-4}	0.121*** (0.036)	0.085** (0.034)				
R_{t-8}		0.086** (0.035)				
R_{t-10}	0.067 (0.036)	0.080** (0.035)	0.141*** (0.038)	0.158*** (0.036)	0.147*** (0.037)	0.099*** (0.039)
P_{t-1}	0.094*** (0.029)		0.054** (0.026)	0.045** (0.019)	-0.059** (0.028)	
P_{t-4}					-0.053 (0.028)	
V_{t-1}	-0.095*** (0.029)		-0.055** (0.026)	-0.042** (0.020)	0.054 (0.033)	
V_{t-4}					0.058** (0.023)	
C	0.007 (0.011)	0.000 (0.000)	-0.003 (0.019)	0.098 (0.054)	-0.003 (0.025)	0.000 (0.000)
DUM	0.044*** (0.004)	0.047*** (0.003)	0.043*** (0.004)	0.098*** (0.054)	0.038*** (0.004)	0.037*** (0.005)
	$R^2 = 0.205$	$R^2 = 0.276$	$R^2 = 0.152$	$R^2 = 0.221$	$R^2 = 0.185$	$R^2 = 0.082$

Notes:
C is a constant.
DUM is a dummy variable.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

influence of firm size, the touch may contribute to the size of return predictability on the market. In the case of weekly price predictability, the predictable R_{t-4} has a coefficient at least 20% larger for portfolio size 1 and around 10% larger for portfolio size 2 when closing as opposed to bid returns are used. This points to a hypothesis that the weekly cycle of significant security prices is exaggerated by the touch, especially for small firms.

Clearly a firm size effect is influencing the number of predictable return components across portfolios. The reason for this may be to do with the constituent companies of each portfolio. For example, large portfolios such as size 6 include securities that are more highly traded and so are subject to less mispricing. This is because information about them is more widely disseminated and hence they are more efficiently priced. It follows therefore, that partly as a result of less information about a security, there is greater uncertainty in the market for smaller firms. As a result these firms are less frequently traded and are more likely to exhibit return predictability.

When analysing the price, p_t, and intrinsic value, v_t, variables one can see that lag 4 has coefficients of similar value but of opposite sign which may point to an adjustment component in returns. p_{t-1} and v_{t-1} are prominent for all the smallest (size 1) and medium (size 3 and 4) portfolios. However, in Table 6.2 the inclusion of the bid-ask spread into prices causes the lag 1 of the dependent variables p_t and v_t to appear in the returns for the second largest (size 5) portfolio. Lag 4 of p_t and v_t are also prominent for the portfolios size 5 indicating some form of weekly adjustment in prices.

Table 6.3 shows the results of restricting lags 1 and 4 of p_t and v_t. The prominence of the unit lags in p_t and v_t may mean that a 'conventional' unit ECM components can be formed by restricting $p_{t-1} = v_{t-1}$. For all portfolios with a unit ECM component, the coefficient is positive. This implies that prices adjust away from equilibrium and hence there is noise in the returns series. Such mispricing is however a short run phenomenon since a Wald $\chi^2(1)$ test that the restriction $p_{t-1} = v_{t-1}$ implies homogeneity, is accepted for each portfolio at the 5% level. Another interesting price adjustment is in portfolio size 5. Here there is a negative coefficient ECM in lag t-4, again implying an adjustment process towards equilibrium around this significant parameter.

When comparing market value classified portfolios, what again is noticeable is that coefficients are larger when closing, as opposed to bid returns are used. This occurs across most lags where coefficients of closing priced portfolios are between 1% and 25% higher. Therefore, while the touch does not explain the predictable behaviour in security returns, it does contribute to it.

Since the touch can induce noise, mispricing, and hence a divergence of price away from intrinsic value, especially in smaller securities, it is not surprising that these portfolios are characterised by an ECM adjustment process. Under the assumption that investors are in a sub-optimal position one would expect that an adjustment parameter (ECM component) would carry a negative coefficient. This in effect would be the usual adjustment towards equilibrium for a returns series.

Table 6.3

Wald Tests of the Restrictions that $p_t = v_t$ hold under the Hypothesis Wald(1) < $\chi^2(1)$ for each of the Equally Weighted Portfolios Classified by Market Value

Bid Price Data

Size	Smallest	2	3	4	5	Largest
Restriction						
$p_{t-1} = v_{t-1}$	0.386		0.046	1.027	0.018	
$p_{t-4} = v_{t-4}$					0.153	

Closing Price Data

Size	Smallest	2	3	4	5	Largest
Restriction						
$p_{t-1} = v_{t-1}$	0.561		0.012	0.844	0.067	
$p_{t-4} = v_{t-4}$					0.083	

In summary, the results of the market value weighted portfolios seem to suggest that weekly and 11 day predictable cycles in prices are quite prominent. Indeed, this cyclical predictability intuitively may support short run weekly calendar anomalies documented in the previous chapter. Alternatively, weekly calendar anomalies may correspond to the institutional arrangements specific to the LSE, such as the settlement system which seems to influence the larger sized portfolios.

The results also indicate that firm size influences the level of return predictability. This is because smaller sized portfolios have a larger number of predictable returns components when compared to larger sized portfolios. The effect of using closing as opposed to bid prices is also documented in these results. This touch or mispricing effect in closing prices increases the size of the coefficients of parameters in the returns regression series and so cannot be overlooked as a contributor to seen anomalies.

6.5.3. *Results for Portfolios Classified by the Touch*

Tables 6.4 - 6.6 show significant coefficients for portfolios classified by touch. When compared to the results for market value portfolios, what is immediately obvious is that there are fewer significant parameters for touch classified series. Generally, the results show that touch sized portfolios are positively related to the number of significant variables. Intuitively, following Kaul & Nimalendran (1990), because the touch is inversely related to firm size, large touch portfolios are characterised by small firms and due to this negative relationship have more predictable returns components. Also theoretically, since market makers widen the touch of stocks when they perceive them to be more risky, these portfolios may be characterised by a greater number of significant predictable variables.

Closer examination of the results shows that a size effect is present in larger touch, smaller market value sized portfolios, where sizes 3, and specifically 4, 5, and 6 have more significant returns components. Due to the fact that the touch is a measure of risk and is inversely related to the level of information, the results indicate that larger touch, higher risk, smaller information stocks are characterised by more predictable exogenous variables. Interestingly a R_{t-4} weekly component occurs in medium touch sized firms such as in size 3 and 4. The weekly effect is therefore not exclusively a small firm effect, as in the case of market value classified portfolios, but is prominent in medium touch, larger firms as well. The coefficient on the weekly component is also positive which is consistent with previous evidence and market value classified portfolios.

The weekly anomaly therefore, may be prominent enough not to be traded away by investors who are transacting in more informationally efficient portfolios, such as FT-SE 100 stocks. In addition, the coefficient on R_{t-4} increases by between 5% and 20% when closing as opposed to bid prices are used to construct a returns series. The inverse is true for the equally weighted size 3 portfolio where the coefficient falls from 0.083 to 0.061. Apart from this latter, seemingly unexplainable result, the touch contributes to the size of the coefficient of the returns parameter corresponding to a weekly effect in this classification of portfolio. Finally, a predictable return variable R_{t-1} occurs in all the portfolios sizes, thus implying that changes in yesterday's prices partly determine current prices[65]. Again all the portfolio classifications are characterised by a positive R_{t-10} component corresponding to an 10 day calendar cycle. Overall the value of coefficients increases on the whole when closing (as opposed to bid) prices are used. However, the extent of this mispricing is such that the effect of the touch contributes an average of around 5% to their coefficients. Again a dummy variable DUM as defined in chapter 5 corrects for outliers in the returns series.

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[65] The coefficients on the R_{t-1} variables implies that between 6.2% and 11.8% of present returns are determined by lagged returns.

Table 6.4

Unrestricted Regression Model of Returns Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by the Touch

Bid Price Data

Size	Smallest	2	3	4	5	Largest
R_{t-1}		0.062 (0.036)		0.079** (0.038)	0.118*** (0.036)	0.098*** (0.037)
R_{t-2}					0.108*** (0.036)	
R_{t-4}			0.084** (0.036)	0.109*** (0.038)		0.082** (0.370)
R_{t-10}	0.085** (0.037)	0.121*** (0.036)	0.141*** (0.037)	0.110*** (0.038)	0.118*** (0.036)	0.097*** (0.038)
P_{t-1}	0.075*** (0.030)		0.029** (0.015)			0.062*** (0.023)
V_{t-1}	-0.079*** (0.030)		-0.029** (0.015)			-0.062*** (0.023)
C	0.025 (0.016)	0.000 (0.000)	0.001 (0.016)	0.000 (0.000)	-0.000 (0.000)	-0.003 (0.008)
DUM	0.042*** (0.004)	0.045*** (0.004)	0.039*** (0.003)	0.038*** (0.004)	0.045*** (0.004)	0.048*** (0.005)
	R^2 = 0.199	R^2 = 0.183	R^2 = 0.203	R^2 = 0.138	R^2 = 0.207	R^2 = 0.172

Notes:
C is a constant.
DUM is a dummy variable.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

Table 6.5

Unrestricted Regression Model of Returns Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by the Touch

Closing Price Data

Size	Smallest	2	3	4	5	Largest
R_{t-1}		0.077** (0.037)			0.100*** (0.036)	0.069 (0.037)
R_{t-2}					0.097*** (0.036)	
R_{t-4}			0.061 (0.036)	0.124*** (0.037)		0.087** (0.037)
R_{t-10}	0.086** (0.037)	0.139*** (0.037)	0.152*** (0.036)	0.116*** (0.038)	0.119*** (0.036)	0.102*** (0.038)
P_{t-1}	0.077*** (0.030)					0.059*** (0.023)
V_{t-1}	-0.081*** (0.030)					-0.058*** (0.023)
C	0.024 (0.016)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.003 (0.008)
DUM	0.041*** (0.004)	0.046*** (0.005)	0.038*** (0.003)	0.037*** (0.004)	0.044*** (0.004)	0.046*** (0.005)
	R^2 = 0.196	R^2 = 0.158	R^2 = 0.201	R^2 = 0.153	R^2 = 0.170	R^2 = 0.170

Notes:
C is a constant.
DUM is a dummy variable.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

Table 6.6 below shows the ECM model results for portfolios classified by the touch. An interesting insight into these models is that only a unit ECM parameter is prominent. Price adjustments at higher lags are not economically or statistically significant. Explanations for this centre on institutional factors. Following Merton (1987), the size of the touch is directly related to the availability of information in the market and hence it is the action of market makers which establishes the level of the touch for each equity in the market. This action is highly dependent on the volume of shares (a direct measure of information) traded on a transaction by transaction basis. It is the constant trading of securities which provides market makers with their information and the strength of this information will generally be determined by the size of buy and sell order placed with them.

Under this framework it is easy to see that market makers through the touch can rapidly adjust the illiquidity, perhaps representative of investor risk, attached to each security as their information set changes. Such rapid adjustment of the touch is not possible when portfolios are characterised by market value since price does not necessarily change on a transaction by transaction basis. Indeed, movement of the closing price within the touch may explain the inefficiency of price adjustment shown in the higher order ECM components when market value classified portfolios are used.

Even under the hypothesis of a rapid touch adjustment, some of the portfolio returns series are still characterised by a positive unit ECM component. This (as before) implies a noisy disequilibrium in the price adjustment process, but again the Wald

Table 6.6

Wald Tests of the Restrictions that $p_t = v_t$ hold under the Hypothesis Wald(1) < $\chi^2(1)$ for each of the Equally Weighted Portfolios Classified by the Touch

Bid Price Data

Size	Smallest	2	3	4	5	Largest
Restriction						
$p_{t-1} = v_{t-1}$	2.440		0.010			0.070

Closing Price Data

Size	Smallest	2	3	4	5	Largest
Restriction						
$p_{t-1} = v_{t-1}$	2.380					0.190

$\chi^2(1)$ test that the restriction $p_{t-1} = v_{t-1}$ implies homogeneity is accepted for all portfolios. Disequilibrium is therefore a short run phenomenon.

In conclusion, the results show that an 10-day returns cycle perhaps corresponding to an LSE settlement effect is consistent across all sizes of portfolios. Also as the size of the touch portfolio classification widens and the information set of securities decreases, each portfolio is generally characterised by a greater number of predictable return components. The size of the predictable anomalies are also determined by the touch which can contribute up to 20% of the returns coefficient. Compared to market value classified portfolios, the principle difference in these results is the greater number of predictable returns components in time periods 1 and 4 and greater efficiency in price adjustment around these cycles. Finally, the rapid nature of the touch adjustment made by market makers which is reflected in each portfolio classification contributes to more efficient pricing and overall to more predictable returns components especially for larger touch, smaller sized stocks.

6.5.4. *Results for Portfolios Classified by Turnover by Volume*

Tables 6.7 - 6.9 show significant predictable parameters of portfolios classified by turnover by volume. Following the theories of portfolio construction reviewed in chapter 3, intuitively smaller sized securities have a fewer number of shareholders. As a result they are characterised by less turnover by volume. Therefore, portfolios comprised of these securities have less information in the market and so consequently firm size is positively related to the turnover by volume.

Information signalled through the volume of transactions will have a direct influence on the exogenous variables of such classified portfolios. Since information in the market is a function of volume, such a classification of portfolio should mimic directly investors actions. Therefore, it is not surprising that there are a large number of predictable components in each portfolio returns series. If we follow jointly the arguments of Kaul & Nimalendran (1990) who showed the inverse relationship between spread and firm size, and Demsetz (1968), who showed that spread is inversely related to the number of shareholders and hence the volume of transactions, it follows that firm size is positively related to the volume of shares traded. Hence, larger volume portfolios are characterised by larger sized equities, and is representative

Table 6.7

Unrestricted Regression Model of Returns Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by Turnover by Volume

Bid Price Data

Size	Smallest	2	3	4	5	Largest
R_{t-1}	0.119*** (0.036)					
R_{t-2}			0.108*** (0.036)			
R_{t-4}	0.087** (0.036)	0.102*** (0.035)				
R_{t-8}		0.082** (0.036)		0.087** (0.037)		
R_{t-10}	0.129*** (0.036)	0.147*** (0.036)	0.125*** (0.037)	0.153*** (0.037)	0.150*** (0.038)	0.100*** (0.039)
P_{t-1}		0.039 (0.021)		0.043** (0.020)		
P_{t-4}	0.076** (0.032)		-0.067** (0.031)			
V_{t-1}		-0.050** (0.021)		-0.047** (0.021)		
V_{t-4}	-0.0863*** (0.032)		0.064** (0.031)			
C	0.063** (0.025)	0.063 (0.017)	0.019 (0.016)	0.022 (0.017)	-0.000 (0.000)	-0.000 (0.000)
DUM	0.034*** (0.003)	0.042*** (0.003)	0.048*** (0.004)	0.045*** (0.004)	0.044*** (0.005)	0.040*** (0.005)
	$R^2 = 0.241$	$R^2 = 0.253$	$R^2 = 0.187$	$R^2 = 0.201$	$R^2 = 0.145$	$R^2 = 0.107$

Notes:
C is a constant.
DUM is a dummy variable.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

Table 6.8

Unrestricted Regression Model of Returns Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by Turnover by Volume

Closing Price Data

Size	Smallest	2	3	4	5	Largest
R_{t-1}	0.133***				0.093	0.128***
	(0.035)				(0.037)	(0.035)
R_{t-2}			0.125***			
			(0.036)			
R_{t-3}	0.136**					
	(0.054)					
R_{t-4}	0.117**	0.103***		0.069**		
	(0.051)	(0.035)		(0.037)		
R_{t-5}						0.098***
						(0.035)
R_{t-8}		0.082**		0.087**		
		(0.035)		(0.036)		
R_{t-10}	0.117***	0.156***	0.127***	0.152***	0.141***	0.124***
	(0.035)	(0.036)	(0.036)	(0.037)	(0.038)	(0.035)
P_{t-1}		0.044		0.043**		
		(0.021)		(0.020)		
P_{t-4}	0.156***		-0.062**			
	(0.051)		(0.031)			
V_{t-1}		-0.055**		-0.047**		
		(0.021)		(0.020)		
V_{t-4}	-0.079**		0.059			
	(0.032)		(0.031)			
C	0.060**	0.064***	0.015	0.022	-0.000	-0.000
	(0.026)	(0.004)	(0.016)	(0.017)	(0.000)	(0.000)
DUM	0.031***	0.052***	0.046***	0.045***	0.050***	0.033***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.023)
	R^2 = 0.261	R^2 = 0.248	R^2 = 0.211	R^2 = 0.201	R^2 = 0.147	R^2 = 0.265

Notes:
Figures in parentheses are standard errors. C is a constant
R^2 is the adjusted R^2. DUM is a dummy variable.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

of a firm size effect. It follows then that small volume portfolios are small in market value. Under this framework one can see that larger volume portfolios should have a smaller number of significant parameters.

In addition, when volume classified portfolios are constructed using closing, as opposed to bid prices the exogenous positive variable R_{t-4} becomes significant. This implies specifically that the weekly effect is a function of the touch in sized 3 portfolios. Unlike market value and touch classifications of portfolios, the use of closing returns does not significantly contribute to the value of the coefficients of higher order significant variables. However, the use of closing returns as opposed to bid returns reveals one R_{t-3} variable for the smallest sized portfolio at the 5% level. Clearly, this is due to mispricing in security returns and hence is the consequence of a touch effect. Finally, the last main statistically significant anomaly is that corresponding to R_{t-10} (the two week cycle) which is significant in all the portfolios.

Results of the tests of the restrictions that $p_t=v_t$, and hence that an ECM representation of the portfolios can be formed, are shown in Table 6.9. The ECM results, as well as showing a firm (or volume) size effect generally across portfolios, also exhibit higher order ECM parameters. Consistent with market value classified models, t-4 parameters are only present in small volume sized portfolios. Portfolios sized 1 have a positive ECM t-4 variable which corresponds to a cyclical price adjustment. What is potentially more interesting is the Wald $\chi^2(1)$ test of the restriction $p_{t-4} = v_{t-4}$, fails at the 5% level for portfolios sized 1. This implies that there is a long run permanent disequilibrium in the cyclical price adjustment process. Given this is in a portfolio

Table 6.9

Wald Tests of the Restrictions that $p_t = v_t$ hold under the Hypothesis Wald(1) < $\chi^2(1)$ for each of the Equally Weighted Portfolios Classified by Turnover by Volume

Bid Price Data

Size	Smallest	2	3	4	5	Largest
Restriction						
$p_{t-1} = v_{t-1}$		14.56		1.612		
$p_{t-4} = v_{t-4}$	4.000		0.998			

Closing Price Data

Size	Smallest	2	3	4	5	Largest
Restriction						
$p_{t-1} = v_{t-1}$		14.28		1.592		
$p_{t-4} = v_{t-4}$	6.232		1.475			

characterised by a small information set, investors may seek out such anomalies since they may be profitable.

More meaningful is the result of the Wald $\chi^2(1)$ test that the restriction $p_{t-1} = v_{t-1}$ for portfolios sized 2, is rejected at the 1% level. Again, since this disequilibrium occurs in smaller portfolios it could be the result of a small information set and hence mis-information by investors as to the adjustment process of prices. All the other Wald tests of equality between p_{t-1} and v_{t-1} are accepted at the 5% level.

In summary, the results suggest that portfolios classified by turnover by volume (a direct measure of information) experience a firm size effect, and that parameters in R_{t-4} (corresponding to the weekly period) occur only in smaller firms. The R_{t-4} predictable variable in size 4 portfolio occurs when closing as opposed to bid returns are used. This is a product of the touch effect documented previously. The R_{t-10} predictable components corresponding to a two week cycle occurs across all portfolios, and permanent disequilibria in the ECM variable is common to the portfolios size 1 (in period t-4) and portfolios size 2 (in period t-1). This disequilibria may mean that investors may be able to seek out profitable investment opportunities corresponding to daily and 4 day calendar anomaly effects.

6.6. CONCLUSIONS

This chapter aims to test for return predictability on the LSE using a model of partial price adjustment which evolves from a restricted multi-lag linear regression model. The robustness of the model was tested using three classifications of portfolios that reflect differing economic influences including, a firm size effect, liquidity or touch effect and a turnover by volume effect.

The results indicate that a positive R_{t-10} component is prominent across all the sizes and classifications of portfolios. This indicates that a two week predictable return cycle may be prominent in the market. This predictability may support previous findings of a settlement effect on the LSE investigated in chapter 5, and supported by Jaffe & Westerfield (1985) and Condoyanni, O'Hanlon & Ward (1987) amongst others. However, because the data is essentially undated, care should be taken when making such an interpretation since we do not know what day of the week corresponds to R_{t-10}.

In addition, the use of closing, as opposed to bid prices, does generally increase the size of the coefficients of predictable variables and contributes between 1% and 25% to return predictability. This touch influence is, however, more prominent in smaller sized portfolios and especially for variables corresponding to the weekly anomaly. Pricing efficiency therefore may be a function of the touch and the pricing mechanism in stocks. Even though weekly anomaly variables are only found in smaller firms they are generally not a product of the touch. This is not the case for portfolios sized 4 classified by turnover by volume where the use of closing returns causes the emergence of a weekly returns component. The touch therefore in this case is a determinant of the weekly effect.

Large sized, lower risk, larger information classified portfolios in accordance with the theoretical market value - touch- volume relationship generally have homogeneous results. Clearly, portfolio classification does not influence return predictability on the market. Also, mispricing in the form of an ECM price adjustment component represented by the restriction $p_t=v_t$ in the portfolios is not just confined to small sized portfolios and is not a product of the microstructure.

In summary, the results point to the prominence of daily and weekly predictability on the LSE, and are to some extent dependent on firm size and microstructure. Overall, predictability is fairly consistent across different types of portfolios which reinforces the justification for their existence.

7. RETURN PREDICTABILITY AND AUTOCORRELATION: NONSYNCHRONOUS TRADING EXPLANATIONS.

7.1. INTRODUCTION

The results in the previous chapter suggest that there is substantial short-horizon portfolio return predictability across differing classifications of portfolios in the UK. Nevertheless, there is a body of evidence to suggest that such return predictability is in some ways dependent upon infrequent or 'thin' trading in security returns[66]. More precisely and following Miller, Muthuswamy & Whaley (1992) we can distinguish between 'non-trading' and 'nonsynchronous trading' as explanations of return predictability. The former implies infrequent trading at the close and/or in other time intervals, while the latter implies infrequent trading only at the close. Scholes & Williams (1977), Perry (1985) and Shanken (1987) are earlier examples of the latter[67]. The terms will, however, be used interchangeably here.

As Perry (1985) for example, has shown, nonsynchronous trading comes about when some of the constituent shares in a portfolio do not trade at every closing time interval. Portfolios which are subject to such trading may contain 'stale' prices. The observed portfolio return as a result, does not reflect its true value. Such so-called

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[66] The first main proponent of 'thin' trading was Fisher (1966).

[67] Additionally there is much evidence of non-trading in the guise of nonsynchronous trading. See Fisher (1966), Dimson (1979), Lo & MacKinlay (1990) and Stoll & Whaley (1990) for example.

thinly traded stocks may react to information with a time lag. This generates positive autocorrelation in observed portfolio returns and consequently may create false interpretations about portfolio return predictability.

Evidence on the effects of nonsynchronous trading has recently made a resurgence in the financial economics literature. Initially, this evidence was confined to problems of measuring betas in the market model [see, as examples Schwartz & Whitcomb (1977), Scholes & Williams (1977) and Dimson (1979)]. The more recent literature is concerned with the influence of nonsynchronous trading on portfolio return predictability [see Lo & MacKinlay (1990a, 1990b), Sentana & Wadhwani (1992), Boudoukh, Richardson & Whitelaw (1993) to name but a few]. Clearly, of interest here is the fact that apparent portfolio return predictability may occur due to the effects of nonsynchronous trading.

In this chapter we test for the presence of nonsynchronous trading in each of the constructed portfolios classified by market value, touch and turnover by volume shown in the previous chapter. Moreover, we examine the first-order autocorrelation coefficient. If all the securities in a portfolio have the same non-trading probability this coefficient following, Lo & MacKinlay (1990b), shows the probability of trading infrequency. Nonsynchronous trading of this nature comes about because smaller, less frequently traded firms react with a lag to market wide information, whereas larger, more frequently traded portfolios react more immediately to the same information.

Secondly, we also test for any cross-correlation effects between portfolios.

Examination of the cross-correlations between differing sizes of portfolios indicates that the cross-effects range between 1% and 15% and that there is an asymmetric lead-lag effect between smaller and (lagged) larger portfolios. Following Boudoukh et al (1993), Mech (1993) and Lo & MacKinlay (1990b), we can say that any substantial cross-correlations between small and lagged large sized portfolios may indicate delayed security price reaction and hence nonsynchronous trading in the smaller sized portfolios.

As well as examining levels of correlation in portfolio returns, we also re-examine the portfolio return predictability question by re-estimating the results from chapter 6. This time, following Miller et al (1992) we adjust the variables for the effects of nonsynchronous trading. Initially only weekly and 10 day return predictability remains after adjusting for these effects. Even the imposition of the touch onto prices devoid of such effects only slightly increases the strength of return predictability. The effect of using nonsynchronous trading consistent parameters also causes the value of the adjusted R^2 to fall from an average of 20% to around 3%. This implies that the independent variables have little or no predictive power and therefore make it difficult to really profit from predictable trading. We can conclude that the results lend support to the *loyalist* explanation of market efficiency.

The rest of this chapter is organised as follows: section 7.2 examines the literature on nonsynchronous trading and portfolio correlation, with section 7.3 showing tests for portfolio correlation and a simple model that adjusts for the effects of thin trading in portfolio returns. Section 7.4 shows autocorrelation and cross-autocorrelation evidence of nonsynchronous trading as well as the results from testing for nonsynchronous consistent portfolio returns, with section 7.5 concluding.

7.2. EVIDENCE OF NONSYNCHRONOUS TRADING

As we have documented in the overview of the literature, the theory of nonsynchronous trading in portfolio returns due to so-called 'thinness' in trading was perhaps given most prominence by Fisher (1966). Infrequent trading by some of the constituent companies of a portfolio may cause closing prices to lag behind more frequently traded stocks. This 'thinness' in trading will lead to positive first-order autocorrelation between portfolio returns which may imply predictability in portfolio returns. Given the nonsynchronous trading problem, and the prominence of the daily, weekly and two weekly predictability shown in chapter 6, attaching meaning to portfolio correlations remains a hurdle. Following Boudoukh et al's (1993) debate about the strength of any correlation and hence predictability in portfolio returns, we are going to examine the *loyalist* school in reviewing the evidence on nonsynchronous trading.

Evidence of the *loyalist* belief that short run predictability measured by autocorrelation and/or cross-correlation is economically spurious is supported by many studies and clearly has implications for the strength of any predictability found in the previous chapter. Perry (1985) was one of the first to examine explanations for serial correlation in portfolio returns. He found that this correlation is larger for a portfolio of large sized firms than for the sum of the correlations of the individuals firms that make up the portfolio so contradicting the theory of nonsynchronicity in smaller firm portfolios.

Perry also shows that as the number of constituent firms in both smaller and larger firm portfolios rises, correlation levels rise to a maximum of 26% and 20% respectively. The implication of this is that factors other than nonsynchronous trading contribute to portfolio serial correlation. From the *loyalist* perspective, this could mean measurement errors such as the bid-ask spread in security returns as well as institutional structures contribute to portfolio serial correlation, and therefore return predictability.

In related work, Atchinson, Butler & Simonds (1987) use the Scholes & Williams (1977) (SW) model of nonsynchronous trading in order to compare the implied theoretical portfolio autocorrelation with the observed market autocorrelation on the NYSE. SW is one of the first well known studies that documented the biases in betas calculated on a daily basis and over other fixed intervals. SW show that nonsynchronous consistent estimates of the intercept and slope coefficients of the market model can be derived by specifying, in their words "the directions and magnitudes of these asymptotic biases .... and then [using them to construct] consistent estimators of alpha and beta." The estimators can then be applied to daily returns in each of the portfolios used, to get nonsynchronous consistent results.

In SW tests for return predictability Atchinson et al use and derive the first-order autocorrelation of portfolio transaction (rather than true) returns as

$$Corr(\tilde{R}^{T}_{pt},\ \tilde{R}^{T}_{pt-1}) = Cov(\tilde{R}^{T}_{pt},\ \tilde{R}^{T}_{pt-1}) / Var(\tilde{R}^{T}_{pt}) \tag{7.1}$$

where Corr is the correlation over time t to t-1, Cov is the covariance over time t to t-1, Var is the variance and $\tilde{R}^{T}_{pt}$ is the observed portfolio return in time t. Also

$$\tilde{R}^{T}_{pt} = \sum_{i=1}^{n} x_i \tilde{R}^{T}_{it}, \qquad s.t. \ \sum_{i=1}^{n} x_i = 1, \tag{7.2}$$

Substituting (7.2) into (7.1) leads to

$$Corr(\tilde{R}^{T}_{pt}, \tilde{R}^{T}_{pt-1}) = \frac{\sum_{i=1}^{n} x_i^2 Cov(\tilde{R}^{T}_{pt}, \tilde{R}^{T}_{pt-1}) + \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j Cov(\tilde{R}^{T}_{pt}, \tilde{R}^{T}_{jt-1})}{\sum_{i=1}^{n} x_i^2 Var(\tilde{R}^{T}_{it}) + \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j Cov(\tilde{R}^{T}_{it}, \tilde{R}^{T}_{jt})} \tag{7.3}$$

where $i \neq j$. x_i is the set of weights applied to each portfolio which in (7.3) are not equal.

In order to account for the nonsynchronous trading problem, SW assume that transactions for each security follow a Poisson process with a transaction arrival rate λ_i. They establish the relationship between transaction returns parameters [shown in (7.3)] and the variance-covariance matrix of true unobservable returns. This is given in (7.4) to (7.12) below

$$Cov(\tilde{R}^{T}_{it}, \tilde{R}^{T}_{jt-1}) = \alpha_{\lambda_i \lambda_j} Cov(\tilde{R}_{it}, \tilde{R}_{jt}) \tag{7.4}$$

$$Cov(\tilde{R}^{T}_{it}, \tilde{R}^{T}_{jt}) = \gamma_{\lambda_i \lambda_j} Cov(\tilde{R}_{it}, \tilde{R}_{jt})$$

where

$$Cov(\tilde{R}_{it}^{T}, \tilde{R}_{it-1}^{T}) = \delta_{\lambda_i v_i} Var(\tilde{R}_{it}) \tag{7.6}$$

$$Var(\tilde{R}_{it}^{T}) = \theta_{\lambda_i v_i} Var(\tilde{R}_{it}) \tag{7.7}$$

$$\alpha_{\lambda_i \lambda_j} = \left[\frac{1}{(1-e^{-\lambda_i})(1-e^{\lambda_j})} \right] X$$

$$\left[\frac{\lambda_j(1-e^{-(\lambda_i+\lambda_j)})}{\lambda_i(\lambda_i+\lambda_j)} - e^{-(\lambda_i+\lambda_j)} - [1+(1/\lambda_i)-(1/\lambda_j)]e^{-\lambda_i}(1-e^{-\lambda_j}) \right], \tag{7.8}$$

$$\gamma_{\lambda_i \lambda_j} = 1 - \alpha_{\lambda_i \lambda_j} - \alpha_{\lambda_j \lambda_i}, \tag{7.9}$$

$$\delta_{\lambda_i v_i} = -\left[\frac{1}{\lambda^2} + \frac{1}{1-e^{-\lambda_i}} - \frac{1}{(1-e^{-\lambda_i})^2} \right] / v_i^2, \tag{7.10}$$

and

$$\theta_{\lambda_i v_i} = 1 - 2\delta_{\lambda_i v_i} \tag{7.11}$$

Applying the covariance equation of true returns below (derived from the market model) to (7.3),

$$Cov(\tilde{R}_{it}, \tilde{R}_{jt}) = \beta_i \beta_j Var(\tilde{R}_{mt}) \tag{7.12}$$

along with the SW relationships between true and transaction-based returns shown in (7.4) to (7.11), the following nonsynchronous trading consistent transaction-based value weighted portfolio autocorrelation can be derived

$$Corr(\tilde{R}^T_{pt},\tilde{R}^T_{pt-1}) = \frac{\sum_{i=1}^{n} x_i^2[\delta_{\lambda_i u_i} Var(\tilde{R}_{it})] + \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j[\alpha_{\lambda_i\lambda_j}\beta_i\beta_j] Var(\tilde{R}_{mt})}{\sum_{i=1}^{n} x_i^2[\theta_{\lambda_i v_i} Var(\tilde{R}_{it})] + \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j[\gamma_{\gamma_i\lambda_j}\beta_i\beta_j] Var(\tilde{R}_{mt})} \quad (7.13)$$

where i≠j, $Var(\tilde{R}_{mt})$ is the variance of the market index, and θ,δ,γ, and α are functions of λ_i the transaction arrival rate shown above and the coefficients of variation $v_i = \sigma(\tilde{R}_{it})/E(\tilde{R}_{it})$.

In the SW study it was found that θ was close to 1, and δ was close to zero. This meant that true and measured variances and autocovariances were very similar. However, Atchinson et al imply that γ does not have to be close to one and as a result observed covariances may understate true covariances. Also given $\alpha \neq 0$, this implies the first-order cross-covariances could be present and true betas appeared not to be related to transaction arrival rates. Therefore, when n is large, the value weighted portfolio autocorrelation becomes

$$Corr(\tilde{R}^T_{pt},\tilde{R}^T_{pt-1}) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \alpha_{\lambda_i\lambda_j}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \gamma_{\gamma_i\lambda_j}} \quad (7.14)$$

where i≠j. The model in (7.14) implies that as n rises the level of positive autocorrelation rises depending on the sizes of α and γ.

Atchison et al (1987) used the SW model of nonsynchronous consistent autocorrelation for value and equally weighted portfolios indices of NYSE and CRSP data as well as a self constructed 280 firm NYSE portfolio[68]. Their results indicate that the 280 firm sample portfolio experiences comparable autocorrelation when compared to the NYSE and CRSP indices. Furthermore, the equally weighted portfolios have a correlation approximately twice as high as for the value weighted portfolio. This difference in correlation would be expected given that smaller sized securities (which generally experience higher autocorrelation due to infrequent trading) in a portfolio have the same weighting as larger, more frequently traded securities.

The results indicate that measures of observed autocorrelation rise to much higher levels than is predicted by the theoretical model in (7.14) as the number of firms in the portfolio rises. This rise in autocorrelation seems to occur as the portfolio-variance associated with non-market risk falls. However, even after using the nonsynchronous consistent SW model of transaction returns, autocorrelation of the order of 15% remains. Clearly, other factors are contributing to autocorrelation. Followers of the *loyalist* argument would suggest that trading mechanism frictions and delayed information processing may account for this remaining predictability. Finally, although we do not specifically compute the autocorrelation in the adjusted manner as suggested by SW in this chapter, we do adjust correlations, although along different lines.

In a similar study Berglund & Liljeblom (1988) test for index correlation by comparing the serial correlation of the market index and individual securities on the

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[68] The equally weighted correlation equation is not shown here but is shown in equations (7) and (9) in Atchinson et al (1987), p114.

Helsinki Stock Exchange. Reported first-order market index autocorrelation proved to be greater than the average first-order serial correlation across individual stocks on the market mainly due to institutional structures operating in the Helsinki market.

More specifically, the procedure of 'calling out' security transaction prices during the first half of the day, one by one from a list, has the effect of causing lags in security returns which are at the end of the list. This contributes to serial correlation in the market index. Furthermore, under the SW model, random nonsynchronous trading effects were also found to be present perhaps due to closed market effects, or even the clustering of transactions during the day. Any remaining serial correlation was theorised to be caused by delays in incorporating information into share prices.

Not content to just examine market correlations, Lo & MacKinlay (1988) in the US, test for the random walk hypothesis with weekly data using variance ratio analysis. Consistent with previous studies they find return predictability in market indices induced by significant positive serial correlation. For individual stocks insignificant negative serial correlation, the opposite effect, was documented. This supports the hypothesis that the procurability of company-specific information on individual securities makes it difficult to forecast returns. However, the formation of portfolios tends to diminish this 'idiosyncratic' noise and makes returns more predictable.

Further tests of the random walk hypothesis for differing market value sized portfolios demonstrated greater serial correlation for smaller sized portfolios (up to 49%) than for larger sized portfolios (as low as 9%). High levels of predictability may be induced by biases associated with nonsynchronous trading. As we have already seen, due to infrequent trading, smaller sized portfolios may react with a lag to information in the market when compared to larger more frequently traded portfolios. It is this lag which induces positive serial correlation, and hence not necessarily any 'true' predictability in the returns process.

Lo and MacKinlay explain the theory behind the nonsynchronous trading problem as one that is determined by the cumulation of returns over a non-trading period. Cumulated returns exhibited spuriously induced correlations due to the non-trading lag. By specifying a probability model (Bernoulli trial) they are able to determine the magnitude of autocorrelation under different probabilities of a trade in a security. Under this contrived test for nonsynchronous trading their results indicate that weekly first-order autocorrelation ranges from 2.1%, when the probability of non-trading is 10%, to 17% autocorrelation under the unrealistic assumption of a 50% probability of a non-trade. Consequently, Lo and MacKinlay rejected the random walk hypothesis, not solely because of the nonsynchronous trading problem, but because of the *loyalist* mispricing explanations for correlations in portfolio returns.

In a later paper, Lo & MacKinlay (1990a) refined their nonsynchronous trading explanation of return predictability by examining the overreaction problem in terms of contrarian investment strategies. Most of the literature on portfolio overreaction had documented negative autocorrelation as evidence for some form of mean-reverting behaviour in stock returns[69]. Lo and MacKinlay approach this issue from another angle by examining cross-autocorrelation effects in portfolios.

Evidence of these correlations enable positive expected profits to be made from a contrarian investment strategy. Positive autocorrelation can occur due to cross-correlation effects for the following reason. Let us assume that there are two stocks in a market A and B. Suppose stock A has a high return today. A contrarian strategist will therefore sell A today and buy B. However, if A and B are positively correlated, a high return for A today will mean a high return for B tomorrow. Hence, by holding B for more than a day, a contrarian can profit without there being any overreaction in the market. What is interesting from this study is that these cross-effects generally always occur when large firms lead smaller sized firms[70]. Therefore it is the lead-lag behaviour (i.e. nonsynchronous trading) between differing sized portfolios that seems to determine contrarian investment strategies.

Similarly, Lo & MacKinlay (1990b) construct estimators that measure the non-trading effects in stock returns and again test for rejections of the random walk hypothesis. Their approach tries to model non-trading under the assumption of stochastic time intervals. This framework allows the formation of expressions of the mean, variance and covariance of observed returns as a function of the non-trading process and shows

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[69] See Poterba & Summers (1986) and Fama & French (1987) for two of the best known examples.

[70] Since these cross-effects may contribute to positive autocorrelation, which implies nonsynchronous trading, tests later in this chapter provide further evidence of the influence of thin trading by examining the extent of these cross-effects in our own portfolios.

a simple estimate for the probability of non-trading. Lo and MacKinlay show that the following ratio determines the degree of nonsynchronicity in security returns, where the relative likelihood of security i trading more frequently than security j is given by the ratio of the (i,j)th autocovariance with the (j,i)th autocovariance. Hence, the degree of nonsynchronicity is determined through the degree of asymmetry in the autocovariance returns matrix.

In order to derive a model of nonsynchronous trading Lo and MacKinlay use 'virtual' or 'true' continuously compounded returns that follow a stochastic process. Here it is assumed that the observed return is just the sum of virtual returns from all past consecutive periods that did not trade. This enables the characteristics of nonsynchronous trading; immediate price adjustment of frequently traded stocks and lagged price adjustment of thinly traded stocks to news, to be captured in a model. Their results indicate that there is a lead-lag pattern of larger stocks leading smaller stocks. This indicates that nonsynchronous trading is present and supports the positive autocorrelation found in the indices.

Conrad, Kaul & Nimalendran (1991) try to reconcile Lo & MacKinlay's (1988, 1990a and 1990b) results of negative correlation in individual security returns and positive portfolio autocorrelation. Here the assumption is that securities are made up of a positively autocorrelated common component as well as a negatively autocorrelated idiosyncratic component related to the bid-ask spread, and a white noise component. Under this framework, Conrad et al (1991) show that for NASDAQ weekly returns, the expected common component reflects asymmetric lagged cross-correlations between large and small firms and that the bid-ask spread can explain the individual negative autocorrelation in security returns, which is consistent with Roll (1984). This suggests that evidence of nonsynchronous trading is prominent after taking account of the effects of the touch in returns. The tests in this chapter hope to show that prices, devoid of the influence of the touch, exhibit nonsynchronous trading and therefore confirm that portfolios are not characterised by any sizeable amount of negative autocorrelation.

More recently Sentana & Wadhwani (1992) in their US/UK study also segregate the pretence between negative and positive autocorrelation. Their results suggest that when stock price volatility is low, short run stock returns exhibit positive serial correlation and when volatility is high, returns exhibit negative autocorrelation due to the influence of positive feedback trading on prices. Positive feedback trading is greater following price declines, rather than price rises and when volatility changes reduced nonsynchronous trading may cause changing autocorrelation. This is consistent with results in chapter 6 showing greater levels of return predictability for smaller firm-sized portfolios. Clearly, given this scenario we should expect nonsynchronous trading consistent returns not to exhibit return predictability, especially in small firm-sized portfolios.

Although not formally tested in either this or the previous chapter, evidence of seasonality in autocorrelation patterns may help to explain the weekly predictability prominent in our results. To this end, Bessenbinder & Hertzel (1993) in the US find that there is a high positive correlation between Friday and Monday equity returns, and similarly on the day before and the day after holiday periods. Also, an inverse relationship exists between autocorrelation and firm size for equally weighted portfolios. Additionally, there appears to be a high negative correlation between the second day after a non-trading period with returns the day immediately after the non-trading period. This correlation is higher than any other lagged correlation and implies that there is a price reversal in this period.

Also, the AR(1) coefficient on a Monday following either a Friday or Saturday dramatically exceeds the average AR(1) coefficient on other days. Also, the last day of the week, either a Friday or Saturday, is characterised by high AR(1) coefficients. Therefore, autocorrelation patterns are dependent upon the proximity to non-trading days rather than to the day of the week. Clearly, such evidence points to evidence of high predictability on a Monday and hence perhaps to cyclical weekly predictability similar to that documented in chapter 6.

In contradiction, these seasonal patterns of autocorrelation do not seem consistent with evidence of positive autocorrelated induced nonsynchronous trading, but perhaps due to market makers behaviour. Following Admati & Pfleiderer (1989), market makers are presumed to try and encourage discretionary liquidity buyers and sellers to trade in different periods. The consequence of this behaviour is that price movements in periods following concentrated trading, will tend to reverse price movements in previous trading periods thus pointing to return predictability. Additionally, a naive trading strategy may be possible given that Bessenbinder and Hertzel show that if the prior days returns are positive then investors should buy on Fridays, Saturdays and

Mondays. If the prior days returns are negative then investors should sell on these days. With regard to Tuesdays, investors should sell if Monday's returns are positive, or buy if Monday's returns are negative and on Wednesdays and Thursdays investors should buy. This is one of the first studies that shows explicit predictability in portfolio returns that is not dependent upon the effects of nonsynchronous trading.

In a review study of autocorrelation patterns in short-horizon stock returns, Boudoukh, Richardson & Whitelaw (1993) identify a debate between the *loyalist, revisionist* and *heretic* school of explanations for return predictability which has already been highlighted. Of the issues in this review paper, what is of most interest to this chapter are the authors' questions about the strength of any cross-autocorrelation between portfolios. They suggest that the strength of any cross-effects, perhaps is determined by the level of contemporaneous correlation between small and large sized portfolios. Clearly, under this scenario lagged large firms portfolios may be just proxying for small firm portfolio's lagged returns if this correlation is high.

In order to examine this issue, Boudoukh et al (1993) consider how asymmetry in cross-autocorrelations arise by using an AR(1) model [see Lo & MacKinlay (1990a, 1990b)] of nonsynchronous trading. This is given as

$$R_{it} = \alpha_i + \phi_i R_{it-1} + \varepsilon_{it} \qquad (7.15)$$

where the unexpected shocks ε_{it} are contemporaneously correlated across size portfolios. This implies that lagged returns on a portfolio completely describe conditional expected returns on that portfolio and $R_{i,t-1}$ are lagged returns reflecting stale prices. Lo & MacKinlay (1990a) show that portfolio returns can be represented by an infinite order moving average disturbance term, such as

$$R_{it} = \frac{\alpha_i}{1-\phi_i} + \sum_{k=0}^{\infty} \phi_i^k \varepsilon_{it-k} \tag{7.16}$$

This enables first-order cross-autocorrelations between returns i, and lagged returns j, to be calculated in terms of i's first-order cross-autocorrelation and the contemporaneous correlation between i and j, as shown in (7.17) below

$$Corr(R_{it}, R_{jt-1}) = Corr(R_{it}, R_{jt}) * Corr(R_{it}, R_{it-1}) \tag{7.17}$$

where R_{it} and R_{jt} are the transaction or bid return on portfolios i and j respectively.

This implies that given a high level of contemporaneous correlation, cross-effects may still be prominent. This, however, is not necessarily evidence of nonsynchronous trading since large sized portfolios may be proxying for smaller-sized portfolios. Under these assumptions, it is the level of autocorrelation *within* portfolios that is important, given that high levels of cross-autocorrelation are possible even though the information set is constant across large and small sized portfolios. Boudoukh et al prove this over-estimation of cross-autocorrelation effects, and so imply autocorrelation is the stronger indicator of infrequent trading.

As we have already seen from the *loyalist* perspective short run predictability measured by portfolio autocorrelation or cross-correlation can be seen as evidence of nonsynchronous trading. Given the prominence of these predictability measures we shall examine the strength of this correlation for our own constructed portfolios. Also, since the previous chapter documents significant portfolio predictability, there is the question as to whether this predictability is dependant on the influence of nonsynchronous trading. Hence, following Miller et al (1992), we can test for predictable returns by using nonsynchronous consistent parameter estimations. The theory suggests that portfolio return predictability should be nullified when using nonsynchronous consistent parameters. These issues are addressed in the next section.

7.3. MODELLING RETURN PREDICTABILITY ADJUSTING FOR NONSYNCHRONOUS TRADING

7.3.1. *Tests for Nonsynchronous Trading in Portfolio Returns*

Much of the literature[71] establishes short run predictability in portfolio returns by testing for the prominence of first-order autocorrelation as follows

$$Corr(R_{it}, R_{it-1}) = Cov(R_{it}, R_{it-1}) / Var(R_{it}) \qquad (7.18)$$

where R_{it} is the transaction or bid return on a portfolio in time t. Here the level of autocorrelation measures the degree of non-trading in portfolio returns. More formally, Lo & MacKinlay (1990a) show that the degree of non-trading is the same as the AR(1) coefficient from (7.15) above.

Additionally, as we have seen, cross-autocorrelations between returns on a small sized portfolio, i, and lagged returns on a large sized portfolio, j, also indicates short run return predictability and is indicative of nonsynchronous trading. This is because news released to the market will affect stocks that trade more frequently first (i.e.

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[71] See Lo & MacKinlay (1990a) for example.

larger firm size stocks). However, for smaller-sized more thinly traded portfolios, news will be delayed, causing lagged adjustment in returns. Cross-correlations in this scenario are just proxying for the level of nonsynchronous trading between differing portfolios, and are known as the empirical cross-correlations.

Confirmation of the lead-lag relationship from larger sized firms to smaller sized firms is shown by the asymmetry of the cross-effects between portfolios. Clearly, the criteria for nonsynchronous trading consistent lead-lag behaviour is if lagged larger-sized portfolio returns lead smaller-sized portfolio returns. This comes about when the upper quadrant above the diagonal of the correlation matrix has higher cross-correlations values.

Following Boudoukh et al (1993) the AR(1) model shown above in (7.15) implies that unexpected shocks ε_{it} are contemporaneously correlated across size portfolios and therefore implies that own lagged returns on a portfolio completely describe conditional expected returns on that portfolio. As we have seen from (7.16) portfolio returns can be represented by an infinite order moving average disturbance term. This enables first-order cross-autocorrelations to be calculated in terms of first-order cross-autocorrelation and the contemporaneous correlation as shown in (7.17). This suggests that given a high level of contemporaneous correlation, cross-effects may still be prominent, but as we have seen this is not necessarily evidence of nonsynchronous trading. What is important is the level of autocorrelation *within* portfolios since this is a stronger indicator of infrequent trading. Both the implied and absolute cross-correlations are examined for our own constructed portfolios subsequently.

7.3.2. *A Simple Model that Adjusts Portfolio Returns for Nonsynchronous Trading*

We already know that portfolio construction can induce significant positive correlation in returns and so perhaps give erroneous estimates of return predictability. Therefore, following Miller et al (1992) we can derive a test that estimates nonsynchronous consistent returns. This involves fitting an AR(1) model to daily data where

$$R_{it} = \alpha_i + \phi_i R_{it-1} + \varepsilon_{it} \qquad (7.19)$$

The estimated residuals, $\hat{\varepsilon}_{it}$, from (7.19) are then used to generate nonsynchronous consistent estimates of portfolio i's returns, $\hat{r}_{it}$, as follows

$$\hat{r}_{it} = \hat{\varepsilon}_{it}/(1-\hat{\phi}_i) \qquad (7.20)$$

These consistent estimates can then be substituted for observed portfolio returns and so purging them of measurement errors (observed correlations) due to nonsynchronous trading. The model assumes that the parameter ϕ (which measures trading frequency) is constant across days of the week, contrary to evidence[72] of deviations in trading volume throughout the week.

7.3.3. *An Adjusted Model of Return Predictability*

The tests for return predictability in chapter 6 suggest that portfolio returns can be specified in the form of a dynamic linear regression model with multiple lags as shown in 7.21 below

$$R_t = \alpha_0 + \sum_{j=1}^{m} \alpha_j R_{t-j} + \sum_{i=0}^{m} \beta_i p_{t-i} + \sum_{i=0}^{m} \gamma_i v_{t-i} + \varepsilon_t \qquad (7.21)$$

where R_t, p_t and v_t represent the logarithms of returns (including dividends), price and

[72] See Lakonishok & Maberly (1990) in the US.

intrinsic value respectively in time t, and ε_t is an error term. Tests of this model (shown in chapter 6) indicate that some parameters, notably weekly and two weekly returns and daily price and value components are predictable across many of the portfolios.

However, in this chapter we use nonsynchronous trading consistent variables to re-estimate returns, R_{it}, and price, p_{it}, in order to test for portfolio predictability. Hence, we re-adjust the variables in (7.21) subject to (7.20), the nonsynchronous trading consistent parameters model, (7.21) then becomes

$$\hat{r}_t = \alpha_0 + \sum_{j=1}^{m} \alpha_j \hat{r}_{t-j} + \sum_{i=0}^{m} \beta_i \hat{p}_{t-i} + \sum_{i=0}^{m} \gamma_i v_{t-i} + \hat{\varepsilon}_t \qquad (7.22)$$

with $\hat{r}$, $\hat{p}$, v and $\hat{\varepsilon}$ being the nonsynchronous trading consistent returns, prices, intrinsic value and unexpected shock to portfolio i's returns, respectively. Hence, under these assumptions about the dependent variables we would expect that any return predictability would be nullified when we test (7.22).

7.4. RESULTS OF TESTING FOR PREDICTABLE PORTFOLIO RETURNS AFTER ADJUSTING FOR NONSYNCHRONOUS TRADING

7.4.1. *The Results of Tests for Nonsynchronous Trading in Portfolio Returns*

As we have already seen from the *loyalist* perspective, short-horizon return predictability and cross-correlation (lead-lag relationships between portfolios) can be seen as evidence of nonsynchronous trading. The results in Table 7.1 show that portfolios returns are predictable since the first-order autocorrelation coefficient (ρ_1) is prominent. This coefficient is generally positive and ranges between 16.2% for the smallest closing priced market value portfolio to 1.2% for the largest bid priced market value portfolio. Furthermore, the smallest touch classified portfolio is one of the few portfolios that has weak negative correlation (around -2%). This is perhaps not surprising given that Conrad, Kaul & Nimalendran (1991) found that the bid-ask spread causes negative autocorrelation in security returns. Hence, our results indicate that the touch classification could be introducing negative autocorrelation into the portfolio returns series.

Furthermore, it is evident that the degree of predictability falls as portfolio size increases. For the touch classified portfolios, of course, the largest touch classified portfolio is also a small firm sized portfolio. So, in this case the predictability relationship is inverted. Moreover, portfolio returns that include the touch (i.e. closing returns rather than bid returns) are generally characterised by higher levels of autocorrelation. Indeed for the market value classified portfolios the touch can account for up to 30% of return predictability, but less so for the other classifications of portfolios.

Even though return predictability is quite prominent in some of the smaller sized portfolios its does not seem as strong as some of the documented evidence from the US would suggest. Specifically, Lo & MacKinlay (1990a) found 33% predictability in small sized portfolios. Explanations for the lower level of first-order autocorrelation may be data specific, since only securities from the alpha classification of stocks (the most frequently traded) were used to construct portfolios.

Table 7.1 also shows that when the autocorrelation in portfolio returns is adjusted for the effects of nonsynchronous trading, due to Miller et al (1992), the level of autocorrelation, in this case, $\hat{\rho}_1$ falls to around +/- 1% for each size and classification of portfolio. Of the 36 sizes and classifications of portfolios considered, 23 experienced a change in the sign of the observed autocorrelation from positive to negative when nonsynchronous trading consistent returns are used. Therefore, these results support the current literature highlighted in section 7.2, that implies that nonsynchronous trading induces positive autocorrelation in portfolio returns and so supports the *loyalist* explanation of short-horizon portfolio return predictability.

Nonsynchronous trading also occurs due to the lead-lag relationship between size-sorted portfolios. Following Lo & MacKinlay (1990a), who found that larger stocks lead smaller stocks, but not vice versa, we have examined the estimated cross-autocorrelation effects between each of the portfolios. The middle panel of Tables 7.2 to 7.4 shows that there is lead-lag relationship in these estimated cross-autocorrelations. In one or two instances the cross-autocorrelation is negative implying that perhaps the effects of the touch dominate any nonsynchronous trading effects[73].

Nevertheless, this is not the norm, since the results support positive cross-autocorrelation that ranges between 1% to 15%. We can hence say that the level of

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[73] Conrad, Kaul & Nimalendran (1991) show that the influence of the bid-ask bounce in security returns causes mean reverting price behaviour and hence negative autocorrelation.

Table 7.1

Estimated First-order Autocorrelation (ρ_1) and Nonsynchronous Consistent First-order Autocorrelation($\hat{\rho}_1$) for Equally Weighted Portfolios

Market Value Classification

Size	Smallest	2	3	4	5	Largest
Bid Price Data						
ρ_1	0.144	0.053	0.093	0.045	0.052	0.012
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$\hat{\rho}_1$	0.009	0.014	-0.005	0.002	-0.006	-0.021
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Closing Price Data						
ρ_1	0.162	0.069	0.093	0.043	0.051	0.009
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$\hat{\rho}_1$	0.010	0.014	-0.008	-0.001	-0.009	-0.008
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)

Touch Classification

Size	Smallest	2	3	4	5	Largest
Bid Price Data						
ρ_1	-0.020	0.073	0.047	0.075	0.113	0.092
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$\hat{\rho}_1$	0.003	-0.007	-0.030	-0.019	-0.021	-0.033
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Closing Price Data						
ρ_1	-0.023	0.073	0.053	0.065	0.121	0.101
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$\hat{\rho}_1$	0.001	-0.017	-0.010	0.012	-0.004	-0.009
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)

Table 7.1 cont.

Turnover by Volume Classification

Size	Smallest	2	3	4	5	Largest
Bid Price Data						
ρ_1	0.141	0.036	0.061	0.098	0.090	-0.001
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$\hat{\rho}_1$	0.014	0.025	-0.012	-0.028	-0.023	-0.003
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Closing Price Data						
ρ_1	0.144	0.043	0.067	0.093	0.087	-0.002
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$\hat{\rho}_1$	-0.002	0.031	-0.009	-0.028	-0.002	-0.007
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)

Notes:
Figures in parentheses are standard errors.

artificial predictability measured by cross-autocorrelation patterns, synonymous with nonsynchronous trading, is generally fairly weak for the portfolios we have considered in this chapter.

As an illustration, one can look at market value classified portfolios constructed using bid prices shown in Table 7.2. Here the first-order autocorrelation between yesterday's returns on the largest sized portfolio, R_{lt-1}, and today's returns on the small sized portfolio, R_{st}, is 0.087. On the other hand, the first-order autocorrelation between yesterday's return on the small-sized portfolio, R_{st-1}, and today's return on the largest sized portfolio, R_{lt}, is very small. Clearly, this is one example of where large firms lead small firms when information comes to the market.

More generally, the overall lead-lag relationship between the smallest sized returns R_{st} and R_{2t} , and the largest sized portfolios R_{5t} and R_{lt}, for both the bid and closing priced market value portfolios, shows that current returns of smaller sized portfolios are more highly correlated with past returns of larger sized portfolios, than vice versa. Both of these results clearly confirms Lo & MacKinlay's (1990a) nonsynchronous trading hypothesis in the lead-lag relationship between portfolio correlations, and supports the conventional view of cross-correlation between large and small market value sized portfolios.

Following Boudoukh et al (1993), we have additionally calculated, using (7.19) above, the implied cross-autocorrelations for our portfolios. In Table 7.2, for the market value weighted portfolios the implied value is close to the actual estimates of the cross-correlation. Taking an average portfolio, for example size 3, we can see that the estimated cross-correlation values of lagged closing returns with respect to the portfolio size s, the smallest portfolio, through to size 1, the largest portfolio, are .082, .100, .093, .078, .041 and .041. In comparison the implied cross-correlation values for these portfolios are .071, .073, .093, .078, .078 and .076. This closeness between implied and estimated values suggests that given high contemporaneous cross-autocorrelation, where large firms have a similar information set to small firms, lagged cross-predictability is still prominent. Therefore, as we have shown the lead-lag relation is just a less efficient way of describing the autocorrelation patterns of short-horizon portfolio returns.

The implied cross-correlations in Tables 7.3 and 7.4, for touch and volume classifications again have values fairly similar to estimated correlation values. For example, for the touch classified size 4 portfolio calculated using closing prices, the estimated cross-correlation values of lagged closing returns between the smallest and largest sized portfolio are .014, .063, .029, .065, .081 and .053, when compared to the implied estimates which are .054, .055, .055, .065, .053 and 0.053. Similar results can be seen for the volume classified portfolios. Again this supports the hypothesis of an over-reliance on cross-autocorrelation effects to measure nonsynchronous trading when compared to the more efficient individual autocorrelation values.

Due to the inverse relationship between market value and the spread highlighted by Kaul & Nimalendran (1991), the estimated cross-autocorrelation effects follow a somewhat different pattern in Table 7.3. For the closing priced portfolios, when the

Table 7.2

Lead-Lag Relationships and Estimated Correlations for Equally Weighted Portfolios Classified by Market Value

Bid Price Data

Estimated Contemporaneous Autocorrelation

	R_{st}	R_{2t}	R_{3t}	R_{4t}	R_{5t}	R_{lt}
R_{st}	1.000	0.771	0.756	0.779	0.770	0.771
R_{2t}	0.771	1.000	0.781	0.817	0.835	0.802
R_{3t}	0.756	0.781	1.000	0.842	0.838	0.816
R_{4t}	0.779	0.817	0.842	1.000	0.867	0.831
R_{5t}	0.770	0.835	0.838	0.867	1.000	0.872
R_{lt}	0.771	0.801	0.816	0.831	0.872	1.000

Estimated Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	0.144	0.101	0.121	0.119	0.080	0.087
R_{2t}	0.066	0.053	0.043	0.050	0.024	0.026
R_{3t}	0.085	0.106	0.093	0.085	0.046	0.041
R_{4t}	0.028	0.033	0.031	0.045	0.003	-0.003
R_{5t}	0.056	0.064	0.051	0.061	0.052	0.037
R_{lt}	0.026	0.015	0.017	0.019	-0.001	0.012

Implied Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	0.144	0.111	0.109	0.112	0.111	0.111
R_{2t}	0.040	0.053	0.041	0.043	0.044	0.021
R_{3t}	0.070	0.073	0.093	0.078	0.078	0.033
R_{4t}	0.035	0.037	0.038	0.045	0.004	-0.002
R_{5t}	0.040	0.043	0.044	0.045	0.052	0.045
R_{lt}	0.009	0.011	0.009	0.010	-0.001	0.012

Table 7.2 cont.

Closing Price Data

Estimated Contemporaneous Autocorrelation

	R_{st}	R_{2t}	R_{3t}	R_{4t}	R_{5t}	R_{lt}
R_{st}	1.000	0.773	0.759	0.779	0.772	0.773
R_{2t}	0.773	1.000	0.789	0.822	0.837	0.807
R_{3t}	0.759	0.789	1.000	0.845	0.840	0.816
R_{4t}	0.779	0.822	0.845	1.000	0.869	0.834
R_{5t}	0.772	0.837	0.840	0.869	1.000	0.874
R_{lt}	0.773	0.807	0.816	0.834	0.874	1.000

Estimated Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	0.161	0.102	0.121	0.117	0.075	0.088
R_{2t}	0.079	0.069	0.051	0.055	0.032	0.036
R_{3t}	0.082	0.100	0.093	0.078	0.041	0.041
R_{4t}	0.024	0.027	0.024	0.043	-0.008	-0.077
R_{5t}	0.055	0.063	0.047	0.055	0.051	0.035
R_{lt}	0.028	0.013	0.013	0.014	-0.003	0.009

Implied Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	0.161	0.124	0.122	0.125	0.124	0.124
R_{2t}	0.053	0.069	0.054	0.057	0.058	0.056
R_{3t}	0.071	0.073	0.093	0.078	0.078	0.076
R_{4t}	0.033	0.035	0.036	0.043	0.037	0.036
R_{5t}	0.039	0.042	0.043	0.044	0.051	0.044
R_{lt}	0.010	0.010	0.010	0.008	0.008	0.009

Notes: R_{st} and R_{lt} are the first-order autocorrelation of returns on small (s) and large (l) portfolios respectively.

when the first-order autocorrelation is, for example, between today's returns, R_{1t}, and yesterday's returns, R_{2t-1}, the cross-correlation is 0.084. When the inverse is true and the first-order autocorrelation is between yesterday's return, R_{2t} and today's return R_{1t-1}, the cross-correlation falls to 0.021, a quarter of the value! This is an example of where the lead-lag relationship shows large sized spread classified portfolios leading small sized touch classified portfolios.

Consequently, because of the inverse relationship between firm size and the touch, this perhaps implies that small firm portfolios lead large firm portfolios, the opposite effect to market value sorted portfolios. Again, a general examination of the comparison between the largest and smallest sized portfolios shows that any size induced lead-lag relationship appears inconsistent.

For the turnover by volume classified portfolios, the results follow the familiar pattern to the market value classified portfolios. This is as would have been expected given that larger turnover by volume is the characteristic of larger sized securities. Indeed the sized based lead-lag relationship synonymous with nonsynchronous trading is the most prominent for the turnover by volume classified portfolios.

Analysis of the all the cross-autocorrelation results shows that generally there is weak positive serial correlation, as well as weak nonsynchronous trading effects in portfolio returns. The level of artificial correlation due to thin trading is therefore small. This is partly confirmed by the contemporaneous cross-autocorrelation effects shown in the upper panel of Tables 7.2 - 7.4. This correlation ranges between 0.759 and 0.874

Table 7.3

Lead-Lag Relationships and Estimated Correlations for Equally Weighted Portfolios Classified by the Touch

Bid Price Data

Estimated Contemporaneous Autocorrelation

	R_{st}	R_{2t}	R_{3t}	R_{4t}	R_{5t}	R_{lt}
R_{st}	1.000	0.863	0.845	0.824	0.806	0.769
R_{2t}	0.863	1.000	0.852	0.849	0.826	0.769
R_{3t}	0.845	0.852	1.000	0.840	0.814	0.794
R_{4t}	0.824	0.849	0.840	1.000	0.804	0.809
R_{5t}	0.806	0.827	0.814	0.804	1.000	0.782
R_{lt}	0.769	0.769	0.794	0.809	0.782	1.000

Estimated Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	-0.020	0.022	-0.005	0.029	0.033	0.004
R_{2t}	-0.004	0.073	0.009	0.047	0.061	0.024
R_{3t}	0.012	0.077	0.047	0.066	0.088	0.062
R_{4t}	0.021	0.068	0.035	0.075	0.091	0.055
R_{5t}	0.029	0.085	0.061	0.075	0.113	0.070
R_{lt}	0.043	0.092	0.074	0.077	0.120	0.092

Implied Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	-0.020	-0.017	-0.017	-0.016	-0.016	-0.015
R_{2t}	0.063	0.073	0.062	0.062	0.060	0.056
R_{3t}	0.040	0.040	0.047	0.039	0.038	0.037
R_{4t}	0.062	0.064	0.063	0.075	0.060	0.061
R_{5t}	0.091	0.093	0.092	0.091	0.113	0.088
R_{lt}	0.070	0.070	0.073	0.074	0.072	0.092

Table 7.3 cont.

Closing Price Data						
Estimated Contemporaneous Autocorrelation						
	R_{st}	R_{2t}	R_{3t}	R_{4t}	R_{5t}	R_{lt}
R_{st}	1.000	0.863	0.844	0.827	0.803	0.772
R_{2t}	0.863	1.000	0.852	0.855	0.826	0.776
R_{3t}	0.844	0.852	1.000	0.845	0.816	0.799
R_{4t}	0.827	0.855	0.845	1.000	0.814	0.817
R_{5t}	0.803	0.826	0.816	0.814	1.000	0.793
R_{lt}	0.772	0.776	0.799	0.817	0.792	1.000
Estimated Cross-Autocorrelation						
	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	-0.023	0.021	-0.006	0.020	0.029	0.004
R_{2t}	-0.007	0.073	0.009	0.036	0.059	0.021
R_{3t}	0.015	0.082	0.053	0.063	0.090	0.067
R_{4t}	0.014	0.063	0.029	0.065	0.081	0.053
R_{5t}	0.041	0.096	0.068	0.080	0.121	0.075
R_{lt}	0.043	0.084	0.071	0.070	0.110	0.101
Implied Cross-Autocorrelation						
	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	-0.023	-0.020	-0.019	0.019	-0.018	-0.018
R_{2t}	0.063	0.073	0.062	0.062	0.060	0.057
R_{3t}	0.045	0.045	0.053	0.045	0.043	0.042
R_{4t}	0.054	0.055	0.055	0.065	0.053	0.053
R_{5t}	0.097	0.099	0.098	0.098	0.121	0.096
R_{lt}	0.078	0.078	0.081	0.083	0.080	0.101

Notes: R_{st} and R_{lt} are the first-order autocorrelation of returns on small (s) and large (l) portfolios respectively.

Table 7.4

Lead-Lag Relationships and Estimated Correlations for Equally Weighted Portfolios Classified by Turnover by Volume

Bid Price Data

Estimated Contemporaneous Autocorrelation

	R_{st}	R_{2t}	R_{3t}	R_{4t}	R_{5t}	R_{lt}
R_{st}	1.000	0.795	0.769	0.771	0.771	0.769
R_{2t}	0.795	1.000	0.827	0.822	0.842	0.813
R_{3t}	0.769	0.827	1.000	0.813	0.828	0.800
R_{4t}	0.771	0.822	0.813	1.000	0.830	0.812
R_{5t}	0.771	0.842	0.828	0.830	1.000	0.830
R_{lt}	0.769	0.813	0.800	0.812	0.830	1.000

Estimated Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	0.141	0.097	0.077	0.144	0.134	0.105
R_{2t}	0.059	0.036	0.016	0.055	0.064	0.035
R_{3t}	0.034	0.034	0.061	0.077	0.094	0.042
R_{4t}	0.051	0.046	0.028	0.098	0.090	0.035
R_{5t}	0.041	0.040	0.031	0.053	0.090	0.025
R_{lt}	0.007	-0.005	-0.009	0.015	0.052	-0.001

Implied Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	0.141	0.112	0.108	0.109	0.109	0.108
R_{2t}	0.029	0.036	0.030	0.030	0.030	0.029
R_{3t}	0.047	0.050	0.061	0.050	0.050	0.049
R_{4t}	0.076	0.081	0.080	0.098	0.081	0.080
R_{5t}	0.069	0.076	0.075	0.075	0.090	0.075
R_{lt}	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001

Table 7.4 cont.

Closing Price Data

Estimated Contemporaneous Autocorrelation

	R_{st}	R_{2t}	R_{3t}	R_{4t}	R_{5t}	R_{lt}
R_{st}	1.000	0.801	0.775	0.781	0.779	0.777
R_{2t}	0.801	1.000	0.834	0.824	0.842	0.814
R_{3t}	0.775	0.834	1.000	0.819	0.838	0.811
R_{4t}	0.781	0.824	0.819	1.000	0.836	0.818
R_{5t}	0.779	0.842	0.838	0.836	1.000	0.830
R_{lt}	0.777	0.814	0.811	0.818	0.830	1.000

Estimated Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	0.144	0.101	0.077	0.144	0.132	0.104
R_{2t}	0.057	0.043	0.026	0.062	0.071	0.043
R_{3t}	0.034	0.036	0.067	0.078	0.090	0.039
R_{4t}	0.041	0.042	0.024	0.093	0.080	0.028
R_{5t}	0.034	0.040	0.030	0.051	0.087	0.025
R_{lt}	-0.002	-0.007	-0.015	0.011	0.048	-0.002

Implied Cross-Autocorrelation

	R_{st-1}	R_{2t-1}	R_{3t-1}	R_{4t-1}	R_{5t-1}	R_{lt-1}
R_{st}	0.144	0.115	0.112	0.112	0.112	0.112
R_{2t}	0.034	0.043	0.036	0.035	0.036	0.035
R_{3t}	0.052	0.056	0.067	0.055	0.056	0.054
R_{4t}	0.073	0.077	0.076	0.093	0.078	0.076
R_{5t}	0.068	0.073	0.073	0.073	0.087	0.072
R_{lt}	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002

Notes: R_{st} and R_{lt} are the first-order autocorrelation of returns on small (s) and large (l) portfolios respectively.

across the portfolios and indicates that despite the lead-lag relationship highlighted above, small and large sized portfolios are closely correlated. The implication of this is that lead-lag effects are weaker if returns of differing sized portfolios are not independent. This is supported by the results of the implied cross-autocorrelation estimates which on the whole are close to the estimated cross-correlation estimates. As we have seen this implies it is the autocorrelation patterns of each portfolio that provides most evidence of nonsynchronous trading rather than any cross-effects.

7.4.2. *Test Results from a Nonsynchronous Consistent Model of Predictable Returns*

In chapter 6 we have documented quite substantial predictable returns, price and intrinsic value parameters across portfolios using a dynamic linear regression model. This section documents these results when using nonsynchronous trading consistent estimates of the model parameters, shown in (7.22). This equation substitutes in consistent parameters for observed portfolio returns and prices. This purges the observed parameters of measurement errors, in this case taking the form of autocorrelation due to nonsynchronous trading.

When compared to the results in chapter 6, Tables 7.5 - 7.7 show that the effect of using nonsynchronous consistent parameters on the level of return predictability, for instance, is substantive[74]. For example the AR(1) coefficient falls dramatically in value and statistical significance, when the effects of infrequent trading are removed. In fact for most of the portfolios, the AR(1) coefficient, a measure of the probability

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[74] We can see from Appendix 3 that these models are well specified, and pass all the familiar diagnostic tests examined in chapter 6.

of infrequent trading, reverts from a strongly positive value to an insignificant negative value. In fact most of the parameters apart from the cyclical $\hat{r}_{t-4}$ and $\hat{r}_{t-10}$ variables become insignificant.

These seemingly significant cyclical parameters seem to suggest that portfolio return predictability remains even after adjusting for the effects of nonsynchronous trading. However, the use of nonsynchronous consistent parameters causes the adjusted R^2 measures to fall from between 15-20% (shown in chapter 6) to around an average of 3%. Given that if the true R^2 is zero, portfolio returns are a martingale differenced process, these results suggest that the consistent parameters models are very near being unpredictable. Therefore, the statistically significant cyclical returns parameters carry little predictive power. Additionally, the results show that the value of the predictable parameter coefficients is greater when the touch is included in daily portfolio returns. Finally, DUM, is the dummy variable highlighted in chapter 5 are corrects for outliers in the data caused mainly by the effects of the Gulf War and the UK General Election.

These results have important implications for models of daily return predictability. Tables 7.5 - 7.7 show that the level of return predictability is dramatically overstated if the effects of infrequent trading are not accounted for. Indeed the results suggest that lagged price adjustment across differing sizes of portfolios, given new market information does not cause portfolio return predictability.

Table 7.5

Unrestricted Regression Model of Returns Adjusted for Thin Trading and Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by Market Value

Bid Price Data

Size	Smallest	2	3	4	5	Largest
$\hat{r}_{t-1}$	-0.003		-0.014			
	(0.040)		(0.041)			
$\hat{r}_{t-4}$	0.135***	0.139***				
	(0.040)	(0.040)				
$\hat{r}_{t-8}$		0.083**				
		(0.041)				
$\hat{r}_{t-10}$	0.129***	0.122***	0.163***	0.200***	0.175***	0.109***
	(0.040)	(0.041)	(0.041)	(0.058)	(0.041)	(0.040)
$\hat{p}_{t-1}$	0.020		0.029	-0.011		
	(0.035)		(0.028)	(0.019)		
$\hat{p}_{t-4}$				-0.023		
				(0.024)		
v_{t-1}	-0.023		-0.029	0.017		
	(0.035)		(0.028)	(0.021)		
v_{t-4}				0.025		
				(0.024)		
C	0.015	0.000	0.000	0.024	-0.009	0.000
	(0.014)	(0.000)	(0.022)	(0.016)	(0.026)	(0.001)
DUM	0.000	-0.001	0.001	0.001	0.001	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)
	$R^2 = 0.03$	$R^2 = 0.04$	$R^2 = 0.02$	$R^2 = 0.03$	$R^2 = 0.03$	$R_2 = 0.01$

Table 7.5 cont.

Closing Price Data

Size	Smallest	2	3	4	5	Largest
$\hat{r}_{t-1}$	0.005 (0.040)		-0.015 (0.040)			
$\hat{r}_{t-2}$					0.078** (0.040)	
$\hat{r}_{t-4}$	0.149*** (0.041)	0.143*** (0.040)				
$\hat{r}_{t-8}$		0.098** (0.041)				
$\hat{r}_{t-10}$	0.102*** (0.040)	0.104*** (0.040)	0.159*** (0.041)	0.202*** (0.058)	0.168*** (0.040)	0.109*** (0.040)
$\hat{p}_{t-1}$	0.006 (0.035)		0.022 (0.029)	-0.014 (0.020)	-0.012 (0.024)	
$\hat{p}_{t-4}$				0.006 (0.028)		
v_{t-1}	-0.008 (0.035)		-0.022 (0.029)	0.020 (0.021)	-0.025 (0.029)	
v_{t-4}				0.032 (0.024)		
C	0.013 (0.013)	0.000 (0.000)	0.002 (0.022)	0.022 (0.016)	-0.005 (0.026)	0.000 (0.000)
DUM	0.001 (0.005)	-0.047 (0.003)	0.001 (0.0054)	0.001 (0.004)	0.001 (0.004)	0.000 (0.005)
	$R^2 = 0.02$	$R^2 = 0.04$	$R^2 = 0.02$	$R^2 = 0.03$	$R^2 = 0.03$	$R^2 = 0.01$

Notes:
C is a constant.
DUM is a dummy variable.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

Table 7.6

Unrestricted Regression Model of Returns Adjusted for Thin Trading and Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by the Touch

Bid Price Data

Size	Smallest	2	3	4	5	Largest
$\hat{r}_{t-1}$		-0.013 (0.040)		-0.026 (0.040)	-0.022 (0.039)	-0.031 (0.040)
$\hat{r}_{t-2}$					0.108*** (0.039)	
$\hat{r}_{t-4}$			0.104*** (0.040)	0.125*** (0.040)		0.082** (0.040)
$\hat{r}_{t-10}$	0.112*** (0.041)	0.136*** (0.041)	0.154*** (0.041)	0.131*** (0.041)	0.149*** (0.040)	0.119*** (0.041)
$\hat{p}_{t-1}$	-0.006 (0.029)		-0.022 (0.015)			-0.002 (0.026)
v_{t-1}	0.002 (0.029)		0.021 (0.015)			0.002 (0.026)
C	0.025 (0.016)	0.000 (0.000)	0.005 (0.016)	0.000 (0.001)	0.000 (0.000)	-0.001 (0.009)
DUM	-0.000 (0.004)	-0.001 (0.004)	0.000 (0.003)	0.000 (0.005)	0.000 (0.001)	0.000 (0.009)
	$R^2 = 0.01$	$R^2 = 0.01$	$R^2 = 0.03$	$R^2 = 0.03$	$R^2 = 0.03$	$R^2 = 0.02$

Table 7.6 cont.

Closing Price Data

Size	Smallest	2	3	4	5	Largest
$\hat{r}_{t-1}$		-0.023 (0.040)			-0.008 (0.040)	-0.002 (0.041)
$\hat{r}_{t-2}$					0.111*** (0.039)	
$\hat{r}_{t-4}$			0.077 (0.041)	0.139*** (0.040)		0.099** (0.040)
$\hat{r}_{t-10}$	0.108*** (0.041)	0.146*** (0.040)	0.151*** (0.041)	0.110*** (0.041)	0.149*** (0.040)	0.105*** (0.041)
$\hat{p}_{t-1}$	-0.012 (0.029)					-0.017 (0.025)
v_{t-1}	0.008 (0.029)					0.018 (0.023)
C	0.024 (0.016)	0.000 (0.001)	0.002 (0.016)	0.000 (0.000)	0.000 (0.000)	-0.003 (0.008)
DUM	-0.001 (0.003)	-0.001 (0.005)	0.000 (0.003)	0.000 (0.004)	0.000 (0.004)	0.046 (0.005)
	R^2 = 0.01	R^2 = 0.02	R^2 = 0.02	R^2 = 0.02	R^2 = 0.03	R^2 = 0.01

Notes:
C is a constant.
DUM is a dummy variable.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

Table 7.7

Unrestricted Regression Model of Returns Adjusted for Thin Trading and Dependent upon Lagged Returns, Price and Value for Equally Weighted Portfolios Classified by Turnover by Volume

Bid Price Data

Size	Smallest	2	3	4	5	Largest
$\hat{r}_{t-1}$	-0.021 (0.049)				-0.032 (0.040)	-0.017 (0.040)
$\hat{r}_{t-2}$			0.129*** (0.040)			
$\hat{r}_{t-3}$	0.043 (0.040)					
$\hat{r}_{t-4}$	0.086** (0.040)	0.119*** (0.039)				
$\hat{r}_{t-5}$						0.090** (0.040)
$\hat{r}_{t-8}$		0.098** (0.040)		0.064 (0.041)		
$\hat{r}_{t-10}$	0.136*** (0.040)	0.166*** (0.039)	0.144*** (0.040)	0.161*** (0.041)	0.151*** (0.040)	0.137*** (0.040)
$\hat{p}_{t-1}$		-0.006 (0.023)		-0.014 (0.022)		
$\hat{p}_{t-4}$	-0.032 (0.049)		0.003 (0.033)			
v_{t-1}	0.016 (0.027)	-0.004 (0.023)		-0.009 (0.022)		
v_{t-4}	-0.005 (0.038)		-0.005 (0.033)			
C	0.064** (0.030)	0.058*** (0.018)	0.013 (0.017)	0.024 (0.019)	0.000 (0.000)	0.000 (0.000)
DUM	-0.001** (0.003)	0.004 (0.004)	0.002 (0.004)	0.001 (0.004)	0.000 (0.006)	0.001 (0.003)
	$R^2 = 0.02$	$R^2 = 0.06$	$R^2 = 0.03$	$R^2 = 0.02$	$R^2 = 0.02$	$R^2 = 0.02$

Table 7.7 cont.

Closing Price Data

Size	Smallest	2	3	4	5	Largest
$\hat{r}_{t-1}$	-0.023 (0.040)					
$\hat{r}_{t-2}$		0.089** (0.040)				
$\hat{r}_{t-4}$	0.117*** (0.039)	0.115*** (0.039)		0.064** (0.041)		
$\hat{r}_{t-8}$		0.110*** (0.040)				
$\hat{r}_{t-10}$	0.150*** (0.040)	0.163*** (0.039)	0.145*** (0.041)	0.161*** (0.041)	0.151*** (0.040)	0.118*** (0.041)
$\hat{p}_{t-1}$		-0.003 (0.022)		-0.014 (0.022)		
$\hat{p}_{t-4}$	-0.028 (0.038)		0.013 (0.033)			
v_{t-1}		-0.007 (0.022)		0.009 (0.022)		
v_{t-4}	0.014 (0.038)		-0.016 (0.033)			
C	0.083*** (0.029)	0.057*** (0.017)	0.017 (0.016)	0.024 (0.019)	0.000 (0.000)	0.000 (0.000)
DUM	0.000 (0.003)	0.003*** (0.003)	0.002 (0.004)	0.000 (0.004)	0.001 (0.005)	0.001 (0.005)
	$R^2 = 0.03$	$R^2 = 0.06$	$R^2 = 0.02$	$R^2 = 0.02$	$R^2 = 0.02$	$R^2 = 0.01$

Notes:
C is a constant.
DUM is a dummy variable.
Figures in parentheses are standard errors.
R^2 is the adjusted R^2.
*** Statistically significant at the 1% level
** Statistically significant at the 5% level

7.5. CONCLUSIONS

Evidence on the effects of nonsynchronous trading has recently made a resurgence in the financial economics literature. After much evidence on the effects of thin trading when measuring betas in market models [see for example Scholes & Williams (1977) and Dimson (1979)], the more recent literature is concerned with the influence of nonsynchronous trading on portfolio return predictability.

Previously in chapter 6, we have found evidence of substantial short-horizon portfolio return predictability in the UK. Nevertheless, there is a body of evidence to suggest that such return predictability is in some ways dependent upon nonsynchronous trading which occurs in constructed portfolios and comes about due to a lagged price adjustment to market news. Portfolios which are subject to such trading may be characterised by 'stale' prices and exhibit positive autocorrelation in observed portfolio returns, which following Lo & MacKinlay (1990a), may create false interpretations about portfolio return predictability.

In this chapter we test for the presence of nonsynchronous trading in each of the constructed portfolios classified by market value, the touch and turnover by volume. Moreover, we examine the first-order autocorrelation in the returns process. In the case of our constructed portfolios, this probability averages around 8% but hardly ever exceeds 10%, except for the smallest sized portfolio. When nonsynchronous trading consistent returns are used, any positive first-order autocorrelation effects are removed and negative weak first-order autocorrelation occurs across many of the portfolios.

Following much of the literature in section 7.2, this indicates that portfolio return predictability is dependent upon the level of mispricing in the form of nonsynchronous trading.

Using similar techniques, we also test for any cross-correlation effects between portfolios. Following Lo & MacKinlay (1990a, 1990b) we can say that any substantial lead-lag cross-correlations between large and small sized portfolios may be indicative of nonsynchronous trading. Cross-correlation occurs because smaller, less frequently traded firms react with a lag to market wide information, whereas larger, more frequently traded portfolios react quickly to the same information. It is this lagged reaction that induces positive autocorrelation in portfolios returns. Examination of the cross-autocorrelations (which do not exceed 15%) between differing sizes of portfolios indicate that there are some asymmetry in the lead-lag cross-effects between larger and smaller portfolios. This is further evidence of nonsynchronous trading. Comparisons between estimated and implied cross-autocorrelations, given a high level of contemporaneous cross-autocorrelation, suggest that cross-effects are just a less efficient way of representing portfolio autocorrelation.

In further analysis of the nonsynchronicity problem we re-examine the portfolio return predictability question by re-estimating the predictable variables found in chapter 6. This time following Miller et al (1992), we adjust the parameters for the effects of nonsynchronous trading. The initial results show that only weekly predictability in the form of cyclical $\hat{r}_{t-4}$ and $\hat{r}_{t-10}$ parameters remains after this adjustment. The imposition of the bid-ask spread onto prices devoid of such effects does increase the strength of return predictability, but does not render any new predictable return components.

Finally, inferences about the amount of predictiveness in the exogenous return variables should be made with extreme caution. This is because when using nonsynchronous trading consistent returns, the adjusted R^2 falls from an average of between 15% and 20% [shown in chapter 6], to around 3%. This implies that the ability of the model to explain return predictability falls close to zero. Therefore, the strength of weekly return predictability is perhaps too small to be really profitable. In the event, these results lend support to the *loyalist* nonsynchronous trading explanation of market efficiency.

8. CONCLUSIONS

This thesis tests for stock market anomalies on the LSE using various sizes and classifications of constructed portfolios. More specifically, it has taken into account the influence that the touch and nonsynchronous trading has on calendar anomalies and return predictability.

An overview of the literature on the efficient markets hypothesis in chapter 2 shows that this evidence is wide and varied. Indeed, the consensus view as to whether markets are efficient has changed through time. Initially most tests, primarily originating from the US, supported the view that securities are efficiently priced. However, throughout the 1980's there was a plethora of studies citing stock market anomalies as evidence in favour of inefficiency in the pricing process. These anomalies have included stock market volatility, portfolio return predictability, calendar anomalies and the small firm effect. Despite this, the most recent evidence has shown that mispricing due to the bid-ask spread (the touch in the UK) and nonsynchronous trading in security and portfolio returns, has at least partly accounted for these anomalies.

The Effects of Portfolio Construction

Many studies, especially in the UK, examined anomalous security behaviour using stock market indices. This thesis however, has tested the robustness of a number of market anomalies by using various classifications and sizes of portfolios. These classifications including market value, closing price, the percentage touch and turnover by volume, have enabled tests to be carried out for the influence of the small firm effect, price effect, illiquidity and measures of information flows respectively, on portfolio returns.

The nature of the relationship between security returns and portfolio weights, (for example market value may be correlated with portfolio returns), means that in order to avoid data-snooping biases highlighted by Lo & MacKinlay (1990c), portfolios are re-ordered periodically. Initial descriptive statistics in chapter 3 show the influence of portfolio construction on calendar anomalies. The results imply that portfolio size determines the level of seasonality, rather than the type of portfolio classification.

Turn of the Year and Monthly Effects: Microstructure Explanations

Subsequently, from these tentative results, examination of the influence of turn of the year and turn of the month calendar anomalies was undertaken using four classifications and five sizes of portfolios constructed using daily data from the LSE. The rationale for this analysis stems from the questions raised in the literature on the well known January effect and tax effects, mostly documented in the US and to a much lesser extent in the UK. Some of the first evidence in this area by Rozeff & Kinney (1976), in the US, documented superior average January returns and risk premiums.

These findings have raised many questions and encouraged many studies. For example, why were returns higher in January? Some studies found that an increase in risk accounted for these anomalous returns, others showed that the January effect occurred only in smaller firms. In the US, the tax year end coincides with the calendar year end. Clearly, tax-loss selling and portfolio re-balancing due to investor portfolio window dressing could cause superior returns at the turn of the year. Evidence from Ariel (1987), also in the US, suggests that returns vary across differing times of the month due to this seasonal behaviour. Additionally, buying and selling by investors at calendar turning points may be reflected in the bid-ask spread both before and after these turning points. In the light of this evidence, this chapter, using daily data has investigated this seasonality using OLS dummy variable regression analysis, and found a number of interesting results.

Initially, a December and January effect seems to occur sporadically across portfolio classification and size. However, intra-monthly results show that seasonality across all classifications of portfolios is prominent to some extent in the last five days of December, but highly prominent in the last five days of January. While none of these seasonal effects coincided with the re-appraisal of the constituents of each portfolio, the former seasonal variable, being positive, is consistent with investors anticipating New Year buying. Subsequently these investors purchase stocks at the end of the calendar year. Furthermore, the results suggest that turn of the year seasonality occurs in spite of an April 5th tax year end, that seasonality is not tax motivated and that portfolio size does not influence the level of seasonality.

Due to the nature of investors' transacting behaviour, seasonality may be dependent upon the touch in prices. This hypothesis is confirmed since when the influence of the touch is removed, seasonal return variables disappear. Despite this, lagged returns synonymous with stale prices and daily return predictability, remain prominent. This suggests that daily returns are dependent upon yesterday's returns and not seasonal variables. The question that remains is what is driving seasonality in portfolio returns - seasonality in returns or seasonality in the touch? Examination of intra-monthly seasonality reveals that it is the touch that is seasonal and not portfolio returns. Turn of the year anomalies therefore occur due to mispricing in securities.

Day of the Week and Settlement Effects: Microstructure Explanations

Chapter 5 continues the examination of calendar seasonals, but this time over shorter horizons. The motivation for examining shorter horizon seasonality stemmed from French's 1980 US study which documents a day of the week effect. Initially, French (1980) found that portfolio returns appear to be positive on a Friday and negative on a Monday. However, tests for this day of the week effect on six sizes and four classifications of constructed portfolios from the LSE, suggest that this seasonality is *not* prominent. Tests for short run seasonality do not end here since the UK has a two week settlement system which up until recently was over a fixed pre-dated period throughout the year. Again using constructed portfolios rather than indices, the results suggest that the first Monday (settlement day) of the two week account period has highly significant positive returns, while the second Monday (account day) has significantly negative returns. Returns are higher, on average, on the former Monday, since investors will enjoy an extra 11 day 'interest free holiday.' Returns on the account Monday are negative since one would expect that on this day investors would settle up their previous account by selling in the market in order to pay for their transactions.

Additionally, evidence of a negative Friday effect on the last Friday of the two week account is documented. Clearly, investors at this time are selling securities. This may be due to investors balancing their account books since this Friday is the last trading day before the next account day (the middle Monday of the following settlement period). Again contrary to any UK evidence, when the influence of the touch is accounted for, all the daily seasonal effects disappear, apart from a fairly significant lagged returns variable. I have shown that the explanation for this, is it that seasonality is in the touch rather than portfolio returns.

Overall, these results have shown that across portfolio sizes and classifications both short run and long run seasonality is not prominent in the returns process, rather the touch. This seasonal touch may be indicative of investor buying and selling behaviour at calendar turning points. Also, daily returns are more dependent upon lagged daily returns which are indicative of returns predictability.

Evidence of Predictability in Daily Stock Returns

Consequently, due to the lack of empirical support for calendar anomalies, I examined more closely, in chapter 6, portfolio return predictability on a daily basis. The impetus for such tests stems from evidence suggesting that prices take divergent swings away from fundamentals and hence returns are negatively correlated and predictable. Using a multi-lag dynamic returns model that mimics more closely investors behaviour I have shown that in the short run, daily, 4-day and two weekly returns are predictable. In addition significant error correction components in the model were indicative of investors adjusting prices towards equilibrium. Evidence from the research suggests that the level of predictability is related to firm size but not substantially to the touch.

Return Predictability and Autocorrelation: Nonsynchronous Trading Explanations

Despite this evidence of short-horizon return predictability on the LSE, there is nevertheless a body of literature to suggest that such return predictability is dependant upon 'thin' or nonsynchronous trading in security returns. Indeed, Perry (1985) has shown that nonsynchronous trading comes about when some of the constituent shares in a portfolio do not trade at every closing time interval. Consequently, the observed portfolio value does not represent its true value. Since thinly traded stocks may react to information with a time lag, this generates positive autocorrelation in observed portfolio returns. Hence, apparent portfolio return predictability may occur due to the effects of nonsynchronous trading. Additionally, any substantial cross-correlations between smaller and larger sized portfolios may indicate delayed security price reaction and so nonsynchronous trading in the smaller sized portfolios.

Tests for nonsynchronous trading and/or apparent return predictability using the first-order autocorrelation in the returns process across the portfolios in chapter 6 reveals that correlation levels averaged about 8%. Additionally, cross-correlation between larger and smaller firms does not exceed 15%. Both these results may be mistakenly indicative of moderate portfolio return predictability. This suspicion is confirmed since when nonsynchronous consistent returns are used correlation levels fall to very small amounts.

When the portfolio return predictability results found in chapter 6 were re-estimated with the effects of nonsynchronous trading removed, only weekly and two-week predictable returns remain, and are not influenced by the touch. However, inferences about the strength of this predictability should be made with caution since the adjusted R^2 falls to 3%. Such results support the *loyalist* mispricing explanation of return predictability highlighted by Boudoukh et al (1993).

Summary

Overall, the research undertaken here has implications for many issues in the UK finance literature. Firstly, contrary to nearly all the UK, and many of the US studies I have examined anomalies robustly using various innovatively constructed portfolios. Most studies use indices; a portfolio which cannot easily be mimicked by investors. Secondly, using rigorous regression analysis I have tested for a wide range of anomalies including the effects of portfolio construction and a firm size effect, a turn of the year effect, an intra-monthly effect, a day of the week effect, various settlement effects, portfolio return predictability using an economic model that more readily mimics investor behaviour, as well as correlations across portfolios.

While the established literature has shown that these anomalies may refute the efficient markets hypothesis, I have shown that mispricing in portfolios returns caused by the touch and nonsynchronous trading account for these results and that profitable opportunities on the LSE have been overstated. Furthermore, I have shown that calendar anomalies are determined by investor behaviour reflected in the touch, and that nonsynchronous trading render predictable portfolio returns unpredictable. The implication is this thesis is that contrary to evidence in the UK, anomalies are not as prominent on the LSE as previously thought and so the results thus lend support to the efficient markets hypothesis.

Further Research

The motivation for undertaking the research shown in this thesis was the lack of rigorous tests, using portfolios, of anomalies in the UK. While the results indicate a mispricing explanation for these anomalies there are a number of issues that may be worthy of further research.

Alternative ways of classifying portfolios could be used, for example by applying different *in sample* weights over different re-appraisal periods. Classifying by beta may be a more appropriate measure of risk, since it reflects company specific risk, whereas the percentage touch may be influenced by market makers behaviour especially in a dealership market [see Naik, Neuberger, Viswanathan (1994)].

The distinction could be made between portfolios comprising companies that have year ends in December and companies with year ends in April, when testing for seasonal and tax effects. Clearly, for companies with year ends in December, the timing of earnings announcements could account for seasonality at the end of January.

Additionally, limits of the database used may have weakened some of the conclusions. The availability of bid and ask prices, in order to measure the touch, was limited to alpha stocks, which has implications for tests of a small firm effect. Clearly, there are no true small firm portfolios in this thesis since I am using data from alpha stocks, the top 160 capitalised companies on the market. The small firm effect is an area in need of more rigorous investigation in the anomalies literature.

In addition to the exclusion of smaller companies, the time series at the time this research was undertaken was limited around 6 years since the LSE only started recording bid and ask prices from 1986 onwards. Hence, for tests of a January effect the analysis was limited to just 5 observations. Clearly, while this is not ideal, further work should use a longer time series in order to answer the questions posed by the 'January Effect' in a more rigorous manner.

Finally, given the importance attached to the touch in explaining stock market anomalies, investigations could be made into whether mis-measurement of the touch itself contributes to anomalies on the LSE. The quoted bid and ask prices, peculiar to this database, are those of the best two market makers (i.e the smallest touch). The data therefore may not reflect the true extent of illiquidity faced by investors, who may not transact with these market makers. Consequently, the true extent of the touch in portfolio returns may be underestimated.

Appendix 1: List of Constituent Firms used in Portfolio Construction

1. Associated British Foods
2. Argyll Group
3. Amstrad
4. Asda Group
5. Barclays Bank
6. Bass
7. B.A.T Industries
8. Blue Circle Industries
9. B.E.T
10. B.I.C.C
11. Burmah Castrol
12. Bunzl
13. B.O.C Group
14. Boots
15. British Petroleum
16. BPB Industries
17. British Telecom
18. BTR
19. Cable & Wireless
20. Cadbury Schwepps
21. Cookson Group
22. Courtaulds
23. Coats Viyella
24. Dalgety
25. Dixons Group
26. ECC Group
27. Fisons
28. Forte
29. General Accident
30. Guardian Royal Exchange
31. General Electric Company
32. GKN
33. Glaxo
34. Grand Metropolitan
35. Granada Group
36. Guinness
37. Great Universal Stores 'A'
38. Hillsdown Holdings
39. Hammerson Property
40. Hanson
41. Imperial Chemical Industries
42. Kingfisher
43. Ladbroke Group
44. Lloyds Abbey Life
45. Land Securities
46. Legal & General
47. Lloyds Bank
48. Lonrho
49. Lucas Industries
50. MEPC
51. Midland Bank
52. Marks & Spencers
53. Next
54. National Westminster Bank
55. Pilkington
56. Peninsular & Oriental
57. Prudential Corporation
58. Pearson
59. Royal Bank of Scotland
60. Racal Electronic
61. Redland
62. Reed International
63. Rank Hovis McDougal
64. RMC Group
65. Rank Organisation
66. Royal Insurance Holdings
67. Ratners Group
68. RTZ Corporation
69. Saatchi & Saatchi
70. Smithkline Beechams 'A'
71. Sainsbury, J
72. Scottish & Newcastle
73. Sedgewick
74. Sears
75. Shell
76. Smith & Nephew
77. Stanhope Properties
78. Sturge Holdings
79. Sun Alliance Group
80. Tarmac
81. T & N
82. Trafalgar House
83. Tesco
84. United Biscuits
85. Unilever
86. Unigate
87. United Newspapers
88. Whitbread
89. Willis Corroon
90. Wellcome

Appendix 2

Diagnostic Tests for Unrestricted Models

Market Value Portfolio Classification - Bid Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,603) = 0.84$	$\eta_1(1,602) = 1.11$	$\eta_1(1,603) = 0.15$	$\eta_1(1,601) = 0.84$	$\eta_1(1,605) = 0.41$	$\eta_1(1,606)=0.00$
$\eta_2(1,603) = 1.22$	$\eta_2(1,602) = 1.18$	$\eta_2(1,603) = 0.02$	$\eta_2(1,601) = 0.25$	$\eta_2(1,605) = 0.18$	$\eta_2(1,606) = 0.04$
$\xi_3(2) = 4.15$	$\xi_3(2) = 6.81$	$\xi_3(2) = 3.23$	$\xi_3(2) = 3.42$	$\xi_3(2) = 1.95$	$\xi_3(2) = 3.68$
$\eta_4(1,609) = 0.05$	$\eta_4(1,606) = 1.04$	$\eta_4(1,608) = 1.56$	$\eta_4(1,609) = 0.23$	$\eta_4(1,609) = 0.26$	$\eta_4(1,608) = 0.95$

Market Value Portfolio Classification - Closing Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,603) = 1.50$	$\eta_1(1,605) = 3.38$	$\eta_1(1,603) = 0.16$	$\eta_1(1,601) = 0.01$	$\eta_1(1,602) = 0.22$	$\eta_1(1,606) = 0.11$
$\eta_2(1,603) = 0.65$	$\eta_2(1,605) = 2.62$	$\eta_2(1,603) = 0.84$	$\eta_2(1,601) = 0.42$	$\eta_2(1,602) = 0.31$	$\eta_2(1,606) = 0.02$
$\xi_3(2) = 3.10$	$\xi_3(2) = 10.84$	$\xi_3(2) = 2.79$	$\xi_3(2) = 3.44$	$\xi_3(2) = 2.86$	$\xi_3(2) = 7.13$
$\eta_4(1,609) = 0.01$	$\eta_4(1,609) = 0.18$	$\eta_4(1,608) = 0.18$	$\eta_4(1,607) = 0.58$	$\eta_4(1,609) = 2.45$	$\eta_4(1,608) = 0.46$

Bid-Ask Spread Portfolio Classification - Bid Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,605) = 0.21$	$\eta_1(1,606) = 0.23$	$\eta_1(1,604) = 0.00$	$\eta_1(1,605) = 0.92$	$\eta_1(1,602) = 0.11$	$\eta_1(1,603) = 2.99$
$\eta_2(1,605) = 0.26$	$\eta_2(1,606) = 3.90$	$\eta_2(1,604) = 0.08$	$\eta_2(1,605) = 0.01$	$\eta_2(1,602) = 1.12$	$\eta_2(1,603) = 1.14$
$\xi_3(2) = 6.20$	$\xi_3(2) = 5.12$	$\xi_3(2) = 3.93$	$\chi(2) = 2.49$	$\xi_3(2) = 4.758$	$\xi_3(2) = 2.45$
$\eta_4(1,609) = 0.98$	$\eta_4(1,609) = 0.15$	$\eta_4(1,609) = 1.29$	$\eta_4(1,609) = 1.43$	$\eta_4(1,607) = 0.05$	$\eta_4(1,609) = 0.22$

Bid-Ask Spread Portfolio Classification - Closing Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,605) = 0.23$	$\eta_1(1,606) = 1.56$	$\eta_1(1,606) = 0.03$	$\eta_1(1,606) = 3.04$	$\eta_1(1,604) = 0.32$	$\eta_1(1,603) = 0.08$
$\eta_2(1,605) = 0.02$	$\eta_2(1,606) = 0.87$	$\eta_2(1,606) = 0.15$	$\eta_2(1,606) = 0.00$	$\eta_2(1,602) = 1.10$	$\eta_2(1,603) = 0.39$
$\xi_3(2) = 6.56$	$\xi_3(2) = 7.02$	$\xi_3(2) = 2.39$	$\xi_3(2) = 5.54$	$\xi_3(2) = 5.04$	$\xi_3(2) = 3.68$
$\eta_4(1,609) = 0.94$	$\eta_4(1,609) = 0.46$	$\eta_4(1,609) = 1.76$	$\eta_4(1,609) = 1.81$	$\eta_4(1,608) = 0.19$	$\eta_4(1,609) = 0.49$

Turnover by Volume Portfolio Classification - Bid Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,601) = 0.61$	$\eta_1(1,603) = 1.48$	$\eta_1(1,604) = 0.48$	$\eta_1(1,604) = 1.03$	$\eta_1(1,606) = 1.96$	$\eta_1(1,605) = 0.03$
$\eta_2(1,601) = 0.57$	$\eta_2(1,603) = 1.14$	$\eta_2(1,604) = 1.53$	$\eta_2(1,604) = 1.68$	$\eta_2(1,606) = 2.19$	$\eta_2(1,605) = 0.29$
$\xi_3(2) = 3.87$	$\xi_3(2) = 5.18$	$\xi_3(2) = 0.39$	$\xi_3(2) = 4.00$	$\xi_3(2) = 2.29$	$\xi_3(2) = 5.01$
$\eta_4(1,609) = 0.24$	$\eta_4(1,609) = 2.84$	$\eta_4(1,609) = 0.17$	$\eta_4(1,609) = 0.52$	$\eta_4(1,609) = 0.22$	$\eta_4(1,609) = 1.11$

Turnover by Volume Portfolio Classification - Closing Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,603) = 0.05$	$\eta_1(1,603) = 1.72$	$\eta_1(1,604) = 0.83$	$\eta_1(1,604) = 1.05$	$\eta_1(1,607) = 3.05$	$\eta_1(1,607) = 0.23$
$\eta_2(1,603) = 0.12$	$\eta_2(1,603) = 0.08$	$\eta_2(1,604) = 0.02$	$\eta_2(1,604) = 1.69$	$\eta_2(1,607) = 0.59$	$\eta_2(1,607) = 0.00$
$\xi_3(2) = 7.47$	$\xi_3(2) = 6.17$	$\xi_3(2) = 2.96$	$\xi_3(2) = 3.99$	$\xi_3(2) = 2.60$	$\xi_3(2) = 3.37$
$\eta_4(1,609) = 1.57$	$\eta_4(1,609) = 0.33$	$\eta_4(1,609) = 1.29$	$\eta_4(1,609) = 0.52$	$\eta_4(1,609) = 0.26$	$\eta_4(1,609) = 0.65$

Notes: η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

Appendix 3

Diagnostic Tests for Nonsynchronous Trading Consistent Unrestricted Models

Market Value Portfolio Classification - Bid Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,603) = 0.01$	$\eta_1(1,605) = 0.15$	$\eta_1(1,604) = 0.26$	$\eta_1(1,601) = 0.22$	$\eta_1(1,605) = 0.09$	$\eta_1(1,607) = 0.25$
$\eta_2(1,603) = 0.97$	$\eta_2(1,605) = 0.13$	$\eta_2(1,604) = 1.96$	$\eta_2(1,601) = 3.43$	$\eta_2(1,605) = 2.43$	$\eta_2(1,607) = 1.53$
$\xi_3(2) = 4.19$	$\xi_3(2) = 6.50$	$\xi_3(2) = 4.48$	$\xi_3(2) = 1.97$	$\xi_3(2) = 4.33$	$\xi_3(2) = 3.14$
$\eta_4(1,609) = 2.94$	$\eta_4(1,609) = 0.50$	$\eta_4(1,609) = 0.01$	$\eta_4(1,609) = 3.39$	$\eta_4(1,609) = 2.86$	$\eta_4(1,609) = 0.95$

Market Value Portfolio Classification - Closing Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,603) = 0.02$	$\eta_1(1,605) = 0.03$	$\eta_1(1,604) = 0.51$	$\eta_1(1,601) = 0.21$	$\eta_1(1,602) = 0.30$	$\eta_1(1,607) = 0.02$
$\eta_2(1,603) = 1.25$	$\eta_2(1,605) = 0.31$	$\eta_2(1,604) = 2.18$	$\eta_2(1,601) = 3.39$	$\eta_2(1,602) = 0.50$	$\eta_2(1,607) = 1.35$
$\xi_3(2) = 3.77$	$\xi_3(2) = 8.42$	$\xi_3(2) = 4.45$	$\xi_3(2) = 1.88$	$\xi_3(2) = 3.43$	$\xi_3(2) = 6.52$
$\eta_4(1,609) = 4.43$	$\eta_4(1,609) = 0.15$	$\eta_4(1,609) = 0.25$	$\eta_4(1,607) = 4.20$	$\eta_4(1,609) = 11.1$	$\eta_4(1,609) = 0.64$

Bid-Ask Spread Portfolio Classification - Bid Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,605) = 0.01$	$\eta_1(1,606) = 1.89$	$\eta_1(1,604) = 1.12$	$\eta_1(1,605) = 0.38$	$\eta_1(1,605) = 0.57$	$\eta_1(1,603) = 0.22$
$\eta_2(1,605) = 0.19$	$\eta_2(1,606) = 0.79$	$\eta_2(1,604) = 4.16$	$\eta_2(1,605) = 0.11$	$\eta_2(1,605) = 3.05$	$\eta_2(1,603) = 2.19$
$\xi_3(2) = 6.00$	$\xi_3(2) = 4.73$	$\xi_3(2) = 3.50$	$\chi(2) = 2.67$	$\xi_3(2) = 4.35$	$\xi_3(2) = 3.73$
$\eta_4(1,609) = 3.06$	$\eta_4(1,609) = 0.10$	$\eta_4(1,609) = 0.09$	$\eta_4(1,609) = 2.29$	$\eta_4(1,609) = 12.6$	$\eta_4(1,609) = 3.48$

Bid-Ask Spread Portfolio Classification - Closing Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,605) = 0.01$	$\eta_1(1,606) = 0.38$	$\eta_1(1,604) = 0.12$	$\eta_1(1,606) = 0.11$	$\eta_1(1,605) = 0.37$	$\eta_1(1,603) = 0.62$
$\eta_2(1,605) = 0.25$	$\eta_2(1,606) = 0.00$	$\eta_2(1,604) = 4.15$	$\eta_2(1,606) = 0.01$	$\eta_2(1,605) = 3.74$	$\eta_2(1,603) = 1.01$
$\xi_3(2) = 6.62$	$\xi_3(2) = 6.72$	$\xi_3(2) = 2.96$	$\xi_3(2) = 5.12$	$\xi_3(2) = 4.66$	$\xi_3(2) = 2.71$
$\eta_4(1,609) = 2.59$	$\eta_4(1,609) = 3.64$	$\eta_4(1,609) = 0.00$	$\eta_4(1,609) = 6.92$	$\eta_4(1,608) = 10.9$	$\eta_4(1,609) = 1.45$

Turnover by Volume Portfolio Classification - Bid Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,601) = 0.19$	$\eta_1(1,603) = 0.03$	$\eta_1(1,604) = 0.15$	$\eta_1(1,604) = 0.64$	$\eta_1(1,606) = 1.33$	$\eta_1(1,605) = 2.33$
$\eta_2(1,601) = 2.66$	$\eta_2(1,603) = 0.02$	$\eta_2(1,604) = 1.45$	$\eta_2(1,604) = 0.95$	$\eta_2(1,606) = 0.19$	$\eta_2(1,605) = 2.79$
$\xi_3(2) = 8.45$	$\xi_3(2) = 5.07$	$\xi_3(2) = 0.77$	$\xi_3(2) = 5.11$	$\xi_3(2) = 2.18$	$\xi_3(2) = 6.41$
$\eta_4(1,609) = 0.69$	$\eta_4(1,609) = 10.3$	$\eta_4(1,609) = 7.16$	$\eta_4(1,609) = 7.33$	$\eta_4(1,609) = 2.84$	$\eta_4(1,609) = 2.57$

Turnover by Volume Portfolio Classification - Closing Prices

Smallest	2	3	4	5	Largest
$\eta_1(1,603) = 0.06$	$\eta_1(1,603) = 0.01$	$\eta_1(1,604) = 0.04$	$\eta_1(1,604) = 0.64$	$\eta_1(1,607) = 0.01$	$\eta_1(1,607) = 0.02$
$\eta_2(1,603) = 0.01$	$\eta_2(1,603) = 0.01$	$\eta_2(1,604) = 1.41$	$\eta_2(1,604) = 0.96$	$\eta_2(1,607) = 2.02$	$\eta_2(1,607) = 3.75$
$\xi_3(2) = 11.9$	$\xi_3(2) = 5.26$	$\xi_3(2) = 4.89$	$\xi_3(2) = 5.11$	$\xi_3(2) = 2.16$	$\xi_3(2) = 2.93$
$\eta_4(1,609) = 5.31$	$\eta_4(1,609) = 7.46$	$\eta_4(1,609) = 1.04$	$\eta_4(1,609) = 7.37$	$\eta_4(1,609) = 2.91$	$\eta_4(1,609) = 0.19$

Notes: η_1 is an F(.,.) distributed test for n^{th} order serial correlation under the null of no serial correlation.
η_2 is a RESET test, F(.,.) distributed for functional form under the null of correct functional form.
ξ_3 is a $\chi^2(n)$ distributed test for normality of the residuals under the null of normally distributed residuals.
η_4 is an F(.,.) distributed test for heteroscedasticity under the null of homoscedasticity.

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