CALENDAR SEASONALITY IN THE IRISH EQUITY MARKET 1988-1998

Brian M Lucey

2003

This thesis is provided in fulfillment of the requirements of the degree of Doctor of Philosophy of the University of Stirling

THANK YOU

I wish to thank a large number of persons for their assistance, encouragement and advice during the course of the last few years; in no particular order, they are

Professor John Murray, for his invaluable persistence in urging me onward; Professor Colm Kearney, for his advice and process encouragement; My colleagues, in particular Dr Patrick Butler, Dr Martin Fellenz, Dr Diane Hogan, Dr William Kingston, Dr Mairead Brady and Ms Mary Keating, for their friendship, collegiality and constant well wishes; Ms Ruth Potterton, of the Lecky Library of Trinity College, without whose advice and skill pursuing a research degree would have been a far more daunting task; Professor John Pantner and Ms Sylvia Huntley-Moore of the Staff Development Unit of Trinity College for their unfailing good advice, wit and urgings to excellence; Valerie McCarthy and Joan Reidy, the administrative core of the School of Business Studies without whose assistance juggling fulltime work and a research degree would have been nigh on impossible; and last my friends, family, especially my mother, and colleagues.

Tremendous and special thanks must also go to my supervisors, Professor Robin Limmack and Professor Jim Steeley, for their always-insightful comments that have made the task so much easier and more enjoyable.

DEDICATION

I wish to dedicate this work to my wife, Mary, without whose constant love, encouragement and good sense this would never have happened.

ABSTRACT

Detection of 'anomalies', empirical regularities that are inexplicable within a pre-eminent or accepted paradigm, is a key aspect of the operation of scientific endeavour. The dominant theories of financial economics, those deriving from the CAPM/APT literature, hold that there should not exist persistent differences in the returns to assets across calendar frequencies. An extensive review of the literature reveals that in a wide variety of assets and markets there is evidence that returns differ according to the calendar frequency, in particular across days of the week and months of the year and around recurrent holidays. However, this review also reveals considerable room for increased methodological and statistical sophistication. In particular, the nature and extent of the data indicate that techniques based on robust regression, non-parametric statistics and Bayesian inference are more appropriate than the predominantly OLS based approaches displayed in the literature. Papers that adopt these more sophisticated approaches generally find much weaker evidence for such calendar anomalies.

In essence, the Irish Stock Exchange operated free from exchange controls and in a broadly homogenous monetary and economic environment from 1988 to 1998. Daily returns from 1988 to 1998, on official equity indices, and from 1993 to 1998 on equal and value weighted equity indices, are examined. The evidence is that even when more sophisticated and appropriate techniques are used there is still some evidence for a daily pattern in the returns to these indices. However this pattern is dissimilar to that found elsewhere, consisting of a midweek positive peak as opposed to the more commonly found low returns at the start of the week and higher returns on Friday. This pattern is not a function of the settlement system, does not appear to be related to the pattern of

either microeconomic (firm-specific) or macroeconomic information releases, nor does it appear to be a function of endogenous news generation.

Previous international research indicates a January peak in returns, while previous research on the Irish market had also found an April peak. While the investigation here of the monthly pattern of returns confirms, in a statistically and methodologically robust manner, the January peak no evidence is found of an April peak.

Examination of the return pattern around exchange holidays indicates that, in common with other markets referenced in the literature, there is a rise in returns before a holiday. However, on decomposition into local and international components we find that although the local effect is strong this effect is negative, which is a major point of departure from previous research findings.

TABLE OF CONTENTS

LIST OF TABLES ETC.

0. Introduction and Overview

This work examines the extent and nature of seasonality in the returns to equities traded on the Irish Stock Exchange between 1988 and 1998. The central thesis of this work can be summarized as follows: there may well exist economically and statistically significant seasonal patterns in equity return indices, in particular at the daily, monthly and holiday frequencies, but the detection of these is highly dependent on factors such as the choice of estimation method, the time period over which the investigator investigates, the amount of data examined and the method of constructio n of the indices themselves.

0.1. OVERVIEW

The work begins in Chapter 0:Introduction and Overview, where an overview is presented of the modern theory of financial economics. From this we see that there is little room for predictable calendar based regularities in this theoretical framework. The chapter continues with an examination from the perspective of the philosophy of science of what such 'anomalies' may mean for a theory. One of the key issues in financial econometrics is the issue of how novel apparently novel facts are. This is also an issue for the philosophy of science. The chapter concludes with a discussion of this issue.

In Chapter 2, Chapter 3 and Chapter 5, I outline the evidence on general calendar regularities, showing that for some, in particular monthly, especially January, seasonality, there exist reasonable, if partial, explanations within the operation of normal science. For others, such as the Friday the 13th regularity there appears, as yet, to be none. Daily seasonality appears to be somewhere in the middle, with many alternative explanatory theories competing but none fully, or in the author's opinion, satisfactorily, explaining them. These theories are discussed in more detail in Chapter 4, wherein it becomes clear that there are yet no convincing explanations.

Chapter 6 introduces the Irish market. In this chapter we note that there has been a natural experiment in the changing of the settlement system from an account based, fixed, settlement system to one of a rolling settlement. As some of the explanations predicated for the existence of daily seasonality is based on the settlement system this allows us to examine this set of explanations in an easy and simple way. This chapter also provides us with the basis for the timeperiod chosen for analysis.

Chapter 7 outlines the basis of the robust statistical methodology employed in the investigation of the existence, the extent and possible causes of this regularity in the Irish equity market. Here we note that there are new methods, in particular that of resampling and bootstrapping, which are intensely non-parametric and thus allow us to have considerable confidence on our results. In addition, significant methodological gaps in much of the previous literature are discussed and remedies proposed.

Chapter 8 introduces the data, providing *inter alia* a set of portfolio based indices to remedy the lack of small capitalization indices over part of the timeperiod.

Chapter 9 presents the results of the application of this methodology to the issue of daily seasonality. The results are mixed, in that while there does appear to be seasonality of a particular pattern not seen elsewhere, this is not statistically robust in the sense of being present across a wide range of estimation procedures and approaches.

Chapter 10 indicates that preholiday effects are present, and that they are both robust and again have an unusual pattern, the local effect dominating the international but in a perverse manner.

Chapter 11 shows the application of the robust methodology to data at the monthly frequency. While the results here are broadly in line with both previous Irish and international work, unlike that for daily seasonality, the findings are still somewhat non-robust and thus those elements that diverge from previous research must be treated with caution.

Chapter 12 concentrates on the issue seeking a potential explanation of daily seasonality, this being the pattern most at divergence with international prior evidence. What emerges is that the available hypotheses are not powerful or even in some cases adequate explanations for the pattern found. Part of this chapter involves the creation of yet more indices from existing data, the official data being inadequate to allow investigation of some crucial hypotheses.

Chapter 13 provides a wrap-up of the work and some tentative conclusions.

0.2. Potential Contribution Of This Work

In doing this, a number of contributions to the research agenda are likely. First, the data that are analysed assist in our understanding of calendar regularities, with some insulation from the charge of data snooping. Their relative neglect heretofore renders the results more powerful than would be a similar set of findings for a market such as the US or the UK. Thus, both from a statistical and philosophical perspective the data speak loudly. Arising from this is the second contribution. Given that the results are to a greater or lesser extent, immune from the charge of data mining, they stand as a potentially highly anomalous set of results. In some cases (monthly seasonality for example) the results are similar in magnitude and nature to those found elsewhere; in others, such as the behaviour of the Irish market around holidays and in terms of the daily pattern, the results are dissimilar to the existing literature. The third contribution is that of completeness. As will be seen later there are sound theoretical reasons for financial economics to examine the higher moments of the data distribution. However, for a number of reasons this has not been the case. This work, unlike the vast majority of papers on seasonality, examines the patterns in the first (mean), second (variance), third (skewness) and fourth (kurtosis) moments. The patterns found are again similar to the literature in some cases and different in others. The final major contribution of the work is completeness of another form. A set of findings, no matter how anomalous, are of greater import if we cannot, as seems to be the case here, find reasonable explanations, explanations broadly congruent with the main precepts of financial economics, for them. Thus, the completeness of the studies carried out in describing and analysing the moments of the data are matched, it is hoped, by the completeness of the attempts to find explanations.

The contributions made are already recognised in that parts of this work have appeared in a number of scholarly journals. In all cases the present author was the lead researcher and the material contained in the articles noted at the beginning of each chapter are fully and comprehensively integrated in this work.

1. Anomalies, Regularities and Finance

This section briefly discusses aspects of the modern theory of finance. In particular, it discusses how the time series properties of asset returns should look, were these asset returns generated according to the precepts of the theories. It then goes on to discuss the nature of inquiry from a philosophy of science perspective, with particular reference to financial economics.

1.1. Asset Pricing & Market Efficiency– A Brief History

Modern scholarship accepts that the work of Bachelier (1900) prefigured a substantial part of what later was termed the efficient markets hypothesis[1]. While many of the main issues subsequently raised in the debates in the late 1950's and 1960's were addressed in this work, economic and financial academicians ignored it almost totally until Paul Samuelson began its recirculation and rehabilitation, a process that was completed by the publication of the entire work in Cootner (1964) This volume also contained a number of papers looking at randomness and statistical properties of stock prices. It is instructive to note that while there was at that stage no formal, generally accepted paradigm of how asset prices are formed and thus how the time series properties of the returns to these assets should look, work by Working (1934), Cowles and Jones (1937),Kendall (1953), Roberts (1957) and Granger and Morgenstern (1963) had confirmed the insight of Bachelier; the time series properties of the returns to financial assets could be described as being indistinguishable from a random walk. The work of Cowles (1933; Cowles (1944) indicated that investment professionals, as reflected in their stock recommendations, do not, on average, outperform the market as a whole.

[1] This magisterial work also contained an early version of the mathematics later used by Einstein in his nobel winning work on the foundations of quantum mechanics in 1905.

This was despite the dominant legacy of Williams (1938)and Graham and Dodd (1934), which works suggested that fundamental valuation of stocks was the proper role for investment analysts and advisors and implicitly that there were gains to be made in stock picking on the basis of these advisors. Combining all these factors left the impression at the end of the 1950's that the market for financial assets in the US and the UK seemed to perform in a manner congruent with what was later described as weak and semi-strong form efficiency.

The mid-to-late 1960's saw much of the foundations of the modern theory of finance brought together in a series of works. Work by Fama (1965) showed that the existing literature on the statistical properties of asset prices strongly favoured the random walk hypothesis. At the same time Samuelson (1965, (1973) and Mandlebrot (1966) showed that a martingale process, a statistical process akin to but less restrictive than a random walk, both fitted the data and had the possibility to provide the as then missing linkage between market efficiency and the observed data. Samuelson and Mandlebrot made a linkage between the statistical formulation of a martingale process and stock valuation[2]. Fama (1970)provides the foundation of the theory and empirical programme of research on market efficiency, while Fama, Fisher, Jensen and Roll (1969)and Ball and Brown (1968)provide the results of the two earliest event studies. At the same time, Sharpe (1964) and Treynor (1961) provided the foundations of the Capital Asset Pricing Model, the CAPM, which became, and remains, the dominant theory of how asset

---

[2] A stochastic process X_t is a martingale with respect to a set of information Pt if it has the property $E(X_{t+1}|\Phi_t) = X_t$, and a stochastic process Y_t is a fair game if it has the property $E(Y_{t+1}|\Phi_t) = 0$,
for which reason a fair game is sometimes also called a martingale difference model.
Mandlebrot and Samuelson showed that based on the fundamental valuation model $P_t = \sum_{i=1}^{\infty}(1+R)^{-1} E_t D_{t+i}$
where R is the discount rate and D the dividend payment rates of return on a stock should follow a fair game.
More detailed derivation of this result can be found in most intermediated level investment texts, such as Cuthbertson (1996)

prices are determined and thus how the time series of their returns should emerge. Ball & Brown also show the first observed 'anomaly[3]', the post-earnings announcement drift. Finally, the modern theory of market microstructure can be traced to the work of Treynor, writing as Bagehot (1971). Further, more detailed, historical overviews of the emergence of financial economics as a discipline are contained in Leroy (1989) especially Part II, Bernstein (1992) and Dimson and Mussavian (1998).

1.2. MODERN FINANCE AND THE RETURN DISTRIBUTION PROCESS

The work of Fama (1970,1976) gives a full account of the mature efficient markets hypothesis.

It also provides the well-known taxonomy of market efficiency into three forms of nested efficiency, which fits perfectly with the martingale/ fair game model.[4]

It is important to realise however that Fama cast his taxonomising and theorising not in terms of the actual prices of financial assets themselves but rather in terms of their deviation from an expected price. The development of the Capital Asset Pricing Model (CAPM) and its subsequent extensions allowed for both the accurate, theoretically justified, measurement of expected returns and prices and also overcame a deficiency inherent in the Samuelson/Mandlebrot formulation of the martingale model, namely that it strictly held only where agents were risk neutral. Papers such as Ohlsen (1977),

[3] The very use of the word anomaly is itself in dispute, as shown by the comprehensive review offered in Frankfurter and McGoun (2001).

[4] Weak form efficiency holds when the information set consists only of past prices, semi-strong when it includes prices and all publicly available information, and strong when all information, public as well as private, forms part of the relevant information set investors use in formulating their investment decisions.

Mehra and Prescott (1980), and Salyer (1988) indicate that risk aversion does not necessarily fundamentally alter the market efficiency argument. However, work by LeRoy (1973) showed that an assumption that investors and agents hold rational expectations was a necessary condition for market efficiency even in the weak sense.

The CAPM gives an explicit formulation for the risk premium, rp_i, the excess return of a stock over the risk-free rate. It is

Eq. 1 $rp_i = \beta_i (ER_m - r_f) = \lambda_m \operatorname{cov}(R_i, R_m)$

where λ_m refers to the slope of the capital market line, and gives the market price of risk. The implication of Eq. 1 is that only the covariance of returns between asset i and the market will affect the excess return on asset i. Issues such as the price-earnings ratio, the capitalization of the stock, or indeed the day of the week on which the stock is trading, should have no effect. The CAPM allows for the possibility that returns are both variable and predictable, as the equilibrium, excess returns are dependent on the conditional variance of the forecast error of these returns. This arises from the fact that the CAPM applied to the market as a whole implies that

Eq. 2 $E_t R_{m,t} - r_{f,t} = \lambda E_t (\delta_{m,t+1})$

Investors make their expectations based on forecasts, which have of course some forecast error involved.

In general, the efficient market approach implies the moment condition for the return on an asset as per Eq. 3:

Eq. 3 $E_t(Q_{t-1} R_{t-1} | I_t) = 1$

, where Q_{t-1} is the pricing kernel reflecting the intertemporal rate of substitution by an agent between present and future consumption and E_t is the conditional expectations operator taken with respect to a given information set I_t. From Eq. 3, it follows that the conditionally expected return is then

Eq. 4 $$E_t(R_{t+1}) = \frac{1 - \text{cov}_t(Q_{t+1}, R_{t+1})}{E_t(Q_{t+1})}$$

Finding therefore that some degree of predictability exists in returns of a stock or a portfolio of stocks is not inconsistent with investors being rational or the CAPM not holding. The CAPM implies that the returns to financial assets, particularly stocks, should follow a martingale. Predictable returns in asset prices can arise through the time varying conditional covariance between the returns and the pricing kernel, or in the pricing kernel itself. The pricing kernel is typically assumed to be an aggregate consumption related kernel, and thus this implies that the asset returns over economic cycles should vary. However, nowhere in finance theory is there offered a satisfactory *theoretical* reason why the calendar should affect the individual pricing kernels. Thus in the absence of theory we are relegated to searching for empirical facts on which perhaps a theory may later be constructed. The only mechanism, accepting the implications of Eq. 3 & Eq. 4, by which this could arise would be in the case where individuals intertemporal rate of time preference for consumption differs as between Monday and other days of the week, or between the time around the turn of the month and other times, and so forth.

The alternative approach to equilibrium stock pricing, the Arbitrage Pricing Theory, APT, is a more general formulation than that of the CAPM[5]. Unlike the CAPM, it requires little or no assumptions regarding the utility theory of the investor, beyond that the central tendency (mean) and dispersion (standard deviation) of the returns generated are of interest to the investor. The APT says little about the causes of individual stock movements, only that these are likely to vary from stock to stock and that the responses of stock prices to general events economy wide will differ. Combining gives potentially as many different factors driving stock prices, as there are stocks. By judicious combination the investor can create portfolios that diversifies the unsystematic or idiosyncratic risk. However, as to what these shocks are, not to mention the reason or even the extent of firm specific reactions thereto, the APT provides no guide. Again, like the CAPM, the APT implies a martingale process for the asset returns.

Put together with the elements of martingales and fair games, we can summarise therefore the market efficiency story as having a number of elements: All agents act as if they have a model of equilibrium valuation of stocks (CAPM or APT for example), these agents act on this information in a rational manner to forecast/predict prices and therefore returns in the future, and these agents, by the principle of arbitrage, cannot make persistent supernormal profits. Jensen (1978) summarizes the issue as

> *" A market is efficient with respect to an information set Ω if it is impossible to make economic profits by trading on the basis of Ω. By economic profits we mean the risk adjusted rate of return, net of all costs "*

Testing therefore of violations of the modern paradigm of finance involves a joint test: that of rational expectations and of the model under investigation. As the model most

[5] However, even though it is a more general formulation the APT, even though a multi-factor model is not inconsistent with the CAPM., a single factor model See Cuthbertson *Op cit*

commonly deemed to hold is the CAPM, this implies that a test of the model involves testing that only systematic risk is priced.

1.3. The Nature And Philosophy Of Inquiry

In this section, I discuss the nature and philosophy of inquiry in the social sciences. The section begins with an outline of the work of Kuhn and Lakatos. It then outlines the characteristics of what Lakatos calls "degenerative work programmes", corresponding to what followers of Kuhn would call 'a period of crisis'. *Inter alia*, I intend to argue that finance as a body of organizing theories and suggested methodologies may fall into this class. This section ends with a discussion of the terminological and philosophical importance of anomalies, regularities and predictabilities.

1.3.1. Popper, Kuhn, Lakatos & The Philosophy Of Scientific Inquiry

The philosophy of science refers to the way in which philosophers have approached the questions of how are and how should scientific inquiries be conducted. On this definition the philosophy of science stretches back to the origins of scientific thought and philosophy, combining for instance in Aristotle and other classical philosophers who speculated as much about how to know as what (and indeed if) to know. The major intellectual forces in the last 50 years in this area have been the work of Popper, Kuhn and Lakatos. An outline of these provides both an introduction to the modern themes in the philosophy of science as well as providing, it is arguable, a mini case in the way that a body of knowledge advances.

The Logic of Scientific Discovery Popper (1959) has been the work that many, particularly in econometrics, have seen as the great influence on the work of economics. This work emerged originally from the Viennese logical positivist school of philosophy[6] in 1934, being translated into English in 1959. The major part of his work taken on board by economics has been the concept of falsification. By this Popper means that we can, in principle, decide if a theory is false far more readily than if it is true. He argues that a 'good' theory is one that is falsifiable. An example, oft quoted, is on swans. If we have a theory that asserts or predicts that all swans are white then the discovery of a black swan is sufficient to prove this theory false. This arises from his rejection of inductive reasoning as a way forward. Discovering that swans are white, no matter how many times, cannot prove the theory. Therefore, the logical way to test the theory is to search for black swans. His view of the process of science is the testing of theories, which arise from practical problems, by means of attempts at falsifying theories adduced to explain these problems rather than attempts at confirming. The highly influential essays by Friedman (1953) advocating that the realism of the assumptions matters little in a theory compared to the predictive or assertive power, derives from a Popperian approach to scientific endeavour.

Popper's view of falsification as the touchstone of scientific methodology has come under significant criticism from modern philosophers however, mainly from five perspectives – sociological, measurement, processual, manifestational and self-inductive.

- First, the sociological superstructure of scientific endeavour is one that many scientists, social and otherwise, have spent their professional life contributing to and being influenced by. It would seem a reasonable observation that few

[6] See Hausman (1994)*Introduction* for more on this school of philosophical thought

persons are willing to discard a well-known and comfortable theory or scientific method.[7]

- More seriously for a science that, like financial economics, is heavily concerned, with the empirical testing of theories, as indeed is the entire work following here, the implied standard of measurement and empirical accuracy in Popper's approach to falsification is absolute[8].

- A third, related, issue is that a survey of the history of science provides us with ample evidence that scientific progress is not, as Popper seems to imply, a process of confronting of theories with empirical facts, but is a rather more elliptical and inchoate process. From the perspective of economics, a more complex issue is that which Lakatos uses as his central organizing theme. Most theories do not exist *sui generis*, but are composed of complex interwoven assumptions and sub-theories. As we have noted above, testing efficient markets hypotheses requires a simultaneous testing of at least two issues – rational expectations and a particular model or class of models of equilibrium asset pricing.

- A related aspect of this problem is that identified by Papandreou (1958) and Boland (1979)– the falsification of a particular version or manifestation of a theory (however intertwined and convoluted the elements of this theory are) does not necessarily falsify the theory itself.

[7] Indeed, as we shall see in the analysis of Lakatos, the existence of an alternative theory or methodology is a crucial pre-requisite to such a discarding.

[8] Popper realises that this is a major problem, even in the natural sciences. He likens science to a house raised on log pilings above a swamp. The pilings are driven in deep enough to gain solidity, but they are not driven to a (possibly non existent) bedrock. In his later works he states explicitly that this is not a problem "... *the following maxim holds for all science: never aim at more precision than is required by the problem in hand*". A more succinct version might be phrased as: *it is better to be approximately right than precisely wrong.*

- Finally, some philosophers of science (Newton-Smith (1981)) have accused Popper of having ultimately fallen into the trap of induction in his own work[9].

The work of Thomas Kuhn seems to have had rather less impact on economics, compared to that of Popper. Kuhn (1970) introduced and expounded both a theory of scientific progress and a theory of scientific decay. Kuhn's main contribution was that he extended the notion of what is investigated beyond the theory based view of Popper to encompass what he calls a paradigm, although nowhere in Kuhn is there a clear statement of what exactly he sees as a paradigm[10]. A paradigm may be defined as a set of guiding, generally accepted, research questions and methods within which a body of researchers work. Kolb (1993) defines it as

> *"... a set of rules or shared assumptions accepted by a community of researchers that constitutes the (at least temporarily) unquestioned background against which research proceeds" p 2*

In the Kuhnian view, a paradigm arises when there is a succession of events, or a single shattering event, which compels a body of researchers to cleave from an existing paradigm, the which cannot accept the new results or events, and adhere to a new, competing, paradigm. A paradigm cannot purport to solve all questions on the area, but must provide both sufficient areas for fruitful investigation and suggest modes of such investigation. Paradigms provide the shared, central, assumptions that all working within them accept, allowing the working of what Kuhn terms 'normal science'. Normal science is research designed to answer the questions posed within the paradigm and to propagate the paradigm to further generations of researchers.

[9] Newton-Smith notes that Popper views scientific endeavour as not a search for the truth but in reality a working out of Zeno's Paradox. The objective is to gain ever more truthfulness, verisimilitude, real content. However, in examining how well one theory fares against another, the only test Popper offers is that of the 'degree of corroboration', how well a theory has stood against severe tests. If a theory has stood up to 100, or 1000, or 100,000 severe tests Popper counsels that we may infer that it will so continue to pass tests. Therefore, induction lies at the heart of the work. A further discussion of this is contained in Redman (1994). It is also perhaps instructive to note that based on this analysis the use of bootstrapping and resampling approaches must be seen as being heavily inductive.

[10] Kolb (1993) notes that some critics have found over 10 different definitions.

Kuhn compares normal science to a mopping up operation, where the main questions are settled by the paradigm and the normal science is a gap filling exercise. Textbook accounts of the paradigm are generated rapidly & normal science proceeds rapidly. Important as Kuhn's characterisation of paradigms is however, it is his view of how paradigms succeed each other that is his most crucial addition.

The operation of normal science generates vast quantities of observations, many of which do not fit the paradigm. These may be for example the retrograde apparent motion of Mars, unaccountable in a geocentric cosmology with circular motion, or the discovery of a series of ever more complexly adapted fossils in ancient strata, inconsistent with a strict biblical view of the emergence of life. Kuhn suggests that the proponents of the paradigm with which the data conflict typically react in one of two ways. First, akin to "naive falsification " in the works of Popper, the followers of the paradigm could accept this datum and its inconsistency with the paradigm, and abandon the paradigm for a competing one. Kuhn states that this almost never occurs, a criticism also levied, as we have seen, at the strict falsification approach adoptable from Popper. The second, much the more common, result is that the anomalous result is treated as part of the paradigm, recognised as a problem for normal science to deal with and, crucially, incorporate into the paradigm. Indeed, Kuhn contends that one measure of success for a paradigm is its ability to incorporate into itself such anomalous results. However, as these anomalies accumulate the paradigm is under increased pressure. *Ad hoc* modifications and changes to the paradigm, designed to save the appearances, accumulate.[11] Eventually, in what Kuhn terms a 'period of crisis' the paradigm begins to shift to a competing one, which must both be in

[11] Kuhn discusses the increasing number of hemicycles, epicycles and other celestial cyclicalities with which the pre Copernican paradigm attempted to save the appearances of the apparent motion of the planets against the competing heliocentric paradigm.

existence and be both incommensurate with key assumptions and predictions of the old paradigm and also be sufficiently well developed as to allow the existence of normal science within it. This paradigm shift is what Kuhn sees as scientific revolutions and as the driving force of scientific change.

Following from the work of Kuhn, Lakatos (1978) provides a more chaotic but perhaps more realistic view of the progress of science and knowledge. He too provides both an analysis of how science works and how it should work. Science should work by means of comparing and assessing competing theories, or in his terminology scientific research programmes. Where Popper is concerned with theories, Kuhn with paradigms, Lakatos is concerned with programmes of research comprising interconnected and overlapping theories and paradigms. A scientific research programme comprises two parts. The 'hard core' (reminiscent of Kuhn's paradigms) consists of a crucial set of theories or beliefs. Around this 'hard core' is then a 'protective belt', auxiliary or supplementary beliefs, methods or theories, which can be altered, discarded or enhanced without affecting the hard core. The hard core contains besides these beliefs a 'positive heuristic', the perhaps imperfectly articulated or partially completed set of methodological suggestions. There is also a negative heuristic in the hard core, directing that the hard core not be itself tested. Thus the hard core directs testing, the confrontation of reality, against the protective belt rather than itself. This is of course similar to the operation of normal science in a Kuhnian world. The protective belt, allied with the positive heuristic provides the specific testable theories that give scientific validity to the scientific research programme.

Lakatos then provides a set of criteria that both define where a scientific research programme lies in terms of its probable future and provides insight into how scientific research programmes evolve and change. He characterises changes as being either progressive or degenerative, distinguishing between theoretic and empirical changes. A theoretically progressive programme has the characteristic that each new theory has new empirical content. These theories must have continuity. By empirical content Lakatos requires that it predict novel facts. A scientific research programme is empirically progressive only if it confirms or discovers some of these novel facts. Only those scientific research programmes that are both theoretically and, at least intermittently, empirically progressive are progressive, according to Lakatos. Otherwise, they are termed degenerative; one of the key hallmarks of these types of programmes being the creation of theories to explain known facts that have been discovered to be anomalous, that is to say inconsistent with the hard core. Based on this, Lakatos sees the replacement of one scientific research programme with another as being less cataclysmic and more gradual than Kuhn. He also stresses however that such shifts are only possible when there is an alternative available, and thus suggests that novel scientific research programmes be given time, perhaps decades, to prove themselves.

1.3.2. THE PHILOSOPHY OF SCIENCE & FINANCIAL ECONOMICS[#]

Although financial economics has elements in its origins of both accountancy and economics, the very name itself indicates that the field is in reality a subdivision of economics. It is curious therefore that, despite there being a substantial and growing literature on the philosophical in economics[12] there has been almost a total lack of journal material in either the mainstream financial economics literature or in the

[#] An abridged version of this section appears in *Lucey, B. M. (2000). "Friday the 13th & The Philosophical Basis of Financial Economics." Journal of Economics and Finance 24(3): 294-301*

[12] Observe for example the emergence of the Journal of Economics and Philosophy and the Journal of Economic Methodology, as well as the survey works by Blaug (1992), Redman (1989; 1990; 1991) & Hausman (1994))

economic methodo-philosophical literature on the philosophy of financial economics. There have been some papers which have adopted arguments from the philosophy of science literature, for example, Kleidon (1986) who provides a detailed discussion within a Kuhnian / Popperian framework of the variance bounds literature in financial economics.

Both Lakatos and Kuhn stress the role played by empirical material that does not conform to the paradigm within which the researcher is working. Both stress that the response of a profession to these anomalies is two-fold. First, the tendency for anomalies to be seen, as even the name suggests, not as counter-examples that contradict the theory but as research problems and special cases. This typically results in the accretion of adjustments that are ever more elaborate to the theories to 'save the appearances'. In Lakatos' terminology, these adjustments then become part of the protective belt around the core. Second, they indicate that while the anomalies may continue to accrete, this is not in itself enough to lead to what Kuhn terms a paradigm shift and Lakatos a change in research programme. This can only come about when an alternative theory, research programme or paradigm exists which encompasses the anomalies and yet has at least the explanatory power and logical consistency of the previous.

Both Kolb (1993) & Frankfurter and McGoun (1999) suggest that financial economics is at present in a state of paradigm crisis, with more and more anomalies requiring increasingly special case theories[13]. In both papers, the authors discuss the additions Ptolemaic cosmologists were required to add to their theoretical.

[13] They cite the French-Fama three factor models as a classical example of this, with other factors being tacked onto the original 'pure' CAPM model with little excuse from within the theory. This is a classical case , it is argued, of making ad hoc adjustments to the model to explain known facts.

Saunders (1994) in an essay on testing and falsification in financial economics, urges that the profession needs

> *'.... tests of economically neutral influences on asset prices that requires no assumptions'*

if the central assumptions of the dominant paradigms of modern financial economics is to be adequately tested. He self-cites Saunders (1993) as an example, where it is found that the weather in New York had a statistically and economically significant influence on asset prices. Popper and others argue that falsification of theories can never proceed from wholly inductive but only from deductive reasoning. Much of financial economic appears to rely on inductive reasoning, with confirmatory findings, even if these require accretions to the protective belt of the theories, vastly outweighing non confirmatory findings in the literature. As will, I hope, be seen from a reading of this work, the existence of empirical calendar based regularities poses a problem to the dominant CAPM/APT based view of asset returns. Finding that days of the week or months of the year, or other calendar regularities partially determined the returns to assets (or could be explained in a statistically robust way be reference to, to be absolutely correct), would be a major problem within the CAPM/APT paradigm/scientific research programme. It would require for instance that the ex ante expected return to an asset be a function not only of its risk free rate and the relative market risk but also as a function of the calendar. This strikes at the core of the mean variance approach that, in the terminology of Lakatos, forms the 'hard core' of the paradigm – risk alone is priced with no role for calendar manifestations.

If the adherents of the CAPM/APT cannot then rationalize, incorporate, dismiss or otherwise resolve the regularities, as they seem to have been unable to do, then a Lakatoshian perspective would classify them to be paradigms 'in crisis', or the rather more apocalyptic sounding 'degenerative work programmes'. At the very least it would pose significant questions for the paradigms validity and direction.

1.4. Data Snooping And The Role Of Novel Facts

We have noted above that novel facts play a centrally important part in the process of replacement of one theory by another. On their own however they cannot provide a theory. A part of this reasoning lies in the role of data snooping, or data mining as it may sometimes be called.

Consider a bag containing 99 black balls and one white one. What is the chance of picking out blindly the white ball? The answer is obviously one in a hundred. Now imagine having 100 chances, replacing the selected ball each time, what now are the chances of getting the white ball at least once? The chances clearly improve with each extra drawing and, in this case, the odds are better than ½ that at least one drawing will produce the white ball. Clearly, plucking the white ball out becomes less remarkable the more dips are made.

Some fear that the results reported on calendar anomalies are simply a more sophisticated version of the above dull game. Academics have been dipping into stock market databases since at least the work of the Cowles commission in Yale in the 1930's, and so it is not surprising that they can pull out such an anomaly. The anomaly would be remarkable if it was discovered in the early days but after a hundred years of trawling by a succession of academics and fund managers an anomaly as strange as this was bound to appear (especially given the intensity of efforts being matched in recent decades by the scaling of computing power and the development of intensive search methods such as neural nets and genetic algorithms). This process, known as 'data mining' or 'data snooping', invalidates the results. Researches have long been wary of this, particularly when reporting calendar anomalies in stock markets but, as Lakonishok and Smidt (1988) make clear, it is difficult to allow for:

> *"Data snooping is sometimes thought of as an individual sin.... However, it is also a collective sin. A hundred researchers using the same data test a hundred different hypotheses. The 101st derives a theory after studying the previous results and tests theory using more or less the same data."*

Indeed, the working of normal science in the sense discussed above can be expected to compound the problem. There is a survivorship bias operating in financial economics: the trading rules, anomalies and regularities that investment analysts and academics have found to perform well historically naturally receive more attention than those that have not. After long periods, only a small sample of all available potential rules is still under investigation. However, pure chance alone would indicate that some rules would in fact be survivors even if in reality they do not allow for accurate prediction of equity returns.

Data mining is a particular worry with stock price data given the large industry of stockbrokers and fund managers seeking to exploit any perceived informational advantage it might give, however slight, due to its financial significance. A forthcoming article by Sullivan, Timmerman and White (2002) goes further than merely worrying about the possibility of data mining: they claim that all calendar anomalies can, in fact, be dismissed as such:

> *"We find that although nominal P-values of individual calendar rules are extremely significant (i.e. pointing to a low probability that the result is due to mere chance), once evaluated in the context of the full universe from which such rules were drawn, calendar effects no longer remain significant."*

Their claim extends beyond calendar effects indicating that stock prices contain little information to the current generation of researchers in this field: stock prices have been data-mined almost to exhaustion.[14] In a working paper Sullivan, Timmerman and White (1999b) show the sort of discipline that should be exercised by the data-sharing scientific community to allow properly for data-mining.

There are of course several solutions that can be applied to the charge of data snooping. These range from the simple, such as waiting till new evidence (typically new observations of relevant asset returns when one is dealing with financial economics) arises, through randomisation and the application of simple bootstrapping techniques, to applications of extreme bounds theory, as applied in Sullivan, Timmerman and White (1999a) and Sullivan, Timmerman and White (2002). A discussion of some of the relevant approaches is contained in Sullivan, Timmerman and White (1999b). Part of the difficulty, from a philosophical perspective, is that none of the calendar regularities were discovered deductively – they were all inductive, in that they are after the fact data discoveries. No theoretical foundation existed to suggest that they should exist. Notwithstanding the importance of anomalous or contradictory data in the Kuhn-Lakatos view of how knowledge evolves, philosophers of science have consistently argued that novel facts on their own are not enough. Campbell and Vinci (1983) state

> *"Philosophers of science generally agree that when observational evidence supports a theory the confirmation is much stronger than when the evidence is novel."*

However, one of the suggested solutions to ascertaining whether the results are a data mining artefact or are really novel facts, namely to wait until new data are available is often impossible. In the case for example of Monday returns there may be as little as 45

[14] Having said that they do find some technical trading rules that work, even after allowing for the intensity of the search. Typically, they remain coy on the rules

in any year – coupled with the knowledge that there are seemingly consistent interrelationships between calendar regularities this may imply that it is beyond any human lifespan to wait until sufficient new, unmined, data are available. Some alternative solutions are available. One is to partition the data into sub-samples, as advocated by Thaler (1987), allowing the individual sub-samples to act as checks on each other. This approach is followed here. An alternative is signalled in Lakonishok and Smidt (1988) , who declare

> *"The statistical tests routinely used in financial economics are usually interpreted as if they were being applied to new data. But the data employed in finance are seldom new. When new data are not available, significance levels on tests ... must be adjusted if multiple tests are performed on the dame data."*

This indicates two approaches; the first is the use of Bayesian methods to take account of the data properties, the second to seek new data. The data here examined comprise a dataset that is little tested, and has had, as will be clear in the review of the relevant literature, little attention paid to it.

2. Daily Seasonality In Security Returns

Well-documented daily seasonality seems to exist across national markets and through time. There is an interesting dichotomy between the literature on daily seasonality and that on monthly. While a large number, perhaps the majority, of the papers on the issue of monthly seasonality combine a description of results with an attempt to provide, and in many cases test, an explanation, a large number of the papers on daily seasonality content themselves with description. Naturally, the co-existence of the CRSP database and the largest number of researchers in financial economics has led to the predominance of research in the area of daily calendar anomalies being carried out on and in the USA. Compared to monthly seasonality however, there also exists a very substantial body of literature internationally on daily regularities.

Researchers have observed two major forms of daily regularity. The first is the tendency for stocks to show systematic variation over the days of the week. In the major, liquid, markets, this has typically manifested as a regular peak in returns on a Friday and a trough on Monday. The other regularity relates to the behaviour of stocks on days before market closings other than weekends. Given that the majority of these closings are associated with public holidays, this is commonly called the holiday effect. The remainder of this chapter and the next examine the magnitude of and variety of explanations for the daily regularity, while I discuss the holiday eturns regularity separately in 5.

It is important to note at the start that the initial research in the US, which concentrated on the behaviour of stocks around weekends, has led to terminological issues being perhaps confused. Within the US literature there exists, as we shall see, a distinction between the 'weekend' and 'Monday' regularity. Internationally however there is, as will be seen, a more complex and different pattern, with empirical regularities appearing important on other days. Thus, a more exact terminology would note that these are all investigations of particular aspects of daily seasonality. Thus Monday does not encompass all daily seasonality, nor does the weekend

2.1. Daily Seasonality: An Overview.

As we have seen already in 1.2, the CAPM/APT tells us nothing about the temporal distribution of the information processing which underlies the asset pricing. Researchers have raised two alternative hypotheses; the trading time hypothesis tells us that the asset pricing mechanism works only when the markets are open and available to process information, and the calendar time hypothesis suggests that the process is continuous. The distinction is important for consideration of the Monday/Friday returns regularities alluded to above.

2.1.1. Evidence From The USA

Examination of the daily seasonal pattern of equities in the US is not new. Evidence from Maberly (1995)indicates that by the early 1930's US researchers (Fields (1931) and Kelly (1930) were aware of the tendency of stocks to decline on Mondays. The paper by Cross (1973) represents one of the first academic papers in the era of modern finance to examine the issue[15]. He investigated the returns of the S&P index over the 1953-1970 period, 'rediscovering' the average negative Monday return of -0.18%. Cross's paper is also interesting methodologically as his paper combines parametric and

[15]Maberly (1995) and Kolb (1993) speculate as to why, given this long history of the existence of daily seasonality, predating even the formalisation of the science of financial economics, this evidence was ignored, concluding that the material was both so aged and published in non traditional academic journals that the profession ignored it as evidence. The work of Merrill (1966) and Fosback (1976) also discuss the Monday pattern, giving further credence to the Kolb/Maberly argument

non parametric approaches, a robust approach to investigation of daily seasonality that is more the exception than the rule.

Published research on the daily return pattern languished until the work of French (1980) who extends the analysis of Cross. Unlike Cross, French distinguishes explicitly between the trading time hypothesis, where returns are generated only in trading time, and the calendar time hypothesis, where returns are generated across all periods, whether trading or not. In trading time, the returns for Monday would not be expected to differ from another day of the week, in calendar time they should be three times the return on other days (representing as they do a three day period). Indeed, in the trading time hypothesis the returns of any day should not differ from those of any other day. French, like Cross, analysed the S&P index. Over the period 1953-1977, he identified an average Monday return of −0.17% with Monday returns negative in 20 out of the 25 years studied. This negative Monday contrasts with an all day average of 0.015%. The riskiness of Monday returns, as proxied by the standard deviation was the highest of all days. This dual anomaly, the inversion of the core precept of risk being compensated for by return and a significant deviation on one-day mean returns was not explicable by French.

French (1980) marks the start of a much more active period in the investigation of daily seasonality. Both Cross and French analysed Friday close – Monday close data, leading to the effect or anomaly being known as the Monday effect, the assumption being that the negative return was a product of some events occurring in the market on Monday, during Monday trading. However, work by Rogalski (1984) and Harris (1986) looking at the returns from Friday closing prices to Monday opening indicated that the effect manifested itself in lower Monday opening , thus perhaps being better called a weekend effect.

Since these papers, a large amount of confirmatory data for broad US based stock indices has emerged. Lakonishok and Levi (1982) examine the CRSP indices, Lakonishok and Smidt (1988) the Dow Jones Industrial Average and Kohers and Kohers (1995) the NASDAQ. These and many other papers and communications have reinforced the pattern of Monday having the lowest, often a negative, return of the week despite having the highest, or at least higher than average, risk as proxied by standard deviation.

There is also some evidence that there is a firm size effect in terms of the daily seasonal in the US. Gibbons and Hess (1981) examined the CRSP Equal and Value weighted indices over the 1962-1978 period. They find that although the average Friday return is greater in the equally weighted index the Monday returns are similar. The effect of this is to give a higher apparent weekend effect in the equally weighted index. Keim and Stambaugh (1984) extend this work. They break their data (NYSE/AMEX companies 1963-1979) into size deciles, finding that the smaller deciles exhibit a stronger negative Monday than larger deciles. Rogalski (1984) and Keim (1983) (both again using AMEX/NYSE firms formed into size based portfolios) find a relationship between size and the Monday return, as well as finding a relationship between the January-small firm and Monday regularities. They find that the Monday negative is only evident in non-January months. Indeed, Monday returns in January are positive and significant. Kohers and Kohers (1995) using an ANOVA analysis find over their entire sample that there is a significant relationship between size and the intensity of the negative Monday return. Smaller firms show a more pronounced weekend effect than larger.

A question does arise however as to the continued existence of the effect. Connolly (1989, 1991)examines both the CRSP equal and value weighted indices and the S&P

500 index over the 1963-1983 period. He finds that the weekend effect largely disappears in the post 1975 period[16]. Connolly utilises Bayesian methods of attributing statistical significance to results, methods that take into account not just the results but also the volume of data that have generated the results. Using these methods he finds that the effect is not evident, while traditional, classical, methods, show the effect persisting. Chang, Pinegar and Ravichandran (1993) support this contention and increase the sophistication of the methodology. Examining the FT-Actuaries indices for the US for 1985-1992[17] and adjusting not just for sample size (Bayesian adjustments) but also for deviations of the data from normality, they find no evidence for daily seasonality in the US index. Further doubt on the stability of the weekend effect over time is found in Agrawal and Tandon (1994), Peiro (1994)and Dubois and Louvet (1996). Agrawal and Tandon find that while the data (the S&P 500 over the 1970- 1987 period) exhibited a significant negative Monday return overall and in the 1970-1979 sub period this disappears in the 1980-1987 sub period. For the DJIA over the December 1987 – December 1992, Peiro (1994) finds no evidence of daily seasonality. Finally, Dubois and Louvet, examining the DJIA and S&P 500 indices over 1969-1992 find that while there exists a negative Monday return over the entire period, this is not evident in the 1985-1992 sub-period.

2.1.2. International Evidence On Daily Seasonality

It is not only for the US equity markets that researchers have found evidence of daily seasonal patterns. As pointed out, the conjunction of significant numbers of researchers and a considerable body of easily accessed securities data has provided the opportunity

[16] This would of course be consistent with the market noting the Cross (1973) article and acting to eliminate this regularity.

[17] A period and an index outside that of Connolly and therefore free from any potential charge of data mining.

for much of the US work to flourish. The increasing availability of data for non-US markets has allowed replication and extension of the studies mentioned above.

The UK: As, historically, the second or third largest equity market after the US, it is not surprising that a considerable number of papers have, evaluated the extent of daily seasonality in the UK market either as the single focus of the paper or in tandem with data from other countries. Theobald and Price (1984) examine the Financial Times All Shares (FTA) and Financial Times Ordinary Shares (FTO) indices from 1975-1981. They provide evidence of a negative and statistically significant Monday return. This return is robust to the statistical technique used. Average Monday returns of -0.2% for the FTA and-0.3% for the FTO, against an all days average of 0.04% for both indices compare in broad magnitude the results for the US found by French (1980). For the FTA the Monday standard deviation is the joint highest of the week while for the FTO it is the highest Again, this joint anomaly is inexplicable. Examining a considerably longer time period (1950-1983), Jaffe and Westerfield (1985b) demonstrate a significant negative Monday in the FTO index, with Monday returns of -0.14% against an all day return of 0.028%, Monday showing the highest standard deviation. Condoyanni, O'Hanlon and Ward (1987) show that the FTA index over 1969-1984 returned a Monday return of -0.95% against an all day average of 0.31%. Other works on the FTO and FTA indices have generally confirmed the existence and stability over long time-periods of results. For the FTA Board and Sutcliffe (1988) and Dubois and Louvet (1996) give consistent negative Monday returns over the 1962-1986 period and 1969-1992 period respectively. In both cases the Monday risk, as proxied by the variance of returns, was the highest of the week. For the FTO Agrawal and Tandon (1994), Peiro (1994),Arsad and Coutts (1996) and Coutts and Hayes (1999) all provide evidence over a considerable period of negative Monday returns. Agrawal and Tandon examine the 1963-1987 period, Peiro 1987-1992, Arsad and Coutts 1935-1994 and Coutts and Hayes 1979-1994. All find a negative Monday return and an all days average positive return comparable in magnitude to that found by Theobald and Price[18], with some evidence that the effect is weaker in the latter years. Evidence on the risk patterns, as proxied by the variance of the daily returns, also indicates that the Monday risk tends to be at the higher end of the daily risk spectrum despite the return being always the lower. Finally, Mills and Coutts (1995) examine the FT-SE indices (1986-1992). They find that all three indices demonstrate a negative Monday, ranging from -0.09% for the FTSE 100 to -0.15% for the FTSE 350. In all cases, the Monday risk was the highest of the week.

Japan: The size and importance of the Japanese market notwithstanding, relatively little appears to have been written on the issue of daily seasonalities in Japan. Such evidence as exists indicates that a different but no less persistent form of daily seasonality may operate in the Japanese market. Jaffe and Westerfield (1985a) utilise the Nikkei-Dow and Tokyo stock exchange indices, over the 1970-1983 period. They report finding that while a negative Monday return was realised, this was accompanied by a more substantial negative Tuesday return.[19] There was, however, evidence of different patterns on the risk profiles. For the Nikkei-Dow Monday had the highest risk, while for the TSE Index neither Monday nor Tuesday showed higher than average risk. Jaffe and Westerfield (1985b) present essentially the same results. Both papers argue that the low Tuesday return may well be a manifestation of the low Monday return in the US, but

[18] 1963-1987, Monday -0.165% all days of .037%; December 1987-December 1992, Monday -0.22% all days .031%, Monday standard deviation highest of all days; July 1935-December 1994, Monday -0.13% all days.02%, Monday standard deviation highest of all days, these patterns persistent throughout all sub periods); June 1979 – December 1994, Monday -0.11% all days.05%, Monday having the second highest standard deviation.

[19] For the Nikkei-Dow, Monday -0.02% , Tuesday -0.09% all days .04%. For the TSE, Monday -0.1%, Tuesday -0.06% all days 03%,

accept that the statistical evidence in favour of this is weak. Neither addresses the cause of the negative Monday. An analysis of the TSE index over a similar time span to that of Jaffe and Westerfield was conducted by Condoyanni, O'Hanlon and Ward (1987). They present different evidence to that found by Jaffe and Westerfield, the negative Monday return apparently disappearing (becoming 0.09% against an all day average of 0.4%) but a persistent negative Tuesday return (-0.95%) remaining. However, this positive Monday is on closer be a reflection of the fact that the paper aggregates the Saturday trading return (.11%) with Monday, leaving a negative Monday return if this is accounted for. This error is not present in Kim (1988) however, who finds a positive Monday return[20] for the 1980-84 periods on the TSE. Other papers (Lee, Pettit and Swankoski (1990) examining the Nikkei-Dow from 1980-1988; Ho (1990) examining the Nikkei-Dow from 1975-1987 ; Agrawal and Tandon (1994) examining the Nikkei-Dow from 1970-1987; Dubois and Louvet (1996) examining the TSE Index from 1969-1992 and the Nikkei-Dow 1971-1992) on daily returns in Japan have presented evidence that Japan shows a negative Monday and Tuesday.

Other Asia-Pacific Markets: Evidence on the other main Asian and pacific markets are congruent with that for Japan. For the major markets, the Australian, Singaporean and Hong Kong equity markets have generally shown significant negative Monday and Tuesday returns. Only in Dubois and Louvet (1996) and Ho (1990) does Australia demonstrate a positive Monday, but in conjunction with a negative Tuesday return , while the latter paper also has a positive Tuesday in Hong Kong as does Lee, Pettit and Swankoski (1990). Although primarily concerned with testing for daily seasonality using robust regression techniques, and therefore not providing estimates of daily returns, Easton and Faff (1994) conclude that the evidence on Australian data is weakly

[20] .06% against an all day average of .05%

in favour of a day-of-the-week effect. There is little agreement on the relative size of the negative returns, some finding that Monday returns are greater in magnitude than Tuesday, others the reverse. Those that provide details on the risk profiles across days of the week (Condoyanni, O'Hanlon and Ward (1987) and Wong, Hui and Chan (1992)) show that these negative patterns are not a manifestation of risk, these days having higher risk than average. Table 1 provides a summary of these and other papers

TABLE 1: ASIA PACIFIC EQUITY MARKETS: MONDAY AND TUESDAY RETURNS

Country	Authors	Index	Period	Monday Return	Tuesday Return	All Days
Australia	Agrawal and Tandon (1994)	Stock Exchange All Ordinary	1972-1988	0.06%	-0.1%	0.041%
Australia	Jaffe and Westerfield (1985b)	Statex	1973-1982	-0.05%	-0.13%	0.032%
Australia	Condoyanni, O'Hanlon and Ward (1987)	Stock Exchange All Ordinaries	1980-1984	-0.49%	-20.0%	0.02%
Australia	Ho (1990)	Stock Exchange All Ordinaries	1980-1992	0.03%	-0.1%	0.03%
Australia	Dubois and Louvet (1996)	Stock Exchange All Ordinaries	1980-1992	0.03%	-0.1%	0.03%
Hong Kong	Agrawal and Tandon (1994)	Hang Seng	1973-1987	-0.09%	-0.16%	04%
Hong Kong	Dubois and Louvet (1996)	Hang Seng	1973-1989	-0.23%	-0.03%	0.04%
Hong Kong	Ho (1990)	Hang Seng	1975-1987	-0.03%	0.0%	0.1%
Hong Kong	Lee, Pettit and Swankoski (1990)	Hang Seng	1980-1988	-0.07%	0.01%	0.09%
Singapore	Condoyanni, O'Hanlon and Ward (1987)	Straits Times	1969-1984	-0.36%	–1.07%	0.02%
Singapore	Chan, Khanthavit and Thomas (1996)	Straits Times	1969-1992	-0.04%	-0.08%	0.04%
Singapore	Agrawal and Tandon (1994)	Straits Times	1973-1987	-0.05%	-0.02%	0.04%
Singapore	Ho (1990)	Straits Times	1975-1987	-0.03%	-0.07%	0.04%
Singapore	Wong, Hui and Chan (1992)	SES All Share	1975-1988	-0.03%	-0.12%	0.06%
Singapore		SES All Share	1980-1988	-0.01%	–0. 035%	0.06%

Source: cited papers

Smaller Asian-pacific markets show a variety of patterns, from the consistent negative Monday and Tuesday returns of Malaysia as found Ho and Cheung (1991), Wong, Hui and Chan (1992), Chan, Khanthavit and Thomas (1996) and Clare, Ibrahaim and Thomas (1998) to the negative Tuesday of Korea as found in Lee, Pettit and Swankoski (1990), Lee (1992) and Ho (1990) to inconsistent results for Thailand, with a finding of a negative Tuesday in Ho (1990) and Wong, Hui and Chan (1992), but all days being positive in Chan, Khanthavit and Thomas (1996). Taiwan and Sri Lanka deserve special notice for having no day with negative returns and no evidence of daily seasonality. Taiwanese evidence is presented in Ho (1990), Lee, Pettit and Swankoski (1990) and Wong, Hui and Chan (1992) while the evidence for Sri Lanka is in Elyasiani, Perera and Puri (1996).

Other European Markets: The main (Paris, Frankfurt, Milan) European equity markets show a variety of daily seasonal patterns. For Frankfurt, the evidence is consistent. Peiro (1994), Agrawal and Tandon (1994) ,Dubois and Louvet (1996) and Kramer (1996) all provide evidence across a variety of time frames and across a variety of indices of a negative Monday and Tuesday return, with the Monday return being greater in magnitude. The evidence for the Paris Bourse is however inconsistent. Condoyanni, O'Hanlon and Ward (1987) and Peiro (1994) find evidence of negative Monday and Tuesday returns in the CAC index. By contrast, Dubois and Louvet (1996) find a negative Monday and Friday while both Solnik and Bousquet (1990) and Agrawal and Tandon (1994) find evidence only a negative Tuesday.

Barone (1990)and Agrawal and Tandon (1994) present conflicting evidence for Milan,. Barone finds a negative Monday and Tuesday return while Agrawal and Tandon (1994) find a negative Monday return with a positive and significant Tuesday return. Corhay

(1991) and Agrawal and Tandon (1994) agree in regard to the Belgian situation, with both finding a negative Tuesday. Alexakis and Xanthakis (1995) for Greece and Pena (1995)[21] for Spain show a negative Tuesday return. A summary of these papers is found in Table 2.

[21] This pattern also holds through seven industrial sectors but disappears for a sub sample of 1989-1993, which period starts after stock market reforms including computerised trading and broker deregulation

TABLE 2: EUROPEAN EQUITY MARKETS: MONDAY AND TUESDAY RETURNS

Country	Authors	Index	Period	Monday Return	Tuesday Return	All Days
Belgium	Agrawal and Tandon (1994)	Stock Exchange Value Weighted	1971-1987	0.05%	-0.07%	0.03%
Belgium	Corhay (1991)	Stock Exchange Value Weighted	1977-1985	0.09%	-0.032%	0.07%
Belgium	Corhay (1991)	Stock Exchange Equal Weighted	1977-1985	0.08%	-0.026%	0.05%
France	Condoyanni, O'Hanlon and Ward (1987)	CAC	1969-1984	-0.5%	-1.57%	0.15%
France	Peiro (1994)	CAC	1987-1992	-0.03%	-0.12%	0.04%
France	Dubois and Louvet (1996)	SBF240	1969-1992	-0.11%	0.06%	0.03%
France	Solnik and Bousquet (1990)	CAC	1978-1987	0.1%	-0.9%	0.06%
France	Agrawal and Tandon (1994)	CAC40	1971-1987	0.04%	-0.11%	0.05%
Germany	Peiro (1994)	Commerzbank	1987-1992	-0.03%	-0.01%	0.012%
Germany	Agrawal and Tandon (1994)	FAZ	1971-1987	-0.08%	-0.02%	0.04%
Germany	Dubois and Louvet (1996)	FAZ	1969-1992	-0.1%	-0.01%	0.02%
Germany	Kramer (1996)	DAX	1960-1992	-0.17%	-0.02%	0.022%
Greece	Alexakis and Xanthakis (1995)	Athens Stock Exchange	1985-1994	0.029%	-0.003%	0.03%
Spain	Peña (1995)	Madrid General*	1986-1993	0.0013%	-0.0009%	0.02%

*Excess of percentage return over the risk free rate

Ireland: Very few studies have examined daily seasonality in the equity markets in Ireland to date. Donnelly (1991), examining the Irish Times Cara Index (an equally weighted index covering only some of the market) over 1975-1988, finds no evidence of a day of the week effect, with a positive return on all days. Donnelly also finds on examination of sub periods that the pattern of daily returns is not stable. Monday, Thursday and Tuesday all appear at some period as the days with the highest return, while in some sub periods Tuesday and Thursday are the lowest. After adjusting the data for the settlement system, the pattern found elsewhere asserts itself, with non-account weeks showing a negative Tuesday, with Thursday providing the highest return. One difficulty with the Cara index is that it was an equally weighted index based on selected components of the Irish market. By contrast, Lucey (1994) examines the official stock market ISEQ Index over the 1987-1991 period and finds a negative Tuesday[22] with evidence of a day-of-the-week effect. Using a longer (1987-1997) series of the same index, Stephenson (1998) finds that dropping the data for October 1987 from the dataset the negative Tuesday effect disappears. Lucey (2000) finds a midweek effect from an analysis of the Irish market over the 1973-1998 period, using Datastream indices. A significant and positive Wednesday and Thursday effect, unusual in this literature, was found. Prior to this study no detailed, long-term, statistically robust examination of the official stock market indices had been undertaken.

[22] Tuesday -0.14% all days .03%

2.2. DAILY SEASONALITY IN HIGHER MOMENTS

While much of the published research on equity returns concentrates on mean-variance analysis, there is theoretical and empirical evidence that higher moments merit investigation.

From a theoretical perspective, Lee and Wu (1985) show how kurtosis impacts on the stationarity of standard deviation, Conine and Tamarkin (1981) show how higher moments affect diversification in investors' portfolios, and Scott and Horvath (1980) show that, under common utility functions, investors have a preference for kurtosis and are averse to skewness. Despite this there exists considerably less documentation on the daily variation in these higher moments. A small body of work does exist that explicitly examines seasonality in the higher moments. For the US, Aggarwal and Schatzberg (1997) examine a sample of 1107 and 889 firms over the 1980-1986 and 1987-1993 periods respectively. Aggarwal and Schatzberg (1997) calculate aggregate skewness and kurtosis firm size classes and weekdays, and examine these directly using ANOVA and Kruskal-Wallis measures. A difficulty with this approach is that it requires, in effect, a rolling estimate of the average skewness and kurtosis of the sample They find a negative Monday return, with smaller firms demonstrating a more intense negative return. They also find, unlike Connolly (1989) that the negative Monday persists over their sub periods. In terms of the higher moments, they find that the pattern of standard deviations is identical to that of the mean returns. Skewness patterns follow those of the first two moments for the first time period, but 'flip' in the second, with the Monday skewness going from lowest to highest. Although this is noted no explanation is provided. Neither is there made an investigation of the potential effects, if any, of the inclusion of data for October 1987. Finally, kurtosis also follows the mean patterns, with Monday kurtosis below average and Friday above. Evidence for Asian markets as presented in Ho and Cheung (1994) and Tang (1997) is that daily seasonality in higher moments does not follow a pattern similar to that of the lower moments. German evidence, from Kramer (1996), indicates that although the pattern of volatility and other higher moments differs from that of mean returns, it is not sufficient to explain daily seasonality in mean returns. Evidence in Choudhry (2000) on South-East Asian markets indicates a significant daily seasonal in the conditional variance of a number of equity indices. There he finds a positive Monday effect in the mean and in the conditional variance.

2.3. Daily Seasonality In Non-Equity Security Returns

Many of the papers, which address the issue of why there is a daily seasonal, rely on some structural element of the equity markets. In the case of Ireland and Spain Donnelly (1991) and Pena (1995) find that the pattern of such seasonality is at least partially a function of the microstructure.

One problem with this approach to 'saving the appearances' is that such special cases may be valid only in the particular national market (easily tested) or more generally may be valid only for the particular asset under investigation. There is significant evidence of persistent daily seasonality across a wide variety of securities other than equities. For fixed income securities, Gibbons and Hess (1981), Flannery and Protopapadakis (1988) ,Jordan and Jordan (1991) , Singleton and Wingender (1994) ,Kohers and Patel (1996) and Adrangi and Ghazanfari (1996) have all detected various degrees of daily seasonality. Gold has been analysed by Ball, Torous and Tschoegl (1982) and Ma (1986), while Chang and Kim (1988), Chamberlain, Cheun and Kwan (1990) and Johnston and Kracaw (1991) all investigate futures markets.

Finally, Redman (1997) finds evidence of daily and monthly seasonality in real estate investment trusts. Surprisingly, a search of ABI-Inform, Econlit and of the Social Science Citation index failed to discover any studies of calendar seasonality, on the lines discussed above, for commodities or 'softs'[23].

2.3.1. Government Securities

Gibbons and Hess (1981) examine short maturity US treasury bills over the December 1962 - December 1968 period, finding that average Monday returns are negative and significant. Flannery and Protopapadakis (1988) find, over the 1977-1984 period, that there exists a significant degree of daily seasonality across a number of bonds, with longer maturity bonds exhibiting a more significant degree of seasonality. The usual stock pattern of negative Monday returns seems to carry across to the bond market. Singleton and Wingender (1994) examine 30-day treasury bills and 30-year treasury bonds, over the same period as Flannery and Protopapadakis, but trim their data to eliminate outliers. They find that while this reduces to insignificance the daily seasonality in treasury bonds it does not affect the shorter maturity bills series.

2.3.2. Corporate Bonds

Jordan and Jordan (1991) analyse the Dow Jones Composite Bond Average from 1963-1986. They find that while they cannot reject the hypothesis of different returns across days of the week, there is no evidence that the Monday return is significantly negative. Their main finding is that Thursday seems to demonstrate an unusually high positive

[23] There are of course a great deal of studies on the seasonal production pattern and demand of certain commodities, such as agricultural and other produces which are inherently seasonal. In addition there are numerous studies of the seasonal pattern of the futures of commodities and softs, but not of the underlying cash markets. What is striking is the lack of studies on such commodities as oil, rubber, cocoa, tin and aluminium, which although having a certain seasonal element embedded in their demand function are traded constantly in highly liquid markets and are of founding importance for the world economy.

return. Kohers and Patel (1996), analysing the Merrill Lynch High Yield Bond Index over the January 1987-June 1994 period, find the lowest daily average return on Monday with the highest on Friday. This pattern is also in the index for investment grade bonds, the Merrill Lynch Corporate Master Bond Index. Non-parametric tests indicate that the two series demonstrate daily seasonality. Finally, Adrangi and Ghazanfari (1996) analyse the Merrill Lynch Corporate Bond Index over the 1986-1991 period, finding no evidence of daily seasonality.

2.3.3. GOLD

Ball, Torous and Tschoegl (1982) investigate the morning and afternoon fixings of gold in the London metal exchange over the 1975-1979 period.

They find little evidence of either a daily seasonal or a negative Monday. This is independent of whether Monday returns are measured as Friday AM – Monday AM or Friday PM – Monday PM .If anything, there appears to be a negative Tuesday return. Ma (1986) provides contradictory results. Ma analyses the afternoon fixings from January He finds that while both pre and post 1981 (when significant changes in settlement procedures and institutional arrangements were instituted) there existed daily seasonality, the nature of this seasonality changes. Pre 1981 there was a negative Tuesday (as found by Ball, Torous and Tschoegl) and a highly significant positive Wednesday. Post 1981 the negative Tuesday disappears and the average return on Monday switches from positive to significantly negative.

2.3.4. FUTURES

Chang and Kim (1988), Chamberlain, Cheun and Kwan (1990) and Johnston and Kracaw (1991) all investigates futures markets.

Examining the Dow Jones Commodities Future Index over the December 1959-December 1986 period, Chang and Kim find that only in the period 1966-1971 was there a negative return on Monday. In respect of financial futures, Johnston et al find that GNMA (1975-1985) and T-bond (1977-1988) contracts exhibit a negative Monday seasonal. This is attributed however to seasonality being strongly present only in the period up to 1980. For T-notes (1982-1988) and T-Bill (1976-1988) futures contracts however there was no evidence of a daily seasonal. This pattern in futures contracts, of greater intensity of seasonality as the maturities of the underlying cash instruments increases parallels the results of Flannery and Protopapadakis (1988) and Singleton and Wingender (1994) for bonds. Chamberlain, Cheun and Kwan (1990) examine the futures contract on the NYSE index over the 1982-1986 period. They find no evidence of daily seasonality.

2.4. THE EVIDENCE SUMMARIZED

The evidence presented above indicates three irreducible and irrefutable elements. First, there is evidence over 70 years, with voluminous evidence over the last 30 that systemic variation in the pattern of mean returns to stocks over days of the week does exist. Second, this systemic variation, although perhaps of a slightly different pattern, is evident not only in the major stock exchanges but also is widespread across different depths of market liquidity, different microstructure patterns, and different trading regimens. Third, there is some, albeit very limited, evidence that analogous patterns of daily return variation occur in other financial assets, notably precious metals, corporate and government bonds and financial futures. The extent of these variations may not in and of themselves be sufficient to allow a profitable trading strategy to be built on them, but it does indicate that some advice as to trading timing may be possible. The dominant theoretical framework of financial economics has no place for such systemic variation. The next chapter therefore examines explanations put forward in regard to such daily seasonality. If we can find explanations that are congruent both with the facts and with the theoretical underpinnings of the modern theory of finance then these daily return variations are not anomalous. If however the theories and hypotheses served are either not sufficient to explain the results or are *ad hoc* theories put forward for particular manifestations of the regularity[24], then we must consider these daily regularities as true anomalies.

[24] Recall that the evidence is that such daily seasonality is not confined to particular days in the US equity market, and as such we must treat with scepticism any purported explanation which is not international in scope, general in terms of days and generalisable in terms of the assets examined

3. Non Daily Calendar Anomalies

3.1. Monthly Seasonality

A significant body of literature exists to suggest that, especially for smaller capitalisation stocks, returns vary across the months of the year. Most typically, the evidence is that high returns can be earned in January, especially the early part of January. This has led, in a similar manner to daily seasonality being shorthand coded as 'Monday' anomalies or effects, to monthly seasonality often being assumed to be identical to January seasonality. More generally, January seasonality is a particular manifestation of monthly seasonality – the tendency for equity markets to show systematic and regular monthly patterns of returns. Like the results on daily seasonality discussed in Maberly (1995), monthly regularities have been known in US equity returns for many years. For example Persons (1919), as noted in Pettengill (1986) noted the tendency for equity markets to rise in January.

Early evidence on the tendency of January returns to exceed those of other months comes from Wachtel (1942), and later from Zinberger (1964), with a gap emerging in the discussion until Officer (1975) and Rozeff and Kinney (1976). From the evidence presented in Rozeff and Kinney (1976) & Gultekien and Gultekien (1983) , the existence of a form of the effect in the USA from 1904[25] cannot be ruled out. Evidence also exists that the effect is international, with significant numbers of papers showing unusually high returns in January in countries other than the US. Much of the discussion on the January effect co-exists with the issue of whether a size effect, the phenomenon whereby small-capitalization firms earn superior returns to large-

[25] Using Cowles Commission indices

capitalization firms, exists and if so, when it manifests itself. From the pioneering work of Banz (1981) and Reinganum (1981), through Brown, Keim, Kleidon and Marsh (1983) and Kato and Schallheim (1985) to Fama and French (1992) and onto the work of Berk (1995), Baker and Limmack (1998) and Garza-Gomez, Hodoshima and Kunimura (1998) it has been a consistent finding that small capitalisation firms produce higher returns than those with higher capitalizations.[26] Evidence from Keim (1983) and Roll (1983) indicates that the majority of the return to small capitalization stocks occurs in January, indeed being concentrated in the first weeks of the month.

As we have seen, a finding that the return of a financial asset varied according to the month of the year would be a direct violation of the EMH. However, a number of possible explanations, with significant explanatory power, are available. These typically fall into four main categories:

- The monthly seasonal is a consequence of seasonal risk factors;
- The monthly seasonal is a consequence of seasonal liquidity factors;
- The monthly seasonal is a consequence of the tax code;
- The monthly seasonal is explainable by the remuneration patterns of market managers.

These explanations are each individually explicable within the CAPM/APT framework, and as a consequence evidence of calendar regularity is not in itself indicative of a degenerative research programme. Rather, through the operation of normal science the regularity may be seen as a reflection of deeper issues than were previously surfaced.

[26] See however Dimson and Marsh (1999), who examines UK data and finds that the small firm premium has reversed in the 1990's

3.1.1. How Large Is Monthly Seasonality?

A very considerable number of papers have addressed the issue of whether equity returns differ systematically across months of the year. One issue in the interpretation of these results is that while some researchers examine average daily returns others examine total monthly returns[27]. The resulting magnitudes are of course considerably different. If we accept that in general there are approximately 20 trading days in January then multiplying the average daily returns by 20 allows comparability between the two strands of the literature.

3.1.2. International Evidence

International evidence on the returns to equities in January exists in a large number of papers. The papers presented below are not by any means exhaustive, but serve to indicate both the extent of international evidence on monthly seasonality and to show the predominant but not undisputable tendency for January returns to be the highest of the year. For example, the evidence on the Spanish market presented in Santesmaes (1986) indicates that February, not January, presents the highest return for the 1979-1986 period. However, this period was one of thin trading and restricted opening, and consequently the operational efficiency of the Spanish market may be doubted. It is notable that the degree of difference between the February mean daily return at 0.12% and that of January at 0.1% is also small[28]. For the Johannesburg stock exchange Coutts and Sheik (2000) report a January return which is negative and statistically insignificant from zero. While no overall month is indeed significant, statistically, the month that

[27] As a consequence it is not as easy to create a synoptic table of results on monthly seasonality as it proved for daily seasonality.

[28] Corresponding to 2.4% and 2% on a monthly basis.

demonstrates the highest mean daily return is June, at 0.186%[29]. For Jamaica Ramcharran (1997) finds no January seasonality, with instead the month of May showing the highest return. January returns were in fact at or close to the mean across the 1974-1994 period examined.

Early results on Canadian equity market seasonality can be found in Berges, McConnell and Schlarbaum (1984). Examination of monthly data from 1950-1980 shows a January return of between 8% (for small stocks) to 2.3% (for larger stocks). More recent work on the Canadian market is summarized in Athanassakos and Foerster (2000). There the evidence is that the average daily return in January on the Toronto equity index is 0.0247%, over the 1959-1991 period. Again however this return was not the highest – December average daily returns being 0.0268%[30].

For Italy, specifically the Milan exchange over the 1975-1989 period, results are presented in Barone (1990). There the January mean daily return at 0.33% is the highest of the year, with February and September tying for second place at 0.24%. The significance of January is confirmed by a regression F test. A test over a longer period is presented in Canestrelli and Ziemba (2000), who examine the 1973-1993 period , with sub period analysis. There the mean returns in January and February were significantly higher, at 0.258% and 0.205% respectively, than other months. The only other month that was statistically significantly different from zero was August, with an average return over the period of 0.116%. These patterns also held over sub periods. Evidence on seasonality in the Amsterdam exchange, from January 1966-December 1982 is contained in Van Den Berg and Wessels (1985), who find that January mean

[29] Corresponding to 3.72% on a monthly basis

[30] These returns correspond to .494% and .53% on a monthly basis

returns amount to 4.39% , the highest of any month. The second highest monthly return was April, at 3.15%.

In south-east Asia, the results reported in Table 3 of Ho (1990), analysing the 1975-1987 period, indicate that out of 12 markets analysed, including the US and UK, 10[31], including the UK and US , have significant January returns. The mean January daily returns range from 0.44% in Singapore to 0.08% in New Zealand. For the south-east Asian countries which show a significant January return, these returns typically exceed the mean of all other months by 10 to 20 times. While it seems, by contexts from the paper, that the countries with significant January effects also have January as the month with the highest returns this is not made explicit. This pattern, of high and statistically significant daily January returns, is confirmed for Hong-Kong, Korea and Taiwan in Wong, Neoh, Lee and Thjong (1990). However, for both Taiwan and Korea the evidence from Tong (1992) is that February (for Taiwan) and May (for Korea) returns are the highest[32]. Chan, Khanthavit and Thomas (1996) present results contradictory to Ho (1990). They analyse returns in Malaysia, India, Singapore and Thailand from 1974 to 1992, and find that only for Malaysia and Singapore are there significant January monthly returns. In addition, it is only for these markets that the F test of equal monthly returns is rejected. It is however only in Singapore that the highest monthly return occurs in January; for Malaysia it is December (0.195%), for India, February (0.306%), and for Thailand, April (0.176%). Malaysian results are further complicated by the results of Wong, Neoh, Lee *et al.* (1990); they present results for the Kuala Lumpur stock exchange which indicate that the return in January is among the highest of all

[31] Hong-Kong, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan and Thailand, as well as the UK and USA

[32] This paper is a good example of a common mistake. Despite the evidence cited, shown by the authors in Table 1, they proceed to test for the presence of a January effect. Unsurprisingly none is found.

months, over the 1970-1985 period on six sectoral indices. The January return was in fact the highest in three of the six indices and in a value weighted index of large firms.

Results for Japan can be seen over a long period, 1949-1994, by combining the findings of Ziemba (1991) and Comolli and Ziemba (2000). There the evidence indicates that over the 1949-1988 period January mean daily returns averaged 0.182%, considerably above the next month, August, at 0.079%. For the 1990-1994 period this has dropped somewhat, January mean daily returns now averaging 0.052% with the highest monthly mean return being October, at 0.189%.

As noted, the work of Officer (1975), although drawing on earlier work (Praetz (1973) noted in the paper), is one of the first 'modern' academic papers to examine seasonality. The paper does not indicate monthly returns, examining instead lag and correlation patterns. It does however allude to a January – February peak in the market. More detailed data for the Australian markets is to be found in Brown, Keim, Kleidon *et al.* (1983). Examining data from 1958-1981 the find that January returns are in fact the highest, a monthly average return of 3.14%, with this being the case across a variety of size measures. Again, as found in Berges, McConnell and Schlarbaum (1984), this is larger in small capitalization stocks.

By contrast, Agrawal and Tandon (1994) examine, over the 1970's and 1980's, a much greater number of countries, 19 in total, finding that the mean January returns are high and positive. In 11[33] instances a non-parametric Kruskal Wallis test rejects the hypothesis of equality of monthly returns[34]. The magnitude of the January returns range from a high of 13.04% in Mexico to a low of 0.94% in New Zealand. The typical return

[33] Belgium, France, Hong Kong, Italy, Japan, Netherlands, Singapore, Sweden, Switzerland (and the UK and US)

[34] Although the KW test is properly a test of median returns, the authors do not note this, discussing mean returns instead.

to January, from Table 6, appears to be in the 3% to 6% range, with other months returning much lower rates.

3.1.3. THE UK

Evidence on the magnitude of monthly seasonal patterns in the UK can also be found in a wide variety of papers. Many of these results can be found in papers that include equity indices from the UK and US as a point of comparison to the index under investigation. Rather fewer have been the papers that have focused in detail on the UK. One of the earlier papers of this sort is Reinganum and Shapiro (1987). They find, using a variety of data sources, that April returns dominated in the period prior to the introduction of capital gains taxation in 1965, while after 1965 January returns were the largest in the year. For example, using the FTA index the January return over the period April 1965 – December 1979 was 5.18%, compared to the next highest month, April, with a return of 3.85%. Using a different dataset, the FT-SE indices, Mills and Coutts (1995) find that over the January 1986 – October 1992 period the mean return to January was the largest of any month. For the FT-SE 100 index mean January returns were 0.159% as against the next highest return of 0.136% (February). The FT-SE 250 index on the other hand showed a February return, of 0.196%, as the highest, with January, at 0.190% being the second highest. In both cases the April return, so significant in the results of Reinganum and Shapiro (1987), was low and insignificant. Examining the FT30 index over the 1935-1994 period, Arsad and Coutts (1997) find results confirmatory to Reinganum and Shapiro (1987). Overall January returns, at 0.104%, were the highest of all months. However, this is driven by two elements. In the pre 1965 period the January returns were high, but the market peak return occurred in

April. After 1965 this April return was diminished somewhat and the January return increased.

3.1.4. THE USA

As noted, much of the work on monthly seasonality in the US has been driven by an examination of 'January effects'. Rozeff and Kinney (1976), using data from 1904 to 1974, find that in all periods the mean January return in the US market was the largest of all months. The return overall was 0.0348%, compared to the next highest month, July, at 0.0190%.[35]. Work by Lakonishok and Smidt (1988) on the Dow Jones index, from 1897 to 1986 , shows however that the January return of 0.818% was in fact only the *fourth* largest return after July, August and December. This is consistent with the results on the interrelationship between the size and monthly issue as seen in Keim (1983) and Reinganum (1983). The evidence here, and that presented in Haugen and Jorion (1996) shows clearly that the US effect is confined to the smaller stocks. Haugen and Jorion (1996) examine the CRSP indices for the New York Stock Exchange from 1926 to 1993, and show that the return in January to the smallest stocks is of the magnitude of 12.4%, falling monotonically to as little as 0.5% for the very largest stocks. More recent work (Riepe (1998, (2001))has indicated that the returns to January may be weaker in latter years.

3.1.5. IRELAND

Evidence on monthly returns in Ireland arises from a small number of papers.

[35] One difficulty with this however is that the paper combines into one data series a set of three different indices. Some of these were equally weighted, others value weighted. Evidence from Theobald and Price (1984) shows that seasonality is more easily detected in equally weighted data.

McKillop and Hutchinson (1989), Donnelly (1991), Gahan (1993) and Lucey (1994) have all addressed the issue of the pattern of returns. McKillop and Hutchinson (1989), without stating why, examine April and August returns, in the context of small firms. They find that an April effect, but not an August effect.

A more detailed examination is that carried out in Donnelly (1991). He examines the Central Statistics Office monthly index, a market capitalization weighted index, over the 1951-1988 period, splitting the data into pre and post 1969 samples. From January 1934 to the mid-1980s the Irish Central Statistics Office (CSO) compiled a capital return index of Irish companies, *the CSO Price Index of Ordinary Stocks and Shares of Companies incorporated in Ireland (except Railways).* Details on the construction of the index are rather scant with, for instance, official sources such as the CSO itself, the annual *Statistical Abstract of Ireland* or its forerunner, the *Irish Trade Journal,* providing minimal descriptions. However, Geary (1944)describes it as an arithmetic, market-capitalisation weighted index with (at that time) complete coverage of the 88 non-railway Irish registered stocks listed on the two Irish exchanges of Dublin and Cork. This method of construction was unusual for that time with, for instance, the Dow Jones Industrial Average being a unweighted arithmetic average of 30 share prices or the British FT Ordinary Share Index being an unweighted geometric average of again just 30 share prices. [36] Overall, the evidence is that mean January returns are substantially larger than those in other months. A return of 2.77% overall, with 1.22% pre 1969 and 4.32% post is found. This compares to the next highest monthly return

[36] The CSO Index is calculated from share prices quoted on the Irish Stock Exchange on the first trading day of each month. There have been a few changes in its method of construction since 1934. Each January beginning in January 1958, the index was adjusted to include only those shares that had been dealt in the previous twelve months. This entailed a reduction of the number of companies covered from 118 in January 1957 to 101 in January 1958 (Murray (1960)). In 1967 the index was again adjusted to include only companies with a market capitalisation in excess of IR£0.5 million (Kirwan and McGilvray (1983)). Finally, the index was later superseded in the January 1988 (Statistical Abstract 1988) by the more comprehensive Irish Stock Exchange Equity (ISEQ) series of indices.

overall (April) of 2% and 1.21% (October) and 3.01% (April) pre and post 1969 respectively. A shorter time span is investigated in Gahan (1993), that of 1983-1993. Examining the ISEQ index, the official market value weighted index of the Irish Stock Exchange, she finds January returns are again the highest, at 6.86%; the next highest month (February) showed a return of 3.97%, with April being the third highest at 2.79%. Only in three years was January not the month showing the highest return. Finally, over a shorter time period again, the work of Lucey (1994) again investigates the ISEQ index, this time over 1987-1991, a period of high volatility in the ISEQ index. In common with Donnelly (1991) January daily returns, at 0.00306% are the highest, February (0.0025%) being the second highest. In contrast to both Donnelly (1991) and Gahan (1993), April returns are negative and close to zero.

A more recent study is that of Lucey and Whelan (2002), who use the CSO monthly index and the ISEQ index with interpolation and splicing, to create a consistent data series from 1930-2000. They find that over the entire period January returns are again the highest, with a mean monthly return of 2.5%, the next highest being April at 1.5%. The pattern of monthly mean returns was not attributable in that paper to risk patterns as shown by stochastic dominance analysis.

3.1.6. RISK AND SEASONALITY

A body of literature exists that suggests that the monthly seasonality, especially the January seasonal, arises from risk factors that, in and of themselves, may be inherently seasonal. If this is the case then clearly the EMH is unchallenged. Two broad threads can be distinguished in this literature, one deriving from an Arbitrage Pricing Theory approach, another from the CAPM. These differ mainly in the initial specification of the return generating process investigated; while the CAPM papers take a Fama and MacBeth (1973) approach and estimate beta coefficients then investigate the seasonal variation of these, the APT papers tend to include directly in the return generating equation a set of hypothesised explanatory variables for assumed seasonality. This is of course in the spirit of the differences between the two models, with the CAPM in its *naive* forms indicating that only idiosyncratic corporate risk is rewarded, while the APT allows for the possibility of other variables influencing risk and therefore the rewards for stocks.

Much of this genre of work derives from Tinic and West (1984) who showed that the relationship between expected return and risk is positive and significant only in January. In all other months, therefore there is no reward for holding risky assets.

3.1.7. APT TYPE MODELS

A number of papers have used the Chen, Roll and Ross (1986) methodology to identify whether or not macroeconomic factors, perhaps acting differentially on small versus large firms, could explain the dual January-Small firm effect. Other papers have taken the Fama and MacBeth (1973) two stage regressions and examined the role of beta over months of the year.

Chang and Pinegar (1989),Chang and Pinegar (1990) & Kramer (1994) find that placing small firms in the Chen-Roll-Ross methodology does provide an explanation that is consistent with market efficiency. However, Sehun (1993) who operates within a Stochastic Dominance framework provides contradictory evidence as to the role of macroeconomic factors in the January-Small firm effect.

Two papers by Chang & Pinegar both use a Chen-Roll-Ross framework to directly examine macroeconomic factors over a range of firm sizes. Rozeff and Kinney (1976) found that there was both a January and July peak in stock prices. Chang and Pinegar (1989) note that growth rates in industrial production, which is partially flow data, have seasonal peaks in February and August. Chen, Roll and Ross (1986) show that this industrial production figure as reported lags actual production by at least part of a month. To some degree, therefore the reported peaks in industrial production and stock returns are contemporaneous. Adjusting the industrial production data for this lag, stock returns & industrial production are positively related. This relationship declines as firm size increases. Chang & Pinegar find that the January effect is stronger in portfolios formed on firm size than on portfolios formed on sensitivity to industrial production. They therefore conclude that the January effect is more of a size effect than a macroeconomic effect. Chang and Pinegar (1990) found that the factor loads (effects on the portfolio returns) of industrial production and corporate-government bond spread were greater in January than in other months. They also find that the market risk premium was priced in January only for small firms for small firms (proxied here by the CRSP equal weighted index) This was further confirmation of the findings of Tinic and West (1984), and supporting evidence on the size effect of Reinganum (1983)& Keim (1983).Tinic & West's conclusion that investors would not be compensated for holding risky assets in months other than January was not altogether justified. For non-January months, Chang & Pinegar found that there was a statistically significant premium from changes in unanticipated inflation. It seems that only in January is the holder of risky assets compensated for default possibilities (proxied by the spread between government and corporate bonds), overall economic risk (as proxied by industrial production) and for risky assets (at least for smaller stocks as proxied by the equally weighted stock index). In the other eleven months of the year there is only a premium for overall economic risk and for inflation induced erosion of wealth (changes in unanticipated inflation), The term structure of interest rates seems to have little impact.

Kramer (1994) analyses default risk and maturity risk (roughly analogous to the corporate bond spread and term structure variables of Chen-roll-Ross), consumption, and inflation expectations. Rather than choose a stock index directly, Kramer uses the residuals from a regression of an equally weighted stock index on the first four factors. He shows that the return on January is significantly higher than other months, and that this is captured more effectively in a multivariate than a univariate model. The multivariate model includes, in addition to the factors noted above, a January dummy to capture seasonality directly. Again, the influences on the small firm portfolios of the macroeconomic factors are higher than on the large firm portfolios. For small firms all factors are priced (except for inflation in the very smallest decile (perhaps reflecting the poor nature of very small firms as inflationary hedges)).

3.1.8. CAPM TYPE MODELS

A further set of papers have examined seasonality in the context of the methods popularised by Fama and MacBeth (1973). The paper by Tinic and West (1984) provided considerable impetus to this research agenda. These papers typically employ some version of the two step direct test of the CAPM as popularised by Fama and MacBeth (1973). As expressed in Hawawini and Keim (2000), this takes the form of a regression of the following type

Eq. 5 $R_i = \alpha_0 + \alpha_1 \beta_i + \alpha_2 \sum c_{ij} + \varepsilon_i$

, where c_{ij} represents particular characteristic j, such as price, size, P/E ratio or whatever, of stock i, Of course, if one is simply testing the CAPM then there does not have, necessarily, to be characteristics included. However, the β coefficients in Eq. 5arise from a previous regression. Under the assumption that there is no time variation in β coefficients for each individual stock, a first pass time series regression of the form

Eq. 6 $(R_{it} - r)_t = \alpha_i + \beta_i (R_t^m - r_t) + \varepsilon_{it}^{*}$

, with the expectation that the constant term, a, is zero for each security or portfolio of securities, gives the estimated β coefficients that can be used as inputs into a regression of the type shown in Eq. 5.[37]

Tinic and West (1984) focus on the fact that to that date there had been no examination of the seasonality of the risk-return relationship. They found that in an examination of the CRSP indices, the risk premium was explicable using January data only. Tinic & West examine this in more detail via a cross-sectional regression of CAPM parameter estimates on February-December dummies. The results show that the monthly dummies for market risk premia are negative, significantly so, for all months. The results were robust as to index choice (value or equal weighted), and are stable over time

In the context of the UK a recent paper on this is that of Chelley-Steeley (1996) while for the US the work of Pettengill, Sundaram and Mathur (1995) may be taken to

[37] Of course, it is immediately clear that tests using the Fama and MacBeth (1973) approach require that there be estimable β coefficients for a sufficient number of stocks. In practice this has meant that in markets where the numbers of stocks are small then tests of this type are rare. They appear more frequently where large numbers of actively traded securities are present, such as the UK, Germany and the USA.

represent this strand. International studies include Heston, Rouwenhorst and Wessels (1999) and Fletcher (2000).

As practical implementations of this approach, consider Chelley-Steeley (1996). There the emphasis is on a joint set of issues – do size and calendar effects exist in the risk return relationship? There an initial equation of the form of Eq. 5 is estimated, the characteristics being relative size and (beta*relative size). The slope coefficients, defined as α_0 and α_1 in Eq. 5, from these regressions are then themselves regressed on calendar dummies. The result is a finding, over the 1976-1991 period, that risk is priced only in January and April, the months that also show the highest raw returns. Unusually, there does not seem to be a systematic small firm risk premium, with larger firms receiving a larger risk premium than smaller. This finding, of January seasonality in the risk premium, confirms the UK results of Corhay, Hawawini and Michel (1987). They find that for the USA, UK, France and Belgium that January risk premia are the largest of the year as well as, in the case of all save Belgium, being significantly different from zero. Again, they adopt a two-stage methodology, dividing the stocks (from 700+ in the USA to 170 for Belgium) into portfolios and using these as the basis for further investigations.

Pettengill, Sundaram and Mathur (1995) examine the CRSP database from 1926 through 1990, and find, consistent with the findings of Tinic and West (1984) that only in January (with February marginally failing to achieve statistical significance) does the risk-return trade-off predicted by the CAPM actually occur. Following the method of splitting the data according to whether the returns are positive or negative as given in Lakonishok and Shapiro (1984), they find that the relationship differs according to market direction. When the market is rising then there exists a positive trade off between risk and return, whereas when the market is falling a negative relationship, as the CAPM would predict, occurs in all months except January. A similar finding is evident in Heston, Rouwenhorst and Wessels (1999), who examine portfolios of stocks across a number of European countries.

Summarizing the debate on macroeconomic factors, it seems that while there is agreement that factors do influence the market the transmission mechanism of such factors influences on the January effect is unclear. Tinic & West found that risk is priced in January only. Kramer finds that an equilibrium pricing mechanism operates across months. Concerning the particular factors that influence stocks there is also disagreement. Thus, while there is evidence that there is a linkage between seasonality in the stock market and macroeconomic factors there is little in the way of plausible explanations offered for the transmission mechanism. However, within an APT framework, which is the theoretical basis for the Chen-Roll-Ross methodologies employed in the debate, there is nothing impermissible with different factors influencing different sized stocks. Thus, the small firm element of the January-small firm regularity is explicable. Even in a CAPM world, allowing for transactions costs and liquidity, higher and lower respectively in smaller firms, could give rise to a higher required return to small firms. The January element remained unexplained however.

3.1.9. Tax Loss Selling and Parking the Proceeds

While the liquidity arguments (on page 66) and the macroeconomic seasonality arguments (on page 66) are primarily US orientated this has the obvious difficulty that it is driven by peculiarities in the US macroeconomic calendar while there is evidence that the January effect is found internationally. If financial economics is to avoid the accretion of special case theories and theories that explain only anomalies then a more general and generalisable theory was required.

Roll (1983) takes his lead from Keim (1983) & Branch (1977) to explicitly investigate the linkages between the small firm and January anomalies. He coins the term 'turn of the year' effect to reflect the joint anomaly. Ritter (1988) claims Roll's paper as the first to explicitly link the two issues together. This is despite the work on the small firm effect that undertaken by Banz (1981) and on the January anomaly by Rozeff and Kinney (1976), Blume and Stambaugh (1983) and Keim (1983).

Roll begins by noting that the last trading day of December[38] and the first four of January contain the largest price changes of any turn of the month, for the difference between an equally and value weighted index. He subsequently dismisses data errors, construction problems, outliers, survivorship bias, and thin trading as possible explanations and reaches the conclusion that this effect is tax loss selling related. The presupposed but not fully articulated mechanism is that investors sell stocks that have realised losses to minimise capital gains taxes, these losses being offset against the other stocks that have gained. This will therefore depress prices; this price depression will last at least up to the US tax year-end of Dec 31. The January price rise is then at least in part a reaction to the removal of this downward pressure[39]. Roll's explanation for why the small firms show a greater sensitivity is that they typically have a higher volatility than larger stocks. Consequently, there is a greater probability that they will show a decline in any given time period.

[38] As we will see later this choice of time frame can be criticised on the grounds that it contains a day preceding a holiday, which days in themselves are the subject of anomalous, but regular, rises in security prices. The so called 'holiday anomaly' is discussed in more detail in section 5

[39] A market participant version of this bounce is the so-called 'dead cat bounce', to the effect that even a dead cat will bounce if it falls from a great enough height.

Reinganum (1983) provides a direct and focused examination of the tax loss selling approach. His work is a synthesis Roll (1983),Branch (1977), and Dyl (1977) on year end tax loss selling, as applied to small firms. Dyl found a significant abnormal increase (decrease) in trading volume in December for stocks that had shown declines (increases). Reinganum's analysis is driven by his classification of portfolios into one of forty – ten size based portfolios and four formed based on tax loss selling potential as measured by his ratio. Three facts emerge. First, smaller firms are more likely to have experienced greater potential tax loss selling Second, firms in the bottom portfolio of potential tax loss selling show a larger average return of all in early January. Third, as one moves from smaller to larger firms, there is a marked reduction in the mean return in early January[40]. Reinganum had thus identified an explanation, tax loss selling, that was consistent with the facts. It was not however fully satisfactory as he had found that even after adjusting for tax loss effects (in effect looking at firms that had had little tax loss) there was still a residual January anomalous return.

Ritter (1988) produces a variant on the tax loss-selling hypothesis that he calls 'parking the proceeds'. This is similar to the portfolio manager based window dressing theory of Haugen and Lakonishok (1988) but differs from it in that its primary focus is on an individual rather than an institutional driver. Ritter's main innovation is that he allows for a less rapidly acting investor than was implicitly assumed in either Reinganum or Roll. Miller (1990) formalises this by pointing out that the period under analysis is a socially and culturally active one. Individuals might reasonably be expected to place a higher than normal opportunity cost on their time during the holiday period, and thus

[40] Reinganum has a measure of tax loss selling potential which is particular to his paper. Others have criticised this measure and proposed alternatives. The literature on this are alone is substantial, and the measures complex. However, the basic insight of Reinganum, that portfolios composed of firms with higher measures of tax loss selling potential are associated with higher excess January returns, is broadly accepted.

the balance of investment decision-making may shift from a (presupposed) costly search for quality investible stocks to a rapidly executed search for sales.

Ritter is aware, however, that tax loss selling cannot alone explain the January anomaly. This arises from the result in Constatinides (1984) that investors as a set may find it advantageous to swap losers for losers to realise capital losses[41]. To explain the January anomaly investors would have to 'park the proceeds' of these loser sales, keeping prices further depressed and then reinvest, in January, providing additional upward impetus. Ritter identifies three requirements for his parking the proceeds hypothesis to work: Individual investors be overweight in lower value small stocks, the price of these small stocks must be affected by selling pressure, and investors who act to realise their tax losses in December do not immediately reinvest the proceeds of sales. The first and second are well accepted[42], so his analysis is to concentrate on the third. By analysing the selling-buying behaviour of a set of individual brokerage account customers, he demonstrates a clear seasonal effect. From regression of the small firm return for the first nine days of January on the buy/sell ratio, over the 15 Januarys in his sample Ritter demonstrates a positive and significant relationship.

The tax loss based explanations are not fully convincing however. If there is a tax-based explanation for the January effect then countries where the end of the calendar and the end of the tax year do not coincide should show no January anomalies. Rather they should show a strong return around the tax year-end. We have seen already (page 46) that one of the very earliest studies of the January anomaly was on Australian data by Officer (1975). Others have examined the existence or otherwise of a January anomaly

---

[41] This result as a result of the distinction between short-term and long-term tax provisions in the US over the period. The interested reader is referred to Appendix 1 of the paper.

[42] Eakins and Sewell (1993) show that there is a strong positive relationship between firm size and percentage institutional ownership.

in the US before the introduction there of taxes on capital gains in 1917. One such study is that of Schultz (1985). He looks at the period 1900-1917, when the US was without a tax on capital gains, versus 1918-1929. In the latter period, but not the former, he finds a January effect. In contrast, Jones, Pearse and Wilson (1987) reject the tax induced January effect as they study the period from 1871 to 1917, and find evidence of abnormally large January returns. Similar results are to be found in Pettengill (1986), Jones and Wilson (1989) and Jones, Lee and Apenbrink (1991).

A more direct test of the of the tax loss selling approach can be taken by examining countries where there is a significant January return but the tax year end is not end December and / or there are no capital gains taxes. This does not of course eliminate the need to pay tax on trading gains. This can be seen from a number of studies, such as Brown, Keim, Kleidon *et al.* (1983), Berges, McConnell and Schlarbaum (1984), Gultekien and Gultekien (1983), Kato and Schallheim (1985), Tinic, Barone-Adesi and West (1987)& Lee (1992). All of these examine countries where the conditions above hold but there is evidence of a January effect. Prior to 1972, Capital gains were not taxed in Canada, and both Berges et al and Tinic et al report the existence of a January anomaly in that period. In the case of Hong Kong, where a zero tax rate on capital gains should imply no tax loss selling pressure, Lee (1992) and Cheung, Ho and Wong (1994) both report a January return that is significantly above other months.

In the case of the UK, Reinganum and Shapiro (1987), Corhay, Hawawini and Michel (1987), , Gultekien and Gultekien (1983) & Draper and Paudyal (1997) have all found evidence of a January and April seasonal. The UK tax year ending in April provides some evidence in favour of a tax-based effect for the April seasonal. McKillop and

Hutchinson (1989), Donnelly (1991), & Lucey (1994)all find April seasonality in Ireland where again the tax year ends in April.

Among recent work for the UK, the paper by Baker and Limmack (1998) indicates that a size-January effect appears in the UK. On examination of an average of over 1800 stocks listed on the London Stock Exchange over the 1956-1991 period, they find, using parametric and non-parametric methods, that the mean return to smaller capitalisation portfolios exceeds that of larger. This was however concentrated at the extremes (the smallest of the 10 size sorted portfolios versus the largest, for example) with little evidence of a size effect in the middle portfolios. They also find that this is persistent over sub-periods. January and April returns, across all portfolios and all periods of analysis dominate all other months, with this dominance being greater in the smaller portfolios. Consistent with the results of Levis (1985), they also note that the effect has changed, with April returns exceeding January in the early years, while the reverse becomes true in the latter periods. Forming the data into portfolios based on previous returns, they find that the portfolios that exhibited the worst previous performance (with a number of alternative time-spans used) performed best in the subsequent periods. In particular, the poorest performing portfolios performed better in January than those that had performed best. This persisted across the sub-periods of the sample. Results for April were mixed. Interpreting these results in the light of the different tax codes on investment income, capital gains and corporate reporting, and in the light of the composition of the investment community in the UK they conclude that while the results do offer some support for tax loss selling (and window dressing, more fully discussed in section 3.1.10 below) the magnitude of the excess return earned in January (and April, to a lesser extent) by the poorest performing stock portfolio is of a relatively small magnitude and is unlikely to offer a full explanation of the high returns earned by UK stocks in January and April

3.1.10. PORTFOLIO REBALANCING ("WINDOW DRESSING")

Haugen and Lakonishok (1988), Lakonishok and Smidt (1988), Ritter (1988), Athannasakos (1997) and Athannasakos and Schnabel (1994) all hypothesise that as the year progresses managers of pension and investment funds hold progressively less and less proportions of risky (usually small) stocks. When the year ends there is a rebalancing by managers towards their desired holdings. The presupposed reason for this is that managerial remuneration has a substantial package based on calendar year returns. A variant on this is the window dressing hypothesis, which is essentially an institutional version of the tax loss selling approach outlined on page 59 seq.

Haugen and Lakonishok (1988) look at both the historical roots and possible explanations adduced for the January effect. Rejecting the tax loss selling approach, they develop the rebalancing argument. An implication of the hypothesis is that there should exist a positive correlation between the stock price changes in January of firms and the percentage of such firm's shares under the control (not necessarily under the ownership) of such professionals. Ligon (1997) rejects this in favour of a liquidity based approach, casting doubt on the validity of the hypothesis, while Ritter (1988) reject the tax loss selling approach in favour of the window dressing approach. Athannasakos (1997) & Athannasakos and Schnabel (1994), provide some evidence supportive of the window dressing hypothesis for Canadian equities. Overall therefore the rebalancing/window dressing mechanisms, developments of the at best partial explanation of the tax loss selling theory, do not provide encompassing explanations of the January-small firm regularity

3.1.11. LIQUIDITY

A potential explanatory mechanism has however been identified through the work of Ogden (1990), Chen and Fishe (1994)& Gamble (1993). Ogden puts two empirical regularities together towards his explanation. The first is the work by Ariel (1987), which recognised that the return in a month occurs primarily in the early part of the month. The second regularity is that while this effect exists in each month, it is much more pronounced in January. Ogden's hypothesis is that both of these can be explained by reference to liquidity conditions.

In short, Ogden's hypothesis is that the standardization of payments towards the end of the month leads to a surge in both corporate and individual liquidity. Good treasury management practice indicates that corporates should demand securities that mature towards the end of the month (the sale of these leading to downward pressure on these markets) and demand investible securities when they have excess liquidity, such as at the commencement of the month (leading to upward price pressure on these markets at that time). Ogden notes that not only are liquidity conditions systematically eased in December, in the run up to Christmas, but also corporate liquidity is enhanced due to Christmas and new year related spending. Ritter (1988) had noted that year-end bonuses and cash incentive payments[43] also occur at this period, which enhances the purchasing power of individuals. Using federal funds spreads as a measure of liquidity, Ogden finds support for his hypothesis regarding the liquidity effect of the

[43] Paid perhaps to successful portfolio rebalancers and creative window dressers?

turn of the month, regardless of whether a value or equally weighted index is examined.

Chen and Fishe (1994) are subtly different in a number of ways to Ogden, but a clear descendent thereof. The major difference is that Chen & Fishe couch their analysis in terms of inflationary and other expectations. For Ogden's hypothesis to work agents would have to be surprised at the end of each month. Chen & Fishe close this reality gap, whose basic mechanism is that excess (unanticipated over and above expectations) liquidity has an effect on stock prices.

In the US, from late November onwards, the Federal Reserve acts to allow increases in liquidity. Chen & Fishe point out that historically the Federal Reserve progressively removes this seasonal increase during January. The easing in liquidity in December acts to depress stock prices, as there is at least the possibility that this will not be fully unwound in January and that thus there will be an increase in inflation. With the January reversal the fear of inflation recedes and stock prices rebound. Thus the Chen & Fishe and Ogden hypotheses are directly opposed to one another.

Testing this hypothesis requires that it be distinguished from Ogden's liquidity hypothesis and from the tax loss selling approach. For tax loss selling to be the cause of the January effect Chen & Fishe note that prices should rebound rapidly after December 31, the end of the US tax year. Separating the first week of trading into days when there is and is not a monetary policy announcement tests their seasonal monetary policy approach. Chen & Fishe show that the tax loss effect is dominated by the seasonal money hypothesis. A further conclusion of the paper is that monetary policy seasonality and expectations causes the January effect per se, while other effects are related to the small firm effect. The work of Chen and Fishe (1994) bears a close relationship with that of Bell and Levin (1998) for the UK.

Gamble (1993) provides a twist on the liquidity issue, arguing that the January effect is consistent with individuals, particularly parents and grandparents, granting monetary gifts to other generations. These other generations, modelled as rational economic maximisers (or maxi misers), resist the temptation to spend this liquidity on transient consumption opportunities (parties and drink for example) and instead invest it in equities, causing a rise in equity prices in the early part of the New Year. In other words, Gamble's argument is that Santa Claus causes the January effect. This paper provides a classic example of a special case theory of the type consistent with a degenerative research programme. It should not however detract from the powerful explanations offered particularly from Chen & Fishe. This paper stands as a good example of how an empirical regularity initially classed as an anomaly can be incorporated into the protective belt of the research programme.

3.2. TURN OF THE MONTH SEASONALITY

Chang and Kim (1988) and Chang, Pinegar and Ravichandran (1993) attribute the January effect to being a particularly severe manifestation of the turn of the month effect as identified formally by Ariel (1987). It is argued that the rise in the markets noted in January is in fact concentrated in the first half of the month, indeed in the first week (see for instance Ariel (1987), Haugen and Lakonishok (1988) and Lakonishok and Smidt (1988)). A general turn of the month effect is also seen in Jaffe and Westerfield (1985) and also in Agrawal and Tandon (1994). No explanation has been offered, although it would appear that the liquidity arguments of Ogden and Chen & Fishe could provide a potential basis for explanation.

3.3. FRIDAY 13TH[#]

Kolb and Rodriguez (1987), Dyl and Maberly (1988) & Chamberlain, Cheung and Kwan (1991), addressed the issue of superstition in the stock market, via an examination of the putative Friday 13th effect. Friday the 13th has a long history of being seen as an unfavourable day for activities, at least in the Judaeo-Christian world. Explanations as to why this might be so are many, ultimately drawing from a conflation of Christian numerology, cabalistic philosophy and Norse myth. Further information is found in most encyclopaedias of mythology, folklore and superstition, such as Pickering (1991). The Kolb & Rodriguez hypothesis was that if the markets are in fact affected by superstition, then this might be reflected in asset prices.

Based on an examination of the CRSP equal and value weighted indices, over the period July 1962-December 1985, they concluded that the mean return for Friday 13th was significantly lower than that for other Fridays. However, this finding was quickly disputed with Dyl & Maberly's and Chamberlain-Cheung-Kwan examination of the S&P 500 index. Over the period 1940-1987 and 1930-1985 respectively, Dyl & Maberly concluded that the mean return on Friday 13th was in fact higher than that of other Friday's, while Chamberlain-Cheung-Kwan concluded that the statistical evidence for differential Friday returns is a function of the turn of the month effect of Ariel (1987). However, it is worth noting that they also show, but do not comment (Table 1, panel A) that Friday 13th returns are in fact negative.

[#] An abridged version of this review appears in *Lucey, B. M. (2001). "Friday the 13th: International Evidence." Applied Economics Letters 8(9): 577-79*

Since then, the Friday the 13th issue has not been re-examined in any detail. Agrawal and Tandon (1994) present a chart (Figure 5, p 101) showing Friday 13th versus other Fridays, for their sample of 20 countries across a wide range of dates. They state, without presentation of statistical evidence that while the typical Friday 13th return is positive it is statistically insignificant. Of their 20 indices, 11[44] show higher mean returns on Friday 13th. They also note that the standard deviations of the two sets of Fridays are similar. More recently, Mills and Coutts (1995) examining the FTSE indices over the 1986-1992 period and Coutts and Hayes (1999)examining the FT-30 index over the period 1935-1994, find a higher mean return on Friday 13th as compared to all other Fridays. No convincing explanations, neither of the original findings by Kolb & Rodriguez, or subsequent refutations of this, have been adduced in the literature. Lucey (2000) and Lucey (2001) addresses the issue over an international dataset, finding that the 'reverse Friday the 13th ', that is the anomalous rise in stocks on this day, persists internationally.

3.4. NON DAILY CALENDAR ANOMALIES REVIEWED

The evidence above provides mixed evidence as to the ability of researchers in financial economics to accommodate anomalous data. The January-small firm regularity is explicable, more or less. This explanation requires some deviation from the perfect world of the CAPM/APT models, requiring that the costs of transactions in the smaller firms be sufficiently large, and the liquidity in these firms sufficiently small to induce a small firm premium, while simultaneously there exist macroeconomic policies that induce a bounce to asset returns in January. The joint effect of these is then the small

[44] Brazil, France, Germany, Hong-Kong, Italy, Luxembourg, New Zealand, Sweden, Switzerland, the UK and the S&P 500 index in the USA

firm-January effect. However, this explanation has not been tested outside the USA and so has difficulty with being a full explanation. In the case if the turn of the month and Friday the 13th regularities there are no explanations forthcoming from the literature. Accordingly, the evidence indicates that as of now financial economics cannot easily accommodate non-daily calendar anomalies.

The next section of this work examines the daily calendar regularities, and then outlines the explanations posed.

4. In Search Of Explanations For Daily Seasonality

The literature on daily seasonality noted above has concentrated almost exclusively on the part of the literature that provides some evidence on the existence of the phenomenon. Literature also exists of course that has taken the existence as given and attempted to formulate explanations. We may discern at least five main strands of potential explanation

i. Daily seasonality arises because of market specific procedures.

ii. Daily seasonality is induced because of systematic measurement issues

iii. Daily seasonality is induced because of the differential behaviour of individual and institutional investors.

iv. Daily seasonality is induced because of the markets reaction to news

v. Daily seasonality is induced because of Psychological factors

The sections below provide an examination of each of these.

4.1. Market Specific Procedures

For the most part, the examination of factors specific to individual stock markets that exhibit a daily seasonality in returns has concentrated on settlement procedures. Researchers such as Gibbons and Hess (1981), Lakonishok and Levi (1982) and Dyl and Martin (1985) have shown that settlement procedures can induce seasonality, albeit of a particular kind. Some, those following the line of inquiry commencing in Gibbons and Hess, have attributed this to the settlement procedures themselves, while others , following the line of research begun by Lakonishok & Levi have examined the induced interest effects arising from such procedures

4.1.1. SETTLEMENT DELAYS

Gibbons and Hess (1981)[45] is an important paper in the study of daily seasonality, as it represents one of the earlier attempts at explanation rather than simple exposition. In relation to the possibility of settlement effects, their argument runs as follows: Stock prices are in fact forward prices (prices are agreed today but delivery of the payment and instrument are not effected for a number of days- the settlement period). Thus, by analogy with pure future markets the cost of carry model, which is the spot plus an interest premium, will determine the price for a stock. In consequence, any settlement period that is not an exact multiple of 5 days will induce a day of the week effect. Using the fact that in the US the settlement period changed in 1968 from 4 to 5 days[46], which by their reasoning should have led to at least a diminution of daily seasonality, they proceed to test this. Before this change, Monday prices would have been inclusive of 4 days interest, Tuesday through Friday prices inclusive of 6 days[47]. This would have the effect of making Monday prices less than those of the other days of the week. By excluding one day of the week from a regression of daily returns on a set of dummy variables representing the remaining days, the Monday and Tuesday coefficients (representing deviations from the excluded day of Wednesday in this instance) should be equal if the difference between the prices is due to the induced

[45] They find a negative Monday return of -0.134% for the S&P 500 over the 1962-1978 period against an all day average of 0.02%, this result also holding in all sub periods.

[46] As we will see in 6.3.3 and **Error! Reference source not found.** a change in the Irish equity settlement system allows a similar natural experiment to proceed in this research/

[47] The 4 days settlement plus the 2 days of the weekend.

interest cost. This was not so, leading the authors to conclude that the settlement effect cannot explain the negative Monday return.

Theobald and Price (1984) examine the settlement system in the UK. Before the introduction of rolling settlement in 1994, account settlement worked by dividing the year into twenty-two two-week and two three-week account periods. Accounts began on Monday and ended on the Friday week (or fortnight). Settlement occurred on the second Monday (Settlement day) after the account period, 10 working days after the last day of the account. Purchasers had to provide funds and sellers stock in time for the stockbroker to settle on the settlement day. Buying and selling within the settlement period resulted in the investor only settling the net gain or loss on the settlement day, without any cash investment having been required. An individual buying on the last day of a settlement period and selling at the end of the following Monday will pay for shares on the settlement day relating to the Friday and receive payment on the settlement day relating to the Monday. Thus, the investor would have had to carry the cost of the transaction for two, or possibly three, weeks. Consequently, the first Monday of an account period would have inbuilt in it the greatest amount of implicit interest and thus the price on this Monday should be higher. Purchases made on the last day of an account period would have the shortest credit period. This implies that the first Monday of an account period should have a substantially higher return compared to other Mondays.

Theobald and Price found to be the case in their analysis, with the first Monday of an account showing positive but insignificant returns, but the other Mondays remaining negative. Thus, along with Jaffe and Westerfield (1985) they find that although the settlement system manifests itself in the data it cannot fully explain negative Monday returns and thus cannot be a full explanation of daily seasonality. Donnelly (1991) found essentially the same results for Ireland. Other studies which have examined the UK settlement system and have concluded that it is at best a partial explanation for the daily seasonal include Board and Sutcliffe (1988), Yadav and Pope (1992) and Coutts and Hayes (1999). Clare, Ibrahaim and Thomas (1998) examine the effect of settlement changes on the Kuala Lumpur stock market on daily seasonality. Before 1990, a fixed settlement day existed, of the Wednesday following a trade. After 1990, the settlement system changed to an account week system. Before the settlement change, an induced Thursday effect was present as was a negative and significant Monday; after, although still negative, Monday returns are not statistically significant. Solnik and Bousquet (1990) find that the settlement system for the Paris bourse cannot fully explain the daily seasonality they find there. In general therefore the evidence on the settlement system as a cause of the daily seasonal is weak. This is perhaps not unexpected as the induced seasonality of particular settlement systems will always be particular to the system and market under investigation[48] and as such cannot provide a generalisable explanation across different regimes.

4.1.2. SETTLEMENT INTEREST EFFECTS

Lakonishok and Levi (1982) invoke a somewhat different aspect of settlement procedure, that of the cheque settlement or clearing system of one day typically. They point out, again noting the 1968 settlement change in the US, that purchase of stocks on any day other than Friday gives eight days usage of funds. Purchase on Friday gives ten days usage. Purchasing on say Wednesday requires settlement on the following Thursday (Thursday, Friday, two weekend days of Saturday & Sunday, Monday,

[48] See for example the work in Jaffe and Westerfield (1985)

Tuesday and Wednesday). Purchase on a Friday gives all the following week, two weekends and then next Monday week. Thus, mean returns on a Friday should be higher by the additional two days interest The mean returns on a Monday should, they argue, be lower by the two days interest. Over the 1962-1979 period they examine this hypothesis, explicitly adjusting CRSP Equal Weighted Index prices for Monday and Friday by the interest rate, and noting that while the disproportional negative Monday and positive Friday returns declined they continued to exist. Thus, they conclude that the settlement interest effect is not sufficient to account for the weekend effect.

The proposal to use appropriate interest rate adjustments as noted in Table 1 of Lakonishok and Levi (1982) as the interest rate adjustments that should be made to data is one that is carried out by Dyl and Martin (1985) and Degennaro (1990). Dyl & Martin examine the S&P 500 from 1957 to 1981, and they partition the sample on the change of settlement procedure in 1968 and. They conclude that settlement effects have little effect on the day of the week effect. DeGennaro produces similar results. This study finds that the risk free rate is the appropriate rate to adjust for the settlement delay, but that the adjustment for this delay is not responsible for the day of the week effect.

Bell and Levin (1998) extend this approach of implied interest for the UK, over the period 1980-1992, including in their analysis a series of variables to account for the liquidity effects of cheques and wire transfers impacting on traders accounts around settlement day. They conclude that allowing for these effects and for the reduction in money demand around weekends, the calendar effects disappear.

4.2. TRADING MEASUREMENT ISSUES

If stocks prices are assigned as opposed to being actually realised, through thin trading perhaps, this, some have argued, could induce seasonality. Gibbons and Hess (1981) suggest that if this is so, then the deviation of Monday prices from the average should be offset by that of Friday. Testing this on S&P 500 and on the CRSP equal- and value-weighted indices they find trading measurement issues not to be a potential source of the Weekend effect. Keim and Stambaugh (1984) also tested as to whether thin trading can adequately explain the Weekend effect. They show those if measurement issues are important, then Friday returns suffer from mean positive errors (are biased upwards) while Monday returns from mean negative errors (are biased downwards). There should then be negative autocorrelation between Friday and Monday returns. Examining the 30 components of the DJIA, for the period 1962-1982, the correlation between Friday and Monday was in fact positive and indeed the largest of any pair of days. Replication of their test for the UK by Jaffe and Westerfield (1985) and Board and Sutcliffe (1988) also refutes the suggestion that the weekend effect is because of systematic measurement errors in closing prices

Pettengill and Jordan (1988) & Fishe, Gosnell and Lasser (1993) both examine trading issues through volume. Pettengill & Jordan examine the S&P 500 and the CRSP equal weight index from 1962-1985. They find calendar anomalies in the volume data of similar patterns to returns. Volume data displays turn of the month, day of the week, January and intra-month seasonals. They also demonstrate a positive and significant causal relationship between volume and return. Fishe, Gosnell & Lasser find similar results, in addition, finding that the Monday anomaly is particularly prevalent during high volume – negative return environments. Jaffe, Westerfield and Ma (1989) examine the international aspect of this, looking at Monday returns for six stock markets (US, Japan, Canada, Australia and the UK) over a variety of periods. They find that, partitioning their datasets on advancing / declining weeks, negative Monday returns follow declines, with little evidence of a significant effect on the Monday return if the previous week was an advance. This effect carries across all markets and all sub periods. This may be evidence of momentum trading, with investors expecting further declines.

Some support is given to this by Abraham and Ikenberry (1994) who indicate that Friday declines are followed in 80% of cases by Monday declines; Friday advances are typically followed by Monday advances. However, the relationship is asymmetric, with a negative prior Friday having a stronger effect on the following Monday than a positive Friday.

A number of other papers have commented on this. Evidence has accumulated that two factors are in operation. First, seasonality is typically measured as being stronger when the markets are in decline. Second, the relationship between Monday and Friday is asymmetric with regard to positive and negative Friday returns. Liano and Gup (1989) classify months into those that fall in expansionary and contractionary periods. Contractions, in their analysis begin on the first trading day of the first contractionary month and end on the last trading day of the last contractionary month. Examining both the equal and value weighted CRSP indices, for 1963-1986 they find that the contractionary Mondays are more strongly negative than expansionary Mondays are positive. This is very similar to the results found by Abraham and Ikenberry (1994) and Jaffe and Westerfield (1985) .Fishe, Gosnell and Lasser (1993) partition their dataset, as do Liano and Gup (1989) on positive and negative return environments, on a daily basis. Again, they find that Monday in the negative return environment is significantly different to positive environment Monday. In the negative return set, Monday exhibits both the lower average returns of all days. Kohers and Patel (1996) who look with the same methodological lenses at the period 1987-1993 find contradictory results to Liano and Gup (1989).

4.3. The Role Of Individuals And Institutions

Miller (1988), Lakonishok and Maberly (1990) & Abraham and Ikenberry (1994) have all noted the tendency for the weekend effect to be more robust in smaller stock indices and deciles. While this may reflect thin trading, if we accept the analysis of Theobald and Price (1984) we would expect to see more pronounced seasonal patterns in indices and portfolios that contain a higher proportion of thinly traded stocks. Some authors have seen this as also being a potential indicator that individual investors may be playing an important part in the propagation of the phenomena.

Miller (1988) focuses his research on individual investors. There are two main assumptions underlying the notion that individual investors may have a role to play. The first is that individuals, sellers of stock on balance, will make decisions over market closures as well as market openings. The second that they make these decisions without benefit of expert advise. Miller hypothesises that individuals make sales decisions every day, causing an imbalance of sell orders to occur on Monday, the markets being closed over the weekend. Brokers and investment advisors typically generate buy orders[49], regardless of whether they are for individuals or institutions. As these work a standard 5-day week, this exacerbates the imbalance noted above. Miller notes that this

[49] Miller gives evidence that buy recommendations can be up to 26 times the number of sell recommendations

hypothesis is congruent with the post-holiday and post-market closure evidence. He does not however attempt to test the hypotheses on any datasets, the paper being entirely theoretical. Dyl and Holland (1990) do provide direct evidence on the Miller hypothesis. They examine odd-lot trading volume on the New York Stock Exchange from 1978-1987, explicitly assuming odd-lot trades are an adequate proxy for individual trades. They find that both net sales and odd-lot volume are higher on Monday than on any other day, evidence in favour of Miller's hypothesis. This evidence is robust to the exclusion of the week around the 1987 market crash. Lakonishok and Maberly (1990) approach the issue based on the research that sell recommendations are far less likely than buy. Thus, those wishing to sell must make the decision essentially alone, the weekend providing time to think the matter over. This should lead to an imbalance of sell orders over buy on Monday. Based on odd-lot data from 1962-1986, they conclude that odd-lot dealings on Monday are indeed substantially higher than on any other day of the week. In addition, block sales (sales of 10,000 shares or more) make up the least proportion of all volume on Mondays compared to other days. Analysing the transactions of Merrill Lynch cash account customers, these also show a sell imbalance on Monday. This evidence is consistent with, but not necessarily causal of, the day of the week effect. Abraham and Ikenberry (1994) analyse deciles of stocks, ranked by size, to investigate the possibility that smaller stocks, wherein individual investors are assumed to be disproportionally represented, exhibit more pronounced daily seasonality. They find that, conditional on the previous trading day return being negative, smaller stocks exhibit a more pronounced negative Monday when compared to larger. Conditional on the previous day being positive, the smaller decile portfolios exhibit lower (albeit positive) returns when compared to larger. This is consistent with the CRSP equal weighted index information, which shows that Monday declines follow Friday declines in 80% of cases and that Friday raises result in a smaller Monday rise than any other pair of days. Again, odd-lot trades support the notion that individuals are more active on Monday than any other day. For Finland, Kallunki and Martikainen (1997), finds evidence in favour of the individual investors playing a significant role in driving a weekend effect.

Sias and Starks (1995), and Kamara (1997) turn this argument on its head, and argue that in fact the weekend effect arises from the influence not of individuals but of institutions. This starting point seems reasonable, as their studies are prompted a number of facts. By the 1990's in excess of 70% of volume on the New York Stock Exchange was from institutional traders. There is also evidence of a low level of activity of institutional traders on Monday (a mirror image of the high level of individual activity). Institutional traders receive the same level and balance of broker recommendation asymmetries as individuals. Combined with the fact that autocorrelations in returns are higher in institutional dominated portfolios, these facts lead Sias & Starks to judge that institutional traders, not individuals, have the dominant role in the weekend effect. They find that size adjusted portfolios comprising stocks that have high institutional holdings have a Monday volume that is lower than similar sized portfolios with low institutional holdings. They also find that, adjusting for size and conditioning on the previous Friday return being negative (positive), high institutional holding portfolios have a lower (higher) return than low institutional holding portfolios. They add an additional argument in favour of the institutional holders to be the dominant source of the Weekend effect. This is the existence of a Tuesday effect in Japan, being they claim a reflection by institutional holders of the Weekend effect in the US. Finally, Kamara (1997) notes that as institutional holdings of stocks have, proportionally, increased, the weekend effect has declined. One problem with this argument however is the evidence that the measured weekend effect in rising markets is lower than in falling markets. As the US market was, generally speaking, in an upward phase from 1989 this needs to be taken into account in any examination.

Clearly, the issue of individuals versus institutions cannot provide a full explanation of the daily seasonal, as it is particular and ad hoc. It is particular to the asset under investigation, equities, and ad hoc in that it fits the US data of a Monday decline, but has nothing to say as to the other patterns found internationally.

4.4. Reaction to News

In economic terms, news is a term that is used to denote unanticipated or unforeseen changes in variables of interest to the actors under investigation. The assumptions of the EMH do not include perfect forecasts by agents. Consequently, these agents will be 'surprised', that is their forecasts will not be perfectly accurate and they will be forced to react to not just the forecast variables but also to the news, the forecast error, in these variables. In the context of daily seasonality, two different types of news are considered. The first is news that acts on more than any one firm, macroeconomic or market news, the second news that, in principle, acts on individual firms. Examples of such studies are those by authors Liano and Gup (1989) & Steeley (1999) on macroeconomic news, Wilson and Jones (1993) on market news and Penman (1987) on firm specific news

4.4.1. Macroeconomic News

Liano and Gup (1989), Kohers and Patel (1996) & Steeley (1999) all purport to examine the effect of macroeconomic news[50], such as GNP figures, inflation or industrial production, on the daily pattern of returns.

However, of these, only Steeley examines the effect of macroeconomic news directly. The others, as we have seen, in reality examine the differences in seasonality across different returns regimens.

A detailed study in the tradition of Liano and Gup (1989) is that of Chang, Pinegar and Ravichandran (1993), which attempts to look at macroeconomic news announcements as such. However, their proxy for macroeconomic news is changes in large firm's stock prices. Substantial methodological sophistication (use of GJR-ARCH models to capture asymmetries and non-normality in the data, the use of posterior odds ratios to capture large sample effects and attempts to control survivorship bias) in this paper makes it an improvement on the previous papers. What they find however is that there is a size effect as well as a Weekend effect, with small stocks being more moved by changes in large stock prices (macroeconomic news) on Monday than on any other day. This, they hypothesise, is due to information processing asymmetries as between Monday and any other day. Investigation of lags and contemporaneous returns indicate that this is true not only for information (large stock price changes) 'released' on Friday but also for information released on Monday.

[50] The role of news in the 1987 crash was examined by Shiller (1987), who dismissed macroeconomic news as a contributory cause.

Steeley (1999) represents an attempt to examine directly the issue of the effect of macroeconomic news releases on the daily seasonal. Using UK data (FTSE 100 index) from 1991 to 1998, he finds that major macroeconomic variables arrive more frequently in the middle of the week than on Friday or Monday. This inverted U shape allows investors to take time over the weekend to consider their reaction to the news announcements which they receive on Tuesday-Wednesday-Thursday, and to trade on the Monday or Friday with little chance of announcements requiring additional processing of information, making them lower cost trading days. Although on average he finds no significant daily seasonality, when partitioned by market direction the returns show is a weekend (lower Monday higher Friday) pattern. Abraham and Ikenberry (1994) show that this partitioning is important for the US, with negative Monday and Friday returns significantly more negative for those days when announcements occur.

4.4.2. Market Specific News

Wilson and Jones (1993) examine whether different US stock markets exhibit different manifestations of well-known daily seasonal effects. This they test by means of an integrated study of the AMEX, New York Stock Exchange (value weighted), Standard & Poor 500 index and NASDAQ index from January 1973 to August 1991. The study incorporates day of the week, turn of the month, January and holiday effects, and incorporates adjustments to account for non-normalities and autocorrelation They find that the negative Monday return is present across all four indices studied, even after taking account of the various other potential anomalies. The effect was strongest, both in absolute and in statistically significant terms, in the NASDAQ index, which at that time would have been, relatively speaking, composed of smaller capitalization stocks than the other indices. Exactly what the market specific characteristics or news that caused these differential'effects might be was not examined however.

One problem that researchers had not solved was how to distinguish between effects caused by firms and those general to the market as a whole. Pettengill and Buster (1994) provide a mechanism to distinguish between an effect caused by firm specific news to one caused by news that affects the entire market. They compare the standard daily pattern in return indices with the daily proportion of securities that show positive, negative or zero returns. If market news caused daily seasonality then the two patterns (indices and proportions of returns signs) would be similar. If there were daily seasonality in the proportions of return signs, with a high proportion of negative Monday and positive Friday returns, that would also indicate market specific information. If the pattern across days of the week in the proportions shows no especial daily seasonality that would indicate that the Monday and day of the week anomalies resulted from negative news announcements after close of business on Friday. The study finds that there was daily seasonality in the proportion series. This indicates a market wide rather than firm specific phenomena

4.4.3. Firm Specific News

Three major studies, focused on the US, have looked at the issue of whether the release of firm specific news to the market can induce a day of the week effect. These are Patell and Wolfson (1982),Penman (1987) & Damodaran (1989). Patell & Wolfson test the hypothesis advanced in French (1980) that the release of negative information takes place during non-trading hours. They classify news in relation to earnings and dividends according to the effect that the release has on the stock price after release (does the stock price rise or fall) and relative to their level in previous years (are the accounting data higher or lower than previous years). Studying the dividends and earnings announcements of 96 firms for the three years 1976, 1977 and 1979, they find that good news (information after whose release stock prices rise, or information whose level is above previous levels) is released during trading hours and bad news after hours. However, the link to daily seasonality is left unspecified, but could be conjectured to work based on bad news being released after trading hours on Friday, leaving the weekend for investors to decide to act on this. This mechanism is similar to that of Abraham and Ikenberry (1994). Penman takes the relationship between information releases and daily seasonality a step further, looking at a much larger sample of over 70,000 announcements. He shows that there is a dual seasonality in the announcement set. Again, the news is categorised as good or bad according to the market reaction after its announcement. Firms appear to release good news in the first two weeks of the quarter, and bad news on a Monday and to a lesser extent on Friday. This clearly does not totally solve the issue of the relative Monday decline, as investors would have to fully incorporate the bad Friday news into their sell orders, but then further react instantly to the other bad news on Monday. As news tends to be released outside trading hours this induces some problems.

Damodaran integrates the two strands of argument above, testing for the joint hypothesis that bad news is released after trading hours, specifically after Friday close, and that there is a processing delay. He studied 30,000 dividend and earnings reports over a four-year period. The data were for all firms that COMPUSTAT listed continuously from 1981 to 1985. Damodaran admits the possibility that survivorship bias may be important. Deleted firms that were so due to being bankrupt by definition have released bad news. Their exclusion therefore biases the study against finding that firms delay bad news until the weekend. Damodaran looks not just at the stock price effect but also at Earnings per share and Dividend per share surprises[51]. He finds that earnings and dividend announcements on Fridays are more likely to be bad news (show declines) than announcements on any other day. He also finds that abnormal returns are negative not only on the announcement day (Friday) but also strongly & significantly, on the following day (Monday). Comparing the Weekend effect with and without Friday announcements shows that the Friday announcements explain only a small proportion of the effect, 3.4% according to Damodaran.

Aggarwal and Schatzberg (1997) examine the potential role that the pattern of earning and dividend announcements may have in explaining daily seasonality. They investigate the possibility that the release of information affects the higher order moments (specifically kurtosis) and the mean returns of securities. They find that, consistent with. Peterson and Damodaran most information (earnings or dividends) is released in the middle of the week, with up to twice as many announcements being made on each Tuesday-Wednesday-Thursday than on Monday or Friday. Nor is there a distinct pattern as to 'good' or 'bad' news being release on Monday or Friday. Consequently, the release of significant information on these days would not seem to be a likely contender for a cause of daily seasonality.

Peterson (1990) looks at the issue of announcement induced daily seasonality via another method. His contention is that if announcements induce seasonality, then indices composed of firms that announce results on any given day should show stronger seasonality than indices of firms not reporting on that day. His study takes in all firms reporting on the NYSE or the AMEX over the period 1980-1986, and indicates that

[51] These are defined not as the residuals or forecast errors from a formal model but rather simply as the percentage change from quarter to quarter.

there is no discernible difference between reporting period indices and non-reporting period indices. He thus concludes that earnings announcements cannot be a full explanation for daily seasonality.

A study by Defusco, Mccabe and Yook (1993) also looks at the issue of information timing. Analysing stock returns around a 20-day window centred on the board meeting of a company, they find that the Monday return in this high news potential period is more negative, while other days tend to be more positive than during lower news potential periods. This is consistent with firms releasing bad news over a weekend.

A further branch of investigation related to firm specific news has examined the potential problem caused by omission of dividends from the indices examined. For the most part, studies have used return data generated from prices. This implicitly assumes that the daily dividend component is small, relative to the price. If however Monday were to be the preferred day for companies to go ex-dividend (the process by which a date is set, shareholders registering thereafter being ineligible for payment of the next dividend), then there would be a perfectly simple explanation for the relative decline. Phillips-Patrick and Schneeweis (1988) examine this; they adjust the CRSP indices for dividends, and find the Weekend effect almost disappears. Branch and Echevarria (1991) extend this analysis, finding that stocks that go ex-dividend on Monday do not exhibit a strong Weekend effect. Schatzberg and Datta (1992) examined 138,824 dividend announcements made from 3484 firms over 26 years. Their findings, akin to those of Aggarwal and Schatzberg (1997) were that dividend announcements were more than twice as likely on Tuesday-Wednesday-Thursday than on Monday or Friday. Thus, they find no support for the contention that information releases drive daily seasonality. Corhay (1991) finds that 40% of dividend distribution for firms quoted on the Brussels stock exchange takes place on Tuesday, but although a negative Tuesday return had been found, with which a dividend distribution of Tuesday would be consistent, dividend adjustment could not completely eliminate the daily seasonal. For Australia, Japan, Canada, USA and UK, Chang, Pinegar and Ravichandran (1993) dismiss the role of information release, as do Yadav and Pope (1992) for the UK.

Again, the role of information release, especially the microeconomic release, is only at best a partial explanation for the daily seasonal. While the microeconomic information release hypotheses are founded on the supposition (unproven) that firms release bad news on the weekend and thus are a particular explanation for the US pattern, the macroeconomic release hypothesis is potentially more general. It is not linked to any individual market or indeed any individual asset, and indeed has the potential to provide an explanation congruent with any given pattern of daily seasonality.

4.5. Psychological Factors

A final set of papers examines whether human psychological traits can be invoked to explain the Monday effect. Rystrom and Benson (1989) report that the psychology literature supports the contention that investors' perceptions differ systematically over days of the week. They hypothesise that this may lead investors to conclude that their market situation is poorer on Monday than it really is, thus triggering a desire to sell. However, a problem with this is that we have seen that for individual investors at least these sell decisions may be made over the weekend. However, the psychological evidence in Rystrom and Benson indicates that perceptions are over-optimistic on weekends. Thus, an argument can be made equally as strongly that the investors would have a desire to purchase on Monday. However, this is inconsistent with the facts that individual investors are net sellers of equities on Monday. Coursey and Dyl (1990) construct an artificial, or experimental market. They report that this is essentially the same as that constructed in a previous experiment, wherein they found.

> *"..patterns of price disturbances associated with trading interruptions that were very similar to the so-called weekend effect" p347*

Unfortunately, the 1990 paper does not go further into detail than this. A further experimental market is discussed in Pettengill (1993). Analysing the portfolio allocations (among investments with different levels of risk and return) of the participants in an artificial market, he finds lower levels of allocation to riskier securities (equities in this market) on Mondays compared to all other days, *ceteris paribus*.

A recent work by Kamstra, Kramer and Levi (2000) investigates a further potential psychological basis for the weekend effect. They point out that the changes in human sleep patterns concomitant on moving to and fom daylight savings time have well known deleterious effects. As these changes occur over a weekend, they posit that the Mondays immediately after these changes may be unusually negative. This is found to be so, with the 'daylight savings' effect being fo und (in the USA, UK and Germany) to be several hundred percent the weekend effect. Allowing for this however does not fully remove the effect.

A more recent survey of psychology and asset pricing Hirshleifer (2001), has a major study on non calendar regularities and 'anomalies'. While he sees great potential for psychologically based explanations of these, the paper has little if anything to say about calendar regularities.

5. Anomalous Returns Around Market Closings: Holiday Effects

A final category of calendar regularity, the Holiday effect, is one of the more perplexing, persistent and important, with one study (Lakonishok and Smidt (1988)) attributing fully 50% of the cumulative change over a century in the Dow Jones to returns on days preceding holidays.

Despite its importance, there is a lack of research relative to the daily and monthly seasonal. Like them, it is neither a newly discovered or newly arrived anomaly. The Holiday, or more correctly, the pre-holiday effect, refers to the fact that share returns exhibit consistent patterns around holidays, with high and consistent returns on days before major holidays. Holidays in this literature includes what are commonly seen as holidays, such as public holidays, and also exchange closing days, where although general economic activity continues the stock exchange is not open for business[52]. Initially examined in the context of the US, there is a body of evidence that the holiday effect, like the January and weekend effects, is international. This precludes the possibility of it reflecting the idiosyncratic market characteristics of any one exchange. As will become evident from the literature, the pre-holiday effect is not a reflection of the weekend/Monday regularity. While in many countries holidays fall predominantly on Monday, this is not universally the case.

One striking characteristic of the literature is that exposition rather than explanation dominates. Whereas we have seen that there exist well-grounded testable theoretical explanations for monthly and daily regularities, there has been little if any effort made

[52] A good example of exchange holidays is Wednesdays in 1968 when the New York Stock Exchange closed to allow for back office processing backlogs be cleared).

to formulate explanations for the holiday anomaly and even less in testing these. There are exceptions to this rule, notably Pettengill (1989), Ariel (1990) and Fabozzi, Ma and Briley (1994). The theoretical issues raised by these form the basis for work to the present day.

5.1. US Evidence On The Holiday Effect

Like the daily seasonal, the evidence on the preholiday regularity is not new. Fields (1934) finds a disproportionally large ratio of advances to declines in the Dow Jones on days prior to long weekends. His dataset comprised daily returns from 1901 to 1932. Other works addressing pre-holiday returns prior to the middle '80's include works by Merrill (1966), Fosback (1976) & Hirsch (1986). These three books, by market participants, discuss well known market pattern-recognition behaviour, noting among these that stocks returns prior to the major US holidays are predominantly positive and abnormally highly so[53].

In the academic literature on stock returns, early contributions include Lakonishok and Smidt (1988), Pettengill (1989) and Ariel (1990). Lakonishok & Smidt examine a wide range of regularities, the preholiday regularity among these. They do not count the special 1968 Wednesday closings as a holiday, nor do they note which days are counted, stating only that they count a holiday as any day when trading would normally have occurred but did not. Looking at a ninety-year dataset (the Dow Jones Industrial average from Jan 4 1897 to June 11 1986) they find that the average pre-holiday daily return is 0.22% (the average post-holiday return being somewhat smaller at -0.017%) compared to 0.0094% for other days. 63.9% of pre-holiday days show positive returns.

[53] Fosback indicates that a strategy of holding stocks for the two days prior to recurrent holidays yields a cumulative return of 800% over a 50-year period.

This statistically significant difference persists across all sub-samples examined. They note that one can attribute fully 50% of the cumulative change in the Dow Jones to returns on days preceding holidays. Lakonishok and Smidt posit that there is a different causal mechanism as between weekend and holiday returns. This they deduce from the observation that although the two sets of returns share a characteristic that the exchange is closed, the pre-holiday returns are between two and five times larger than pre-weekend returns. Thus they posit that an additional factor is at work on the days preceding holiday that is not there on the days preceding weekend closings.

Pettengill examines a smaller dataset (S&P 500 and a CRSP small firm index, July 1962 – December 1986) but in greater detail than Lakonishok & Smidt. He confirms that a small firm effect is present in the holiday return, with the small stock index showing more pronouncedly anomalous pre-holiday returns. He finds that small firms show an average pre-holiday return of 0.46%, large firms 0.26%, as opposed to 0.066% and 0.018% respectively for non-holiday trading. Further partitioning the dataset by day of the week reveals that the increased return achieved on pre-holiday days persists across days of the week. Pettengill states, without going into detail, that while the returns vary according to the holiday under examination, in general every holiday, regardless of firm size, exhibits the anomaly. Only for one holiday (Presidents Day) and for large firms is the average return for the trading day preceding below the average for all trading days. Also reported is that 24 of the 30 stocks that comprise the Dow Jones Industrial Average show a statistically significant pre-holiday return.

Pettengill adduces two explanations for the holiday effect. The first is an application of the calendar time hypothesis of French (1980). This states that price information is generated continually across all days, regardless of trading or otherwise. Consequently, Pettengill's test is whether the post holiday returns encompass returns for a two-day period. Comparing the post holiday return for any weekday with the average two-day accumulated return for the two relevant days, Pettengill cannot validate the time diffusion hypothesis. A problem with the time diffusion hypothesis however is that while it offers a convincing, albeit not empirically validated, mechanism, it in reality addresses the post holiday as opposed to the pre-holiday return. A body of evidence exists that indicates that the last trading period prior to closing tends to have high returns. Examples include Jaffe and Westerfield (1985) and Keim and Stambaugh (1984) in relation to the last trading day of the week, and Harris (1986) on intra-day data. If this is the case then non-holiday related closings should be observationally equivalent to holiday closing. Pettengill examines the 1968 special closes of the NYSE, finding that the pre-closing returns are statistically significantly different to, and lower than, public holiday closings.

Further evidence against the closing effect is the fact that holidays with no associated market closings exhibit significant returns. Fosback (1976) indicates that St Patrick's Day, and Pettengill (1989) that Rosh Hashanah (a major Jewish holiday ending in Yom Kippur) are associated with significant rises on the New York Stock Exchange[54].

Ariel (1990) presents very similar results to Lakonishok & Smidt and Pettengill. He examines the 1963-1982 period. Looking at the same holiday set as Pettengill, the eight regular US public holidays that are associated with stock market closings, he finds that the average return pre-holiday is 0.528% (equally weighted CRSP index) and 0.364% (value weighted CRSP index) as opposed to 0.059% and 0.026% respectively. In terms of proportions of advances and declines, the situation is even starker. Pre-holiday

[54] Given the high proportion of New York inhabitants who are of Irish or Jewish descent this is an interesting result.

trading days that are positive are 85.6% (in the equally weighted index) and 75% (in the value weighted index) as opposed to 55.8% and 53.8% of days positive for non-holiday returns. Ariel finds that 34.7% of the cumulative returns over the period are attributable to the 3% of days that precede holidays. These differences persist across sub-samples, and, like Pettengill, Ariel finds that while different holidays have different returns there is a statistically valid assumption of homogeneity in the returns for holidays. Standard t and non-parametric Mann-Whitney tests indicate, that these differences in mean returns are statistically significant. Ariel explicitly tests and rejects the hypothesis that the holiday regularity is driven by monthly or daily seasonality. He also rejects the hypothesis that this is a small firm effect, while accepting that small firm portfolios do show higher but statistically insignificant pre-holiday returns[55]. This is in contrast to Pettengill. The size issue is unresolved however, as Brockman and Michayluk (1997) draw upon the work of Bhardwaj and Brooks (1992) to test for the effect of share price as opposed to firm size. They find that, correcting for weekend and January, price is at least as important as size in explaining returns pre holidays.

Recent work by Brockman (1995) and Brockman and Michayluk (1997, (1998)) demonstrates the resilience of the holiday effect, showing its persistence across market types (auction v dealer) and size portfolios. Brockman and Michayluk (1997) extend the Kim and Park (1994) US analysis from 1986 to end 1993. Partitioning by price and separately by firm size they find that they duplicate the Kim & Park findings of a holiday effect, and that this continues in the 1987-1993 period. This finding is robust to adjustment for monthly seasonality. Although not tested formally, they show that there

[55] Without testing, he states that the 'clientele' hypothesis, that there exist classes of stock market participants that preferentially avoid (or seek out) holidays, is consistent with the data.

is a tendency for the holiday effect to be concentrated in the smaller / lower priced portfolios.

Financial assets other than stocks show preholiday effects. Fabozzi, Ma and Briley (1994) examine the futures market. They demonstrate a significantly higher return pre-holiday compared to other days. This is confined mainly however to domestic (US) exchange closed holidays, as opposed to exchange open public holidays or international holidays. They also see lower trading volume before exchange-closed holidays. They hypothesise that this may be due to inventory adjustments. Traders may be more reluctant to take a short position before a non-trading period. This would be consistent with reduced downward pressure (increased returns) and depressed volumes.

5.2. INTERNATIONAL EVIDENCE ON THE HOLIDAY EFFECT

International evidence indicates that the holiday effect, like other calendar regularities examined, is found worldwide.

Cadsby and Ratner (1992) examine the Canadian, Japanese, Italy, French, German, UK, Australian, Swiss and Hong Kong markets. They find that pre-holiday effects are evident for US, Canada, Japan, Australia, and Hong Kong. Unlike later studies, UK returns (here the FT-500 from 83 to 88) do not exhibit a holiday effect. Perhaps the main contribution of this paper, one that is later confirmed by Kim and Park, is that the holiday effects, where they exist, appear to be local phenomena. They are not reflections of the US, with the possible exception of the Hong Kong Market. There is some evidence that joint Local / US holidays exhibit higher returns.

Kim and Park (1994) examine the NYSE, NASDAQ and AMEX markets, the S& P 500 index as well as the UK (FT-30) and Japan (Nikkei-Dow). For the US, their dataset is 1963 (start of the CRSP dataset) to end 1986. For Japan and the UK, the data extend from 1972 to June 1987, with the S&P 500 index also examined over the same period. Kim & Park confirm the Cadsby & Ratner finding that non-US holiday regularities are not reflections of the US experience. The holiday returns experiences of the countries analysed are independent of the US. They also test the closing effect hypothesis national and exchange holiday closings for Japan. They find, consistent with Pettengill, that national holiday closings have a greater effect than exchange holiday closings. Further Japanese evidence comes from a study on Japanese ADR's by Fatemi and Park (1996). Although not statistically significant, the preholiday returns on these ADR's are consistent with the general stock return evidence. Returns on days before US or Japanese holidays are greater than on other days, with the greatest returns coming on days before common Japanese and US holidays. It is anomalous that there should be returns on the ADR's that are high before Japanese holidays, as these are not US holidays and are days on which there are no trades on the underlying (Japanese based) stocks.

Agrawal and Tandon (1994) examine stock returns in 18 countries (Australia, Belgium, Brazil, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Singapore, Sweden, Switzerland, the USA and the g) over the 1970's and 80's. They concentrate on the pre Christmas and pre new year holiday period, finding that the pre-holiday returns are significantly higher than the average daily return in eleven of the eighteen countries. Only New Zealand shows a pre Christmas holiday decline while only Brazil shows a pre New Year holiday decline.

Barone (1990) finds that the Italian stock market exhibits a strong pre-holiday effect, with an average return of 0.27% versus an average non-holiday return of -0.01%. He also shows that this is not risk related, as the standard deviation of these pre-holiday returns is lower than that of other days.

Lauterbach and Ungar (1991, (1992) examine Israeli stock market data. Examining data from 1977 to 1990, they find a statistical significant difference between the post holiday and other daily return.[56] This result is unusual; the majority of the evidence is that the post-holiday return is lower than the pre-holiday, sometimes negative. This result is however consistent with that found in Asian markets by Lee, Pettit and Swankoski (1990) and for Sri Lanka by Elyasiani, Perera and Puri (1996). A larger scale study of south east Asian stock market data was undertaken by Chan, Khanthavit and Thomas (1996). Malaysia, India, Singapore and Thailand provide a large set of local, religious and worldwide holidays. In addition, the degree of internationalisation of the markets varies from India at the lowest level to Singapore at the highest. They find that while state and cultural holidays both show, in general, positive pre-holiday returns, the effects of cultural holiday are stronger. Arsad and Coutts (1997) have found evidence of a significant and positive pre-holiday effect in the UK, in support of the evidence found by Mills and Coutts (1995). Arsad and Coutts reject the closing effect argument as an explanation of the holiday effect. No published work exists examining the holiday effect for the Irish market.

[56] They find a pre-holiday return of .296%, a post-holiday return of .587%, with all other days showing a return of .256%. There is

6. The Irish Stock Market

6.1. Early Beginnings And History To 1990's

An excellent account of the development and growth of the Irish stock exchanges to the early 1980's is found in Thomas (1986).

The Irish Stock exchange was first formed in 1793. Prior to this, control of all Irish governmental expenditure rested with the British exchequer. The passing of the *Consolidation Funds Act* of 1793 transferred this responsibility to the Commons of the Irish Parliament. The parliament then adopted a contractor system akin to that then existing in London to regulate and administer the large number of debenture and loan stocks outstanding. The *Act for the Better Regulation of Stock Brokers* of 1799 (one of the last acts of the Irish Parliament prior to the Act of Union of 1800) stipulated licence requirements and schedules of charges chargeable by stockbrokers.

Initially housed in a coffee house, the Exchange moved to Commercial Buildings and finally to a purpose built building incorporating trading floors in 1878. This building in Anglesea Street still serves as the home of the Stock Exchange. In 1886 the Cork Stock exchange was formed along similar lines to that of the Dublin Stock Exchange. Belfast also had an exchange by 1897, and a number of brokers in other Irish towns operated as part of The Provincial Brokers Stock Exchange (PBSE).

Activity in equities was limited in the early years, with only Bank of Ireland and two canal companies stocks being listed in 1799. Over the ensuing quarter century the numbers of equities quoted remained small, until the advent of railway construction from 1825 on requiring much larger sums of capital than would have heretofore been the norm. The collapse of the railway shares boom of 1843-45 depressed the market, a slump that lasted to mid-century. The *Joint Stock Companies Act* of 1856 and the *Companies Act* of 1862, which introduced and codified limited liability and facilitated the easy trading of shares in enterprises prompted a surge in company formation in Ireland, centring on finance and public utility companies initially, thereafter brewing, hotel and leisure, distribution and transport related enterprises. By 1880 economic recovery was in full flight and the stock exchange witnessed a large number of larger enterprises seeking quotations with substantial funds raised.

The first decade and a half of the 20th century witnessed increasing prosperity and this was reflected in the stock exchange. The economic dislocation which resulted from 3 years of war with the UK, 2 years of civil war thereafter, partition and emigration (sometimes forced) of many industrialists left the economy and the stock exchange weak, the exchange losing 20%p. a. of its value in the 1922-1926 period. Autarkic economic policies, the Great Depression and WWII ensured that by the 1950's, Ireland was impoverished, its population in decline and its stock market, despite occasional short-lived booms, was not an attractive source of investible funds nor an attractive investment for shareholders.

Changes in government thinking and a focus on international trade and inward investment began in the early 1960's, with the economy beginning to grow rapidly thought the period leading to the first oil crisis of 1973.

The entry to the EEC (sic) in 1973 marked a major turning point in Irish economic and financial activities. It also, coincidentally, marked the culmination of a process of integration and consolidation in stock exchanges.

Throughout its history substantial collaboration had been evident between the London and Dublin exchanges. 1965 saw the formation of the Federation of Stock Exchanges in Great Britain and Ireland, with the (successfully realised) aim of harmonising, streamlining and making more efficient issues such as membership criteria, settlement procedures and quotation requirements. In 1971 the Cork and Dublin Exchanges amalgamated and admitted the members who had been trading as part of the PBSE, creating the Irish Stock Exchange. In 1973 the Federation was admitted to membership of what was then called the International Stock Exchange of Great Britain and the Republic of Ireland (ltd). Membership was highly attractive, as apart from being then the largest organised market in the EEC, non membership would have resulted in Irish brokers being forced to trade as outside members and thus losing many concessions and ultimately trade.

The Dublin exchange retained effective independence, some essential differences persisting. Thus, while London employed single capacity membership, Dublin allowed for broker-broker transactions. The difference has persisted, the Irish market remaining quote driven while the London market has become essentially order driven with market makers. No market makers in equities exist in the Dublin system.

Throughout the 1970's and 80's the number of member firms in the Dublin market continued to consolidate, with 4 main players (National City Brokers, J&E Davy, Riada and Goodbody) dominating the trade.

The exchange continued to grow in volume over this period. The breaking of the parity linkage between the Irish Punt and the Pound Sterling in 1979 stimulated much of this growth. The consequent introduction of exchange controls made it relatively more attractive to invest in and raise funds from the Irish exchange than from London. Much of this growth however was in the form of government-gilt trades rather than equity issues or trading.

6.2. THE 1990'S, RELATIVE PERFORMANCE AND HISTORY

Clearly, having two countries with separate legal establishments and divergent traditions and rules, especially in the area of company law and take-overs, with but a single exchange for equities carried with it potential for confusion and uncertainty. The Company Act (Part 5) 1990 provided the Irish Stock Exchange with powers of self regulation (removing this from the ambit of the regulatory regimen set in place by the Financial Services Act 1986). In conjunction with the Central Bank of Ireland, the Department of Industry and Commerce (sic) and the Department of Finance, the Irish Stock Exchange set up the Capital Markets Advisory Group. This provided both a forum for exchange of views relating to the new regulatory regimen and provided a core basis of agreed practice for the implementation of the provisions of the then forthcoming EU investment services directive

The adoption of the Investment Services Directive and its implementation in Ireland as the Stock Exchange Act 1995 transferred regulation from the self-regulation described above to the formal regulation of the Central Bank of Ireland. Since the introduction of Central Bank regulation, it is interesting to note that whereas from 1965 to 1995 only one stock exchange member firm was found to be in default, a Cork based company which was unable to meet its obligations in the late 1970's, since 1995 the imposition of sanctions and direct regulatory control has been more frequent. Thus, MMI stockbrokers were suspended and subsequently liquidated while two smaller brokers, FEXCO and BCP, specialising in execution only trading, were instructed by the Central

Bank to cease taking new business for a period of time during which they were required to enhance their back office procedures.

During the latter half of the 1990's, and especially from 1998 onwards, the issue of electronic trading versus the traditional floor method used became a topic of considerable concern to Irish market participants. This issue seems to have been resolved with a decision by the Irish exchange to participate in the XETRA system of the Frankfurt Bourse as of mid 2000. Further details on this are contained in the section on trading and execution

The level of listing activity on the market during the 1990's was low, with only 4 companies obtaining a full listing on the official list between 1990 and 1996 (Golden Vale, Irish Life, DCC and Irish Permanent)

Table 3 below indicates the relative performance of the Irish market against a number of benchmark indices over the last number of decades. As can be seen, the overall performance has been impressive. The Irish stock market is represented by the Central Statistics Office Month End Share Price Index, which, at a monthly level, is the data series with the longest run of availability, being a consistent series from 1933 to present.

TABLE 3: IRELAND, THE UK AND THE USA: RELATIVE PERFORMANCE, LOCAL CURRENCY, OF SELECTED STOCK INDICES; JANUARY 1970-DECEMBER 1998

Average annual return by decade	Ireland	USA: S&P 500	USA: DJIA	UK: FTA	UK: FT30
1970-1998	8.35%	7.28%	6.63%	7.81%	5.30%
1970-1979	4.94%	0.26%	-1.28%	2.23%	-2.02%
1980-1989	13.22%	10.96%	10.69%	14.83%	13.32%
1990-1998	6.74%	11.00%	10.91%	6.22%	4.51%
Standard Deviation of returns by decade	Ireland	USA: S&P 500	USA: DJIA	UK: FTA	UK: FT30
1970-1998	0.286	0.149	0.153	0.258	0.248
1970-1979	0.377	0.177	0.188	0.408	0.392
1980-1989	0.200	0.109	0.115	0.092	0.079
1990-1998	0.238	0.121	0.105	0.107	0.088

A number of lessons can be drawn from this long-term performance.

First, over the period January 1970 – December 1998, an investor (in local currency terms) would have achieved a superior return in the Irish market compared to an investment designed to mirror the major market indices in the USA (DJIA or S&P 500) or the UK (FTA or FT30).

Second, this has been achieved partially perhaps due to the higher risk associated with the Irish market, as evidenced by the higher standard deviations associated with the Irish market. This relative strength has not survived entry into EMU however, with Irish markets falling in 1999, against a trend worldwide of a continuing bull market. A number of factors conspired to produce this: The Irish exchange has not reached the importance in the national economy of other exchanges. Details in Table 8 indicate that in terms of importance in the economy as measured by total market capitalisation %GDP, it shares an intermediate position along with nations such as Belgium, Finland, Australia and France, but ahead of other countries such as Germany and Austria and Portugal. At end 1998, the market capitalisation to GDP ratio stood at 67%. This is well below figures for the USA, the UK and Sweden.

The Irish market, with a market capitalisation of $67b at end 1998 was the 30th largest in the world and the 14th largest in the Europe–Middle East–Africa time zone. Thus, while extremely small in absolute terms, it is not insignificant internationally. Indeed, the market capitalisation at end 1998 was larger than Lisbon, Oslo or Vienna.

6.3. Organisation Of The Exchange

6.3.1. Markets And Listing

The number of separate levels at which a listing could take place on the Irish market reached a peak in 1994-5, with 5 separate levels.

The Official List: this is the highest level of listing, with the most stringent level of listing requirements. The stringency of these requirements, the perception that the Irish exchange was particularly rigid in their application, along with the costs of listing led to a decline in the number of companies listed on this market from the mid 1960's. The number halved between 1965 and 1975, stabilising thereafter at around 60-70 companies. As already pointed out the level of listing in the early 1990s was low From 1997 to 1999 5 companies (Ryanair, Marlborough, Donegal Creameries, Iona Technologies, Athlone Extrusions and Viridain) listed on the official list, nearly as many as in the previous 6 years.

The Unlisted Securities Market (USM): This was launched in London in 1980, and therefore also in Dublin[57]. This was designed with a the major aim of being both a bridge between and an intermediate market to the then existing rule 4.2 and Official

[57] The Irish exchange at that time being an element of the International Stock Exchange of Great Britain and the Republic of Ireland (ltd),

List. Despite high hopes for this market it met with little success. After an initial flush of enthusiasm, with listing rising in London to 103 in 1988, the market declined. In Dublin, only 15 companies were members of the USM by 1995. In December 1995, the USM closed, with companies allowed to move to either the Rule 4.2 or Official Lists.

Rule 4.2/ Third Market: No Irish companies had taken the rule 4.2 route. The Alternative Investment Market has now essentially replaced this market. A small number of companies had operated on the Third Market, since its time as Rule 535.3. These however transferred to the Exploration Securities Market on its inception in 1991

Smaller Companies Market (SCM): launched in 1986 this market was unique to Ireland. The aim was to foster a flow of investible capital to smaller, indigenous companies. With less stringent rules again than the USM it was expected that there would be great interest in this market among corporates seeking funds. This did not materialise however, with only eight companies taking a listing.

Exploration Securities Market: The 1970's and 80's saw a large number of minerals and petroleum exploration companies formed in Ireland. Requiring large sums of capital but being unsuitable for listing on any of the existing markets, a separate set of regulations was put in place from with rules similar to the Rule 4.2 market. This market reached a peak in 1994 with 13 listings. The 'crisis' in smaller equity trading manifested in the problems experienced by the USM and the SCM, in Dublin and London, was partially alleviated by the creation of the Alternative Investment Market. In parallel with this, the Irish exchange created the Developing Companies Market.

Developing Companies Market: started in January 1997 this market carried the possibility of companies having a dual AIM/DCM listing. This market has not proven popular, at the time of writing having only 5 listings, all companies with a dual AIM/DCM listing. These companies were as of end 1999 ITG, BCO, Rapid Technologies, Pan-Andean Resources and African Gold. Two companies transferred from the DCM to the Official list, Ryanair and Marlborough.

In addition to listing domestic firms, equity trading in Dublin also takes place on Northern Ireland registered companies, and a number of UK companies with larger operations in Ireland, such as Tesco, Guinness and Ashquay. Very little trading in the shares of these companies actually takes place.

Clearly, there has been a relative failure on the part of the Irish Stock Exchange in terms of attracting small companies to listing. A number of for a and reports have debated this issue. The most recent was a report on the strategic development of the Irish market, produced by a former president of the exchange. According to Bacon Associates (1999) section 4, the main elements that have led to this failure can be summarized as

- The preponderance of family ownership among Irish SME's, with consequent lack of familiarity with and perhaps suspicion of third party and external shareholders.;
- A general perception of the regulatory and disclosure requirements of an exchange listing as being oppressive and onerous;
- A perception of lower than fair value for small companies, consequent on the small weight of the Irish market in international terms. This of course rapidly becomes a vicious circle of self-fulfilling prophecies. Coupled with an increasing shift in the makeup of the economy towards high-tech and IT based businesses, the attractiveness of a NASDAQ flotation in particular, as opposed

to a floatation on the Irish market with its lack of familiarity regarding these company types, this has accelerated in the latter half of the 1990's.

- The relatively lack, until the mid 1970's at earliest, of indigenous companies sufficiently large to actually warrant a listing. This implies that the current ownership structure is predominantly first or second generation. Tax provisions relating to quoted and unquoted shares act as a disincentive.

- Inherited family businesses must be held for a minimum of 6 years to avail of relief from Capital Gains and Capital Acquisitions Tax. This acts as a bar on rapid floatation of larger family businesses, even with the widening of ownership bases that typically accompanies intergenerational transfers.

Table 4, Table 5 & Table 6 provide some detail on the stock market over the 1990's. The most striking feature is the relative stability of the largest firms, with much the same companies dominating in 1998 as had done in 1990. Another feature immediately evident is that the concentration of top companies in terms of market capitalization has increased over the decade. Also evident is the relative stagnation of the exchange in terms of both money raised and number of companies.

TABLE 4: TOP 15 COMPANIES BY MARKET CAPITALISATION, 1990, 1994 & 1998.

Rank	Company 1990	Market Capitalisation 1990	Company 1994	Market Capitalisation 1994	Company 1998	Market Capitalisation 1998
1	Smurfit	1088	Allied Irish Banks	2007	Allied Irish Banks	10,324
2	Allied Irish Banks	975	Smurfit	1497	Bank of Ireland	7,683
3	CRH	641	Bank of Ireland	1428	Irish Life	2,009
4	Bank of Ireland	556	CRH	1311	Irish Permanent	950
5	Fyffes	273	Elan Corporation	949	Elan Corporation	6,109
6	Woodchester Investments	261	Irish Life	672	CRH	4,476
7	Elan Corporation	171	Kerry Group	442	Kerry Group	1,573
8	James Crean	168	Independent	353	Smurfit	1,307
9	Waterford Glass	148	Waterford Glass	330	Ryanair	803
10	Power Corporation	145	Woodchester	312	Independent Group	672
11	PJ Carroll	114	Greencore	293	AWG	611
12	Clondalkin Group	93	Fyffes	292	Greencore	593
13	Independent	90	Golden Vale	170	Fyffes	509
14	Fitzwilton	88	Hibernian Group	124	First Active	461
15	Golden Vale	85	IWP	124	Waterford Group	419
Top 5 % Concentration		56%		59%		58%
Top 10 % Concentration		70%		76%		77%
Top 15 % Concentration		77%		84%		82%
All Shares		6339		12228		46707

All Data End December, All Data £M

TABLE 5: NUMBER OF COMPANIES BY LISTING TYPE, IRISH STOCK EXCHANGE

Listing Level	1990	1992	1994	1996	1998
The Official List:	59	61	62	61	65
The Unlisted Securities Market (USM):	25	18	13	1	
Smaller Companies Market (SCM)	6	4	3	1	
Exploration Securities Market (ESM)		13	13	13	11
Developing Companies Market (DCM)					3
Third Market / Rule 4.2	12				

Source: Irish Stock Exchange Annual Reports; All Data End December.

TABLE 6: TURNOVER AND MONEY RAISED

	1990	1992	1994	1996	1998
Turnover	3460	3266	6012	7318	58358
Money Raised (New issues and Seasoned Equity Offerings)	736	234	879	921	938

Source: Irish Stock Exchange Annual Reports

6.3.2. TURNOVER AND MARKET CONCENTRATIONS

The Irish market has also shown substantial concentration of market capitalisation and turnover, a trend that has increased over the 1990's.

With few exceptions, turnover concentrations follow the pattern of market capitalisation. The relationship is not one-one, as typically there tends to be a high degree of turnover in companies quoted on the Exploration Companies Market. Stripping these out, the relationship between overall annual rankings in terms of turnover and market capitalisation is much closer.

While these concentration ratios are high, comparing especially unfavourably to the UK[58], they are not especially out of line with the majority of other EU exchanges. Table 7 and Table 8 indicate that the Irish market ranks in about the middle tier in terms of concentration by turnover and by market value. Note that the data in Table 7 differ from the data in Table 4 due to differences in calculation. The trends are however clear.

[58] Compare for example the FTSE-100 top 10 concentration level of 32% at end 1998

TABLE 7: MARKET CAPITALISATION AND SHARE TURNOVER CONCENTRATION 1998.

Time zone	Exchange	% Of Market Capitalisation of top 5% of companies	% Of Turnover attributable to top 5% of companies			% Of Market Capitalisation of top 5% of companies	% Of Turnover attributable to top 5% of companies
North America	American	63.2	NA	Europe, Africa	Amsterdam	73.3	67.1
	Chicago	44.2	NA	Middle East	Athens	62.8	50.1
	Mexico	50.2	63.2		Barcelona	63.7	82.1
	Montreal	38.8	37.5		Bilbao	65.7	82.4
	NASDAQ	75.2	78.8		Brussels	56.5	54.9
	NYSE	63.8	51.4		Copenhagen	69.1	67.4
	Toronto	67.7	48.3		Deutsche Börse	77.8	85.5
	Vancouver	41.8	63.9		Helsinki	47.7	55.7
					Irish	64.2	60.6
South	Buenos Aires	67.5	75.6		Istanbul	54.9	NA
America	Lima	69.3	74.3		Italy	59.6	60.0
	Rio de Janeiro	43.7	18.8		Johannesburg	62.8	53.3
	Santiago	51.7	65.5		Lisbon	52.8	59.9
	Sao Paulo	60.8	73.4		Ljubljana	53.3	65.0
					London	80.7	59.8
Asia, Pacific	Australian	77.4	83.6		Luxembourg	33.1	61.9
	Colombo	42.5	32.3		Madrid	66.9	93.5
	Hong Kong	81.4	76.6		Oslo	55.7	49.2
	Jakarta	67.4	63.5		Paris	68.6	63.4
	Korea	67.5	50.5		Stockholm	64.0	72.7
	Kuala Lumpur	54.9	59.7		Switzerland	82.3	72.1
	New Zealand	55.8	68.4		Tehran	41.6	67.9
	Osaka	57.8	79.7		Tel-Aviv	63.9	72.2
	Philippine	63.2	47.8		Vienna	36.7	44.4
	Singapore	67.1	43.4		Warsaw	67.1	38.7
	Taiwan	33.5	NA				
	Thailand	64.5	49.0				
	Tokyo	58.1	62.0				

Source : International Federation of Stock Exchanges

TABLE 8: RELATIVE IMPORTANCE OF STOCK EXCHANGES 1998

	Country	Market Cap as % of GDP		Country	Market Cap as % of GDP
North	Canada	92%	Europe, Africa	Austria	18%
America	Mexico	39%	Middle East	Belgium	57%
	United States	133%		Denmark	55%
				Finland	61%
				France	49%
South	Argentina	20%		Germany	39%
America	Brazil	32%		Greece	28%
	Chile	93%		Iran	9%
	Peru	24%		Ireland	67%
				Israel	45%
Asia, Pacific	Australia	75%		Italy	30%
	Hong Kong	-		Luxembourg	229%
	Indonesia	14%		Netherlands	130%
	Japan	53%		Norway	43%
	Korea	9%		Poland	9%
	Malaysia	95%		Portugal	36%
	New Zealand	45%		Slovenia	10%
	Philippines	38%		South Africa	164%
	Singapore	113%		Spain	55%
	Sri Lanka	14%		Sweden	116%
	Taiwan	-		Switzerland	226%
	Thailand	19%		Turkey	-
				United Kingdom	155%

(Source: Federation International des bourses des Valour)

6.3.3. SETTLEMENT & EXECUTION

As a secondary as well as a primary market, liquidity is an essential prerequisite to successful operation of the Irish stock exchange. The structure of the market influences the ease with which the investor perceives that she can enter and leave the market. Having the ability to trade easily allays the fears of being caught holding a security that has deviated in price either from its perceived fundamental value or from the price prevailing at the time of the decision to trade. The form of the market has also implications regarding the method of execution.

Also known as auction markets, order driven markets exist in a number of forms. The auctioneer does not take positions in the commodity being traded, merely announces the prices at which clearing of the aggregated buying and selling orders can occur. The classic form of such markets is the Call Auction, where there exists a price-setting auctioneer who periodically announces these prices and thus facilitates clearing of the market. A batch auction market by contrast, such as the Milan bourse, has an auction for each commodity, in this case stock, at a different time for each commodity. A continual auction system allows continual clearing by permitting dealers, usually electronically, to execute their orders against the orders of other dealers placed in the system. These can be limit (dealing only in a certain price range) or market (best price) orders. Sequential execution occurs in these cases, earlier placed orders being executed prior to later placed orders.

In contrast, the quote driven market systems permit continual trading via a market maker. This is a specialist who takes positions in securities and quotes bid (prices at which securities will be purchased) and offer (prices at which securities are offered for sale) for each security. The bid/ask spread can be seen as the price of immediacy, offering the opportunity of certain dealing, albeit perhaps at an unfavourable price compared to what may be possible after a delay (but maybe also at a favourable price).

6.3.4. EXECUTION ON THE IRISH EXCHANGE

The Irish stock exchange, an auction or order driven market, lies between a continual and batch auction. Unlike the situation in the government bond (gilt) market, member firms have never been permitted to take positions in equities on their own behalf. Firms may take up to £2,000 worth of stock onto their own account for a private (non member firm) client when there is no matching deal available with another firm. This clearly improves the liquidity of smaller transactions, guaranteeing in effect that a small trade investor is able to trade. Effectively therefore market makers in individual stocks do not exist.

Over the 1990's the number of stockbroking firms licensed to operate by the relevant authorities has remained at or around a dozen firms. Of these, 4, J& E Davy, NCB, Goodbody and Riada are pre-eminent in equity trading. These have moved from private ownership to ownership by major retail banks as part of the banks move to provide full service banking. J & E Davy are owned by Bank of Ireland, Riada by ABN-AMBRO., Goodbody by Allied Irish Banks and NCB by Ulster Bank

The commissions charged by the Irish stockbrokers have historically been high[59]. Table 9 shows the commission rates charged as of Mid 1994. Despite the addition to the exchange of three new members since 1994, Dolmen Butler Brisco, FEXCO and TIR, with FEXCO operating primarily as an execution only dealer, there has not been either

[59] Source ; World Federation of Stock Exchanges

a reduction in charges nor a widening of differentials in charges. *Prima facia*, it seems that there is little price competition between Irish stockbrokers. Excluded from the table are a number of UK based institutions which are members of the stock exchange for the purpose of government gilt dealing, and which do not deal in equities.

TABLE 9: COMMISSION CHARGES OF IRISH STOCKBROKERS

Company	Minimum Commission £	Transactions up to £10,000	Next £10-20,000	Balance
BCP	£35	1.5%	1%	1%
Bloxham	£30	1.65%	1%	.5%
Campbell O'Connor	£15	1.65%	.55%	.5%
Davys	£30	1.65%	1%	.5%
Dolmen Butler Briscoe	£40	1.65%	1%	.5%
FEXCO	£15	1.65%	1%	.5%
Goodbody	£40	1.65%	1%	.5%
MMI	£40	1.65%	1%	.5%
Murrogh	£15	1.5%	1%	.5%
NCB	£40	1.65%	1.25%	.75%
Riada	£30	1.5%	1%	.5%
TIR	£35	1.5%	1%	.5%

Source: Finance Magazine, various issues.

Two forms of trade typically occur. The first is the normal trade, where the order is matched with another member firm. The second is a put-through, which is where a member firm is able to match a buying and selling client at the same price. This is permitted by the exchange only where there is no advantage to either client to be accrued by dealing with another firm. Special forms of Put-through, where the buyer and seller are the same, occur in the form of 'bed-and-breakfast' trades. These are used to allow investors to utilise their full capital gains allowance prior to the end of the tax year.

The market, as I have noted, falls between the continuous and batch auction. Brokers deal with one another over the telephone on a continuous basis, but the actual legal trades are executed on the floor of the stock exchange. There are two floor-trading sessions per day, 0930-1030 and 1415-1515. Each member firm is obliged to have a representative on the exchange floor at these sessions, and orders previously agreed by telephone are communicated to the floor representatives who then execute them. When a deal is struck the price is noted on a chalkboard. Orders thus filled are then communicated back to the member firms by a 'blower' system, a telephone based system over which the exchange clerk informs all members of the details of the deals made. Sequential execution of orders occurs.

In 1995 a book on financial management practices in Ireland was published(Kennedy, Maccormac and Teeling (1995)). The authors were an accounting professor with a background in financial services industries and two businessmen, both of whom had extensive experience as directors, chairmen and chief executives of Irish plc's

Writing in chapter 8 they state in relation to the batch auction element of the stock exchange they note: *"it is expected that this ancient method of marking deals will disappear in coming years"*. 6 years on from the writing of this quote the system remains in place. In January 2000 the Deutche Bourse and the Irish Stock Exchange agreed that Irish listed companies would be quoted as part of the XETRA system. This came into effect in June 2000.

6.3.5. Settlement

Settlement on the Irish Stock Exchange has mirrored that in place in the London exchange, for reasons that are obvious from the previous sections. In summary, the major methods and changes in settlement procedures are as laid out below.

Up to July 1994 the stock exchange operated an accounts settlement system. This has potentially important implications for the examination of daily seasonality. An account system can induce daily seasonality into a system.

Account settlement worked by dividing the year into twenty two two-week and two three-week account periods. Accounts began on Monday and ended on the Friday week (or fortnight). Settlement was effected on the second Monday (Settlement day) after the account period, 10 working days after the last day of the account. Purchasers had to provide funds and sellers stock in time for the stockbroker to settle on the settlement day. Buying and selling within the settlement period results in the investor only settling the net gain or loss on the settlement day, without any cash investment being made. An individual buying on the last day of a settlement period and selling at the end of the following Monday will pay for shares on the settlement day relating to the Friday and receive payment on the settlement day relating to the Monday. Thus, the investor will have to carry the cost of the transaction for two, or possibly three, weeks. Consequently, the first Monday of an account period would have inbuilt in it the greatest amount of implicit interest and thus the price on the Monday should be higher. Purchases made on the last day of an account period would have the shortest credit period. This implies that the first Monday of an account period should have a substantially higher return, rather than lower. Clearly, this would be in direct conflict with the typical pattern of a lower return on Monday compared to other days of the week. A number of papers, particularly Jaffe and Westerfield (1985),Condoyanni, O'hanlon and Ward (1987),Theobald and Price (1984) & Donnelly (1991) discuss the settlement effect. Generally the first Monday of the account period has a higher return than the other Mondays.

In July 1994 the exchange introduced a rolling settlement system, initially on a 10-day cycle. In July 1995 this moved to a 5-day cycle. All deals are settled, initially 10, and from July 1995, 5 working days after the deal are struck.

6.4. POLICY ISSUES AFFECTING THE STOCK EXCHANGE

A number of important policy elements unique to the Irish market are also worth noting. Over the 1990's the main policy issues that have had an impact on the equity market have been in relatio n to exchange controls and exchange rates, capital gains taxation, and other tax biases against equity trading.

6.4.1. EXCHANGE CONTROLS AND EXCHANGE RATES

Exchange controls were introduced in Ireland in 1979 following the entry in the European Monetary System and the consequent breaking of the parity link with sterling.

During the early and mid 1980's very large exchequer borrowing requirements and poor economic performance resulted in very few new issues of equity. As reported in Jones (1993) & Devine (1996), domestic institutional portfolios became overweight in fixed interest securities The consequent relative overvaluation of Irish equities, caused by the difficulty in investing outside the Irish pound zone, drove price/earnings ratios and dividend yields of Irish equities above international peers. The relaxation and subsequent removal of exchange controls in 1989 and 1991 led to a considerable bear market as money flowed out, pension and other funds readjusting their asset mix. Having risen nearly 50% from the 1987 crash to 1990, the market fell rapidly and consistently over the 1990-1993 period, ending up in a range not much above the 1987 low.

6.4.2. Capital Gains Tax

Capital gains tax was first introduced to Ireland in 1975. The Capital Gains Act made realised gains a taxable charge. No distinction was made between short-term and long-term holdings. This distinction was introduced in 1978, with reduced rates applying when the asset had been held for three or more years. The longer the holding period the lower the tax rate that would arise. This also introduced inflation adjustments. The capital tax regimen on equities was further changed in 1992 with the introduction of favourable treatment for realised gains on equities of small and medium sized companies where the shares had been held prior to listing. Further changes were made in the 1997 and 1998 budgets, reducing the capital gains tax to 20% from the 40% which had applied since 1978. Capital gains tax legislation is the same for companies (whose main business is not trading securities for profit) and individuals.

6.4.3. Other Tax Biases Against Equities

A number of other taxes bias have existed against investment in Irish equities.

- Stamp Duty. Stamp duty on purchases of Irish shares is 1%, while purchases of non-Irish quoted shares is 0.5%. This is a clear disincentive to trade on the Irish market, is a source of long standing disagreement between the investment community and the government, and does not seem likely to be resolved. This general level of stamp duty is the highest in the world among developed exchanges (although 1.25% is chargeable on foreign securities by the Swiss exchanges, compared to 0.75% on Swiss). In terms of attempts to realise supernormal profits from any anomaly such as a weekend effect, clearly this will be made more difficult. When combined with the high rates of commission which Irish stockbrokers charge the possibilities become more difficult

- Special Savings schemes: In common with other countries, the Irish government has operated special tax concessions for 'small' investors. Interest income from deposits held in Irish banks by Irish resident taxpayers has tax deducted at source, that rate being the lowest marginal income tax rates operating at the time. This does not absolve the recipient of tax liability: the interest has to be declared and tax paid at the appropriate marginal rate, with the withholding tax carried as a tax credit. The marginal lowest and highest tax rates over the 1980's and 1990' varied from 25-35% at the lowest rate and 45-65% at the higher. The special savings schemes carried special tax rates of 10-15%, this being deducted at source and no further tax liability being leviable on that income. Indeed, the income was not even declarable to the tax authorities. Coupled with deposit insurance limits which were above the maximum permissible investment in these schemes, this promised an effectively riskless (the deposit insurance scheme being state backed) low tax return to savings. Recognising that these essentially riskless returns were acting as a disincentive to equity market investment, Special Portfolio Investment Accounts were introduced in 1993. These schemes provided for similar tax concessions to investors who held a basket of securities heavily weighted towards Irish companies. While the tax reduction was som degree of equalisation as between the special savings schemes and investment in domestic equities, the inherent riskiness of equity returns as compared to the effective guarantee on capital when making an investment in the special savings schemes was a major disadvantage. These were not the success in attracting small investors to the equity market that had been hoped, and were discontinued.

- Interest Relief: While monies borrowed to purchase shares in unquoted companies attract full tax relief on the interest, this is not the case for borrowings to purchase shares in quoted companies. This implies in particular that companies, which have gone from family shareholdings to wider ownership by MBO, are unlikely to come to the market. To do so would imply forfeiture of the tax relief by the owners.

6.5. Previous Econometric Studies On The Irish Market

Despite the considerable administrative linkages between the Irish and London exchanges, the evidence is not overwhelming that the two markets are fully integrated over the period under investigation. Relatively little has been written about this issue, a situation not uncommon in the financial economics literature relating to Ireland.

Cooper (1982) finds that the Irish market, at monthly frequencies, displayed significant serial correlation and was non-random. Lucey (1994) finds significant deviations from normality, using a variety of parametric tests, over the 1987-1991 period, using daily data for the official index of the stock exchange

Although not primarily focused on. integration per se, Kearney (1998)finds that the main determinant of market volatility in Dublin was the contemporaneous volatility in the London market. However, Kearney looks at a long time period in capital market terms, with monthly data. Thus, high frequency dynamics are not captured. In addition, although using a well tried and trusted method, that of GLS, this method used by Kearney cannot easily cope with significant deviations from normality in the dataset.

A higher frequency dataset is examined by Gallagher (1995). In addition, he examines a shorter, more focused period, that of 1979-1994. He finds, using both cointegration and granger causality methods, that the Irish market, had not been fully integrated with the UK or the German market over the period. Gallagher also examined sub periods, broken according to pre and post 1987 and also according to the exchange rate experience in the ERM. Again, the evidence is mixed and not indicative of integration over the long-term. Finally, Howlett (1998) examines a more focused dataset again, consisting of the daily returns to five stocks with dual listing on the London and Dublin exchanges over the January 1995- June 1998 period. These stocks were those with the largest average daily turnover over the two years prior to the start of the dataset., accounting for over half of total average turnover. She finds, again using cointrgration methods, that the markets for these shares are integrated.

A major problem with these studies is that in general they do not take adequate account of the time series properties of the data. There is considerable evidence that the Irish market is characterised by non-normality. This should therefore temper any results found using method such as OLS, a cornerstone of simple cointegration and ECM modelling as used in Gallagher and Howlett

6.6. SUMMARY & REVIEW

The Irish market has grown considerably in terms of market value over the 1990's. However, this has come about with increasing concentration of market value and trading. There has been a failure to attract a steady (or indeed, almost any) stream of small companies to listing. This has a number of reasons rooted in history and in the tax system. The outlook for the market in the EU is uncertain, with expectations of increasing concentration and consolidation among exchanges. This has been the historical experience in Ireland and the UK. The market is also very illiquid, and investors face considerable transactions costs and potential delays in execution of trade. This will mitigate against the possibility of any identified anomaly actually being exploitable.

7. Methodological Issues In The Investigation Of Seasonality

We have seen that although systemic differences in the mean return of stocks across predictably recurring calendar events such as holidays, days of the week and months of the year, have been found, no wholly satisfactory explanation exist in many cases. In the absence of this confirmation and compounded by the absence of a theoretical reason for such regularities, methodological considerations are even more important than otherwise. Social science research is always at best an imprecise undertaking, and as such, anything that decreases the degree of uncertainty is welcome. Many social science research methodology texts and guides, for example, urge triangulation, in some form, as a possible route to ensure optimal results. A number of forms of triangulation can be identified.

Data Triangulation: The collection of data on the same phenomena at different times or from different sources is data triangulation. In the case of finance research, this implies that searches for daily seasonal patterns should proceed on different databases (not simply relying on CRSP tapes in the US for example), such as data from a series of different stock exchanges, from different regulatory regimens, and using different aggregation and index number approaches. This form of triangulation is perhaps the most easily applied to financial research, with the growth of stock markets around the world and with the growth of electronically readable data from these.[60] This work makes a contribution to the data triangulation in a number of different ways, as will be discussed in the next chapter.

[60] A subset of data triangulation may be of particular interest for financial research in asset returns. This is moment triangulation. By this, I mean that the same phenomena, that of systemic variation in the first moment of asset prices across the calendar may also manifest itself in other moments such as the second (proxying for risk), third (Skewness) and fourth (Kurtosis). We have seen already that evidence exists both for the usefulness of higher moments to the investor and for the existence of calendar anomalies in these higher moments.

Investigator Triangulation: Different investigators at work on the same set of data pertaining to phenomena, or replication, is investigator triangulation. While this triangulation method would be immediately beneficial in primarily qualitative research, where the perceptions of the intervening researchers may reasonably be assumed to have a mediating influence on the results, it is not clear that investigator triangulation will assist greatly in quantitative research. An over-reliance on investigator triangulation can lead to misleading results. This issue is well addressed in Lakonishok and Smidt (1988). There, they claim

> *'Data snooping is sometimes thought of as an individual sin. .... However, it is also a collective sin. A hundred researchers using the same data test a hundred different hypotheses. The 101'st derives a theory after studying the previous results and tests <the> theory using more or less the same data. The best remedy for data snooping is new data.' P 405*

They point out that in examining seasonal patterns there exist a multitude of potential hypotheses to be tested. In testing these, even if there is not a single actual real pattern, there exists a non-trivial probability that one or more of the tests will show statistically significant results at the 5% level[61].

Methodological Triangulation: Qualitative and Quantitative methods used in the investigation of phenomena gives methodological triangulation. Probably this is the most underused method of triangulation adopted in finance research. For the purposes of investigation of daily seasonal anomalies, one could consider evidence drawn from psychology (are there issues in the psychology of market participants that manifest on particular days, the pattern of manifestation being symmetric or asymmetric to the observed daily patterns of returns) or sociology (do different sets of market participants

[61] There are (2^N -2) hypotheses for N periods; this is 30 (5 periods) for days of the week and 4094 for months of the year. Testing these hypotheses, the Bonferroni inequality gives the significance level of the induced test as $\left|1-(1-\rho)^{(2^N-2)}\right|$. In the case of days of the week with a 5% level of significance this equates to 0.79, giving a 21% probability that one or more of the t -statistics will exceed 5%, by chance, even if no such pattern exists. More detail is given in Footnote 2 of Lakonishok and Smidt (1988).

act, from social biases, in different ways such as to perhaps cause markets to act in daily patterns).

Theory Triangulation: When theory from one discipline is used to assist in the explanation of a phenomenon under investigation within another discipline we have theory triangulation. Again, an example that comes readily to mind might be that there is (at least popular) psychological opinion that Mondays and days following holidays are generally 'bad' compared to other days of the week. If market participants are subject to the same psychological effects as the rest of the population, we might expect to see Monday and post holiday effects. While this is so, a fully specified test would require that we include quantitative measures of the 'badness' of various days to test for their explanatory power. A major problem with psychological measures is that in general we cannot observe these states. Instead, we measure either outcomes or other measures. These, we predicate, correlate with these states. This raises that possibility that we are in fact not observing an effect from the psychological state but an effect from the proxy variable. Separating the effects can be difficult. At least one form of theoretical triangulation can assist us directly however. In terms of statistical testing, the basis for inference usually used is the so-called 'classical' theory of statistics. Using Bayesian theory, or non-parametric tests, or a combination of these, one can include theory triangulation and thus, it is claimed, reasonably hope to gain greater explanatory power.

Such methodological and theory triangulation might provide what Karl Popper has called falsification. Falsification requires a refutable hypothesis. The more methods that can be deployed in refutation, it may be said the more 'falsified' the hypothesis is. This is well discussed in Saunders (1994). The basic issue is that, as we have seen in Chapter

1, testing the efficient markets hypothesis in any form relies on a dual hypothesis of market efficiency and a model of market equilibrium. Using different methodologies drawn from different theoretical approaches might allow for findings that directly contradict, falsify, the theory or theories under investigation.

In the finance area, the dangers of relying on a single methodology and a single source can give rise to charges of data snooping or data mining. The dangers of this have been pointed out clearly in Lakonishok and Smidt (1988), who declare

> *"The statistical tests routinely used in financial economics are usually interpreted as if they were being applied to new data. But the data employed in finance are seldom new. When new data are not available, significance levels on tests ... must be adjusted if multiple tests are performed on the dame data."*
>
> *P405*

Thus, ideally we need to test the predictions or hypotheses derived from one theory on data that have not been used in the formulation (most probably inductive) of the theory.

7.1. Methodological Considerations In General

Researchers have deployed a wide variety of approaches, classifiable into three broad categories, in their search for seasonality. These three families are:

- Simple, usually OLS based, dummy variable based methodologies;
- Methods that rely on Bayesian or non-parametric methods of inference, including papers that adopt a stochastic dominance approach;
- Methods that explicitly incorporate higher moments and known statistical properties of the data, typically using one of the ARCH family.

It is unusual for papers to mix these methodological approaches, although such papers do exist, notably Aggarwal and Rivol (1989),Chang and Pinegar (1989),Connolly (1989) & Easton and Faff (1994). Within these families some further subdivision occurs. This section overviews these approaches, and concludes with some methodological suggestions for future work. It mainly concentrates on the issues involved in daily seasonality, although in all cases, unless otherwise noted, the issues are germane to the investigation of monthly seasonal patterns.

Many of the works cited in previous sections are not here examined, as the emphasis now is on outlining and evaluating the statistical methodologies used to detect seasonality. Papers, such as Lakonishok and Maberly (1990), DeGennaro (1990), Chen and Fishe (1994), Kallunki and Martikainen (1997) or Ligon (1997) which have as their primary focus the search for an explanation, as opposed to an elucidation, of seasonality, are not examined in detail. Their main contribution is to suggest lines of inquiry for further work, presupposing that there actually exists a substantial, robust, statistically well-founded pattern for investigation.

7.2. TESTING DISTRIBUTIONAL ASSUMPTIONS

Underlying the testing of most forms of seasonality is an assumption regarding the distributional characteristics of the dataset. Thus tests that rely for example on the t-statistic implicitly assume either that the distribution of the data approximates that of a normal distribution or that the law of large numbers will allow this approximation to be invoked. Papers that rely on OLS models implicitly or explicitly assume that the data are such that the OLS estimates of parameters are Best Linear Unbiased Estimates of the true population parameters. Tests that rely on the Kolmogorov-Smirnov statistic rely on the full *a priori* specification of the distribution being known. The purpose of this section is to outline methods that can be deployed to investigate the assumptions underlying the appropriateness of using parametric tests and to outline both the modifications that may be made to these and the non-parametric alternatives available.

7.2.1. THE KOLMOGOROV-SMIRNOV TEST FOR EQUALITY OF DISTRIBUTIONS

The Kolmogorov-Smirnov (KS) test is most commonly used to decide if a sample of data comes from a specific distribution. Thus it can be used to test the hypothesis that the data approximate the normal, cauchy, or any other distribution. It can also be used to test whether two series come from the same distribution (test the equality of distributions). The Kolmogorov-Smirnov (K-S) test is based on the empirical cumulative distribution function (ECDF). Given N data points $Y_1, Y_2, \ldots, Y_N$, the ECDF is defined as $E_N = \frac{n(i)}{N}$ where $n(i)$ is the number of points less than Y_i. This step function increases by 1/N at the value of each data point. The Kolmogorov-Smirnov test statistic is then calculated as

$$\text{EQ. } 7: D = \underset{1 \le i \le N}{MAX} \left| F(Y_i) - \frac{i}{N} \right|$$

where F is the theoretical cumulative distribution of the distribution being tested (which must be a continuous distribution[62] i.e., no discrete distributions such as the binomial or Poisson), and it must be *a priori* fully specified (i.e., the location, scale, and shape parameters cannot be estimated from the data). The hypothesis regarding the

[62] But this distribution can of course be another set of data points, in which case the KS test is on of the equality of two distributions

distributional form is rejected if the test statistic, D, is greater than the critical value. An attractive feature of the test is that the distribution of the K-S test statistic itself does not depend on the underlying cumulative distribution function being tested. Another advantage is that it is an exact test. Despite these advantages, the K-S test has several important limitations:

- It only applies to continuous distributions.
- It tends to be more sensitive near the centre of the distribution than it is at the tails.
- Perhaps the most serious limitation is that the distribution against which the data are being compared must be fully specified. That is, if location, scale, and shape parameters are estimated from the data, the critical region of the K-S test is no longer valid. It typically must be determined by simulation. In the case of the normal distribution this problem does not, of course, arise.

7.2.2. ALTERNATIVE DISTRIBUTIONAL TESTS

Alternatives to the KS test exist. In particular, one test that is very commonly used in financial econometrics is that based on the Jarque-Bera statistic. This tests the joint hypotheses that the skewness and excess kurtosis of the (empirical) distribution are zero. It is therefore a test of the normal distribution

The statistic, based on the empirical estimates of skewness and kurtosis, is given as

Eq. 8 $JB = \frac{T-k}{6}\left(S^s + \frac{1}{4}(K-3)^2\right)$

where S is skewness, K kurtosis and k the number of parameters estimated. The JB statistic is distributed as a χ^2 with 2 degrees of freedom under the hypothesis of normality.

7.3. Investigating First Moments

The majority of studies that have addressed the phenomenon of seasonality in the returns to equity assets have concentrated on the search for seasonal variations in the first moment of the series, that is to say in the mean. This is somewhat inexplicable when one considers the key role that the second moment, the variance of a series, plays in financial economics. In addition, as we have noted earlier there are good reasons why investors should have well expressed preferences for moments above the first two. Thus the concentration seems misplaced. Regardless, that is the case. As noted earlier there are a number of routes to the testing of such moment conditions.

7.3.1. Simple Dummy Variables

The majority of the papers that have examined whether there exists differential seasonality in the first moment have used a statistical specification that incorporates dummy variables. Other methods exist, but the predominant method is for the utilisation of a statistical procedure that investigates the significance under a given set of statistical assumptions of a series of dummy variables. The family of approaches that use dummy variables, in the form of a regression of the returns of an index or portfolio on a selection of dummy variables, as per the equations below, can be further divided into a number of main areas of analysis.

The most common form of regression, used by French (1980) in his paper that begun the modern era of investigation in to the existence of daily seasonalities and by Brown, Keim, Kleidon and Marsh (1983) on monthly seasonality, is one of the returns on a series dummy variables, each for a particular realisation of a calendar event. In these cases, the typical research focus is on evaluating the hypothesis of equality of means across the calendar events. Testing is typically by means of an F or χ^2 test. The formal regression is then

$$\text{EQ. 9}: R_t = \sum_{t=1}^{n} \alpha_t D_t + \varepsilon_t$$

where the number of D, dummy variables, corresponds to the number of seasonal patterns (months of the year, days of the week) in the market under investigation.

Testing proceeds by means of a standard F test, examining the hypothesis that the individual coefficients on the dummy variables are equal to one another. Typically the individual coefficients t-statistics are reported, to assist evaluation of the extent to which they differ from zero. If the expected return was the same across the calendar periods for which the dummy variables proxy, then the dummy coefficients should be individually close to zero[63] and the explanatory power of the equation as a whole as measured by the F test would be weak. Taking this approach imposes little in the way of predetermined structure on the expected pattern of returns beyond the assumption that returns are generated in trading time. Such an imposition seems reasonable, as there exists no paper that provides support to the calendar time hypothesis. Applications of this approach include French (1980), Brown, Keim, Kleidon *et al.* (1983), Schultz

[63] This being a one-sample t test, the test being whether the mean (here the estimated coefficient on a particular dummy variable) is equal to a specified constant, here zero. The alternative is a two sample t test, testing the equality of a pair of means, or estimated coefficients

(1985), Santesmaes (1986), Athannasakos and Schnabel (1994), Haugen and Jorion (1996), Coutts and Hayes (1999) & Coutts and Sheik (2000),

Investigation of the holiday effect typically also proceeds along the line of dummy variable analysis, with dummy variables usually representing the day immediately prior to the holiday. The null examined is that these dummies add nothing to the explanatory power of the equation, and testing proceeds by means of standard parametric tests. The form of the regression then is

EQ. $10: R_t = \beta_0 + \beta_h D_h + \varepsilon_t$

with the intercept measuring the average return on days that are not a pre-holiday and the dummy variable measuring pre-holiday returns.

A subset of this approach takes as given the existence of a seasonal pattern in the daily returns. These use a variant of equation 1, with the dummy variable for the calendar regularity hypothesised to be 'the seasonal' omitted and the equation estimated with an intercept. This gives an equation of the following type in the case of a search for daily seasonality.

Eq. $11: R_t = \beta_0 + \beta_a + \beta_b + \beta_c + \beta_d + \varepsilon_t$

Thus the intercept measures the mean return on the daily seasonal, and the other coefficients measure the difference in mean returns between this seasonal and the individual days. Again, an F test is used to determine equality of the dummy variable coefficients. The day represented by the intercept coefficient need not in this case be restricted to Monday. Corhay (1991), on finding that there appears to be a Tuesday effect in the Brussels market, employs an analysis suppressing the dummy variable for Tuesday, Elyasiani, Perera and Puri (1996) test for Friday effects while Connolly

(1989)tests for weekend effects with a Monday dummy. A large variety of papers adopt this approach for monthly seasonality, 'especially when examining the US, where the generally accepted evidence is of a January seasonal, such as Ramcharran (1997) and Tong (1992).

The F statistic reported in the papers quoted above is typically the regression F statistic, as opposed to the ANOVA F statistic. The regression F is used to test the hypothesis that there is no linear relationship between the dependent variable and the independent variable(s). The total variation in the dependent variable is divided into two components - one that can be attributed to a particular regression model and one that cannot. The ANOVA F Test is a test used to test the hypothesis that several means are equal. This technique is an extension of the two-sample t test. One key assumption here is that each group is an independent random sample from a normal population although ANOVA is robust to departures from normality. A second is that the groups should come from populations with equal variances. The F statistic produced is the ratio of the between group and within group mean squared differences. The key issue of ANOVA is that like the regression F test it is a joint test – what is being tested is that all the means are equal one to another.[64] The F statistic produced is the ratio of the between group and within group mean squared differences. The between group differences measure the variation in the dependent variable that is accounted for by differences in group means, while the within groups measures that part which is accounted for by errors in the fitted values.

More formally, let

---

[64] If the significance value of the F statistic obtained indicates that there do exist differences in means, there are a variety of tests, the most common being Tukey's and Tamhane's T^2 Test which allows the researcher to determine exactly which means differ and from which they differ.

EQ. 12 $\sum_{j=1}^{k}\sum_{i=1}^{n}\left(X_{ij}-\overline{\overline{X}}\right)^2 = n\sum_{j=1}^{k}\left(\overline{X}_{ij}-\overline{\overline{X}}\right)^2 + \sum_{j=1}^{k}\sum_{i=1}^{n}\left(X_{ij}-\overline{X}_j\right)^2$.

Then the sum of squared differences between the groups is given as

EQ. 13 $SS_{bg} = \sum_{i=1}^{k}\left(\frac{\left(\sum_{i=1}^{k} X_i\right)^2}{n_i}\right) - \frac{\left(\sum_{i=1}^{k} X_T\right)^2}{n_T}$

and those within groups as

EQ. 14 $SS_{wg} = \sum X^2{}_T - \sum_{i=1}^{k}\left(\frac{\left(\sum X_i\right)^2}{n_i}\right)$

Thus, the mean squares estimates of variance are given as the ratios of the sums of squared expressed as a ratio to their respective degrees of freedom, and the F[65] statistic as the ratio of the between and within group mean squares. This ratio is of course distributed as an F statistic.

EQ. 15 $MS_{bg} = \frac{SS_{bg}}{df_{bg}},\ MS_{wg} = \frac{SS_{wg}}{df_{wg}},$

EQ. 16 $df_{bg} = k-1, df_{wg} = n_T - 1$

EQ. 17 $F = \frac{MS_{bg}}{MS_{wg}}$.

If we find, using ANOVA, that there is a statistically significant calendar effect, this does not inform us as to which calendar events differ from which. A variety of so called

[65] Called so by Sir Ronald Fischer.

post-hoc tests are available to assist. Some, such as Scheffe's, test for all possible interactions. Others adopt a Bayesian approach, relying on the investigator to specify priors relating to the assumed relationship.

7.3.2. Tukey's Honestly Significantly Different T Test

An alternative approach to using the standard t-test to examine mean differences is to use Tukey's HSD test. The "Honestly Significantly Different" (HSD) test is based on the studentized range distribution. It allows the researcher to test all pairwise comparisons among means, in this case the mean return by day of the week. In using the Tukey HSD one computes t_s for each pair of means using the formula:

Eq. 18 $$t_s = \frac{M_i - M_j}{\sqrt{\frac{MSE}{n_h}}}$$

where M_i - M_j is the difference between the i_{th} and j_{th} means, MSE is the Mean Square Error, and n_h is the harmonic mean of the sample sizes of groups i and j. The critical value of t_s is determined from the distribution of the studentized range. The number of means in the experiment, here 5 as there are 5 days in the week, is used in the determination of the critical value, and this critical value is then used for all comparisons among means. Typically, the researcher compares the largest mean with the smallest mean first. If that difference is not significant, no other comparisons will be significant either, so the computations for these comparisons can be skipped. The advantage of the Tukey HSD procedure is that it keeps the experimentwise error rate (EER) at the specified significance level[66]. This advantage comes at a cost, however:

[66] Another post-hoc procedure that controls the EER is the Neuman-Keuls test, although the control is not as tight as in the HSD test.

the Tukey HSD is less powerful than other methods of testing all pairwise comparisons.

The experimentwise error rate (EER) is the probability that one or more of the significance tests results in a Type I error. Two kinds of errors are possible in significance testing: (1) a true null hypothesis can be rejected incorrectly and (2) a false null hypothesis can fail to be rejected. The former error is called a Type I error and the latter error is called a Type II error. A Type II error is only an error in the sense that an opportunity to reject the null hypothesis correctly was lost. It is not an error in the sense that an incorrect conclusion was drawn since no conclusion is drawn when the null hypothesis is not rejected.

If the comparisons are independent, then the experimentwise error rate is: $\alpha_{ew} = 1-(1-\alpha_{pc})^c$ where α_{ew} is experimentwise error rate α_{pc} is the per-comparison error rate, and c is the number of comparisons. For example, if 5 independent comparisons, such as comparing the mean return of a stock index across each of the days of the week, were each to be done at the 0.05 level, then the probability that at least one of them would result in a Type I error is: $1 - (1 - 0.05)^5 = 0.226$. If the comparisons are not independent, then the experimentwise error rate will be less than $1-(1-\alpha_{pc})^c$. Finally, regardless of whether the comparisons are independent, $\alpha_{ew} \le (c)(\alpha_{pc})$. For the days of the week example, $0.226 < (5)(.05) = 0.25$

The studentized range distribution may be used for testing all differences among pairs of means. It is similar to the t distribution, differing only in that it takes into account the number of means under consideration. The more means under consideration, the larger the critical value of t_s (studentized t). This makes sense since the more means there are, the greater the likelihood that at least some differences between pairs of means will be large due to chance alone.

First, consider the case in which there are only two means. The formula for t used to compare two sample means is:

$$\text{EQ. 19: } t = \frac{M_d - (\mu_1 - \mu_2)}{S_{M_d}}$$

where i $M_d = M_1 - M_2$,the difference in the two means, $\mu_1 - \mu_2$ is the value specified by the null hypothesis (almost always zero), and

$$\text{EQ. 20: } S_{M_d} = \sqrt{\frac{2MSE}{n_h}}$$

where MSE is the means square error and n_h is the harmonic mean of the two sample sizes. If the null hypothesis is that $\mu_1 - \mu_2 = 0$, then the formula for t can be written as

$$\text{EQ. 21: } t = \frac{M_d}{\sqrt{\frac{2MSE}{n_h}}}$$

The formula for the studentized t is then:

$$\text{EQ. 22: } t_s = \frac{M_d}{\sqrt{\frac{MSE}{n_h}}}.$$

The only difference between the formulas is that "2" in the denominator of the t-test is not present in the formula for the studentized t. The value of t_s is therefore the square root of 2 = 1.414 times the value of t. The significance test using the studentized t compensates for the difference in the formulas by using a critical value of t that is 1.414 times the critical value of t. If an experiment were conducted with two groups and 13 subjects per group, then a t either less than - 2.06 or greater than +2.06 would be needed to be significant at the 0.05 level. Since 1.414 x 2.06 = 2.91, a t_s either less than -2.91 or greater than 2.91 would be needed to be significant.

Since the computed value of t_s is always 1.414 times the value of t, the tests using t_s and t are identical whenever there are only two means in an experiment. The difference between the t and the studentized t distributions occurs when there are more than two means. Naturally, the more means, the higher the critical value of t.

7.3.3. TAMHANE'S T^2 TEST

An assumption underlying the Tukey's HSD Test is that the variance across the sub samples is constant. If this does not hold, then an alternative, Tamhane's T^2 test most commonly, may be used. This test assumes that both the sample sizes (number of occurrences of each day of the week) and variances of returns by day of the week are unequal. The test defines two means to be unequal if

Eq. 23: $$\left|\overline{x_i} - \overline{x_j}\right| \geq \left(\sqrt{\frac{\sigma_i^2}{n_i} + \frac{\sigma_j^2}{n_j}}\right)\left(F_{\gamma,1,\nu}\right), \; \gamma = 1-(1-e)^{1/k}$$

where e is the experiment error rate and k the number of possible effects, 5 here for the 5 days of the week, or 12 for the months of the year.

7.4. NON PARAMETRIC APPROACHES TO THE FIRST MOMENT

Using OLS methods, there is an underlying assumption that the data are independently, identically distributed, drawn from a normally distributed population, with constant variance and no serial correlation. It has been well accepted for many years however those these are assumption that, for the most part, stock data do not follow. Papers that have addressed this issue are many, with some of the more relevant being Mandlebrot (1964),Fama (1963), & Fama (1965). In the Irish context Lucey (1994) and Cotter (1998) have shown that these assumptions are questionable in the Irish context.

There are attempts in the literature to address this issue. Indeed, one of the first papers on daily seasonality in the modern era, Cross (1973) used a pair-wise comparison of days using a Mann-Whitney U test. This form of test was also employed by Pettengill (1986) in his examination of the pre-1917 behaviour of monthly equity returns. In general, at the simplest, such as in Theobald and Price (1984), Elyasiani, Perera and Puri (1996; Theobald and Price (1984),Arsad and Coutts (1997) Baker and Limmack (1998)or Steeley (1999),the use of non-parametric methods involves the use of an alternative to the standard F test. The papers above employ the Kruskal-Wallis H statistic and note that the results in terms of equality of returns across all calendar frequencies are invariant to the nature of the test statistic employed, i.e. the results are the same regardless of whether parametric or non-parametric methods are employed. In terms of triangulation mentioned earlier, this theoretic triangulation, by deploying statistical methodologies differing fundamentally in their assumptions about how the data are generated, provides us with greater subjective confidence that a daily seasonal anomaly exists, it being confirmed by different methodologies using different theoretical bases for acceptance or rejection of a hypothesis. Non-Parametric tests may be used in place of their parametric counterparts when certain assumptions about the underlying population are questionable. For example, when comparing two independent samples, the Mann Whitney U test does not assume that the difference between the samples is normally distributed whereas its parametric counterpart, the two-sample t test does. Non-Parametric tests may be, and often are, more powerful in detecting population differences when certain assumptions are not satisfied. All tests involving ranked data, i.e. data that can be put in order, are non-parametric.

7.4.1. THE KRUSKAL-WALLIS TEST

The Kruskal-Wallis test is a non-parametric alternative to ANOVA. It is an extension to many samples of the Mann-Whitney U Test. The Wilcoxon Mann-Whitney Test is one of the most powerful of the non-parametric tests for comparing two populations. It is used to test the null hypothesis that two populations have identical distribution functions against the alternative hypothesis that the two distribution functions differ only with respect to location (median), if at all.

Let R_j^2 be the average rank of observations (returns to the index in this work) in the j_{th} group (in this work each day of the week will form one group) and nj be the number of observations in the j_{th} group. Then with k groups and N observations in total the Kruskal -Wallis H statistic is then

Eq. 24: $$H = \left(\frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j} \right) - 3(N+1)).$$

The H Statistic is distributed as a χ^2 distribution with N-1 degrees of freedom.

7.5. INVESTIGATING SECOND MOMENTS.

7.5.1. THE LEVENE TEST FOR EQUALITY OF VARIANCES

The Levene test is an alternative to the well-known Bartlett test for equality of variance. Although it is more commonly used, the Bartlett test is sensitive to departures from normality. The Levene test is less sensitive to non-normality than the Bartlett test. The Levene test tests the following hypotheses:

H_0: $\sigma_i = \sigma_j \forall i, j$, Ha: $\sigma_i \neq \sigma_j$, at least one i, j pair

The test statistic is defined as in Eq. 25

Eq. 25:

$$W = \frac{(N-k)\sum_{i=1}^{k} N_i\left(\overline{Z_i} - \overline{Z_{\dots}}\right)^2}{(k-1)\sum_{i=1}^{k}\sum_{j=i}^{N}\left(Z_{ij} - \overline{Z_i}\right)^2} \text{ where}$$

1 $Z_{ij} = \left|Y_{ij} - \overline{Y_i}\right|, \overline{Y}_i$ the mean of subgroup i, or

2 $Z_{ij} = \left|Y_{ij} - \tilde{Y}_i\right|, \tilde{Y}_i$ the median of subgroup i, or

3 $Z_{ij} = \left|Y_{ij} - \bar{Y}_i^{10}\right|, \bar{Y}_i^{10}$ the 10% trimmed mean of subgroup i.

The three choices for defining which Z_{ij} to utilise in any situation determine the robustness and power of Levene's test. The definition based on the median is the choice that provides good robustness against many types of non-normal data and is more in keeping with the nature of non-parametric testing. Using the median retains good power, and is the one used hereafter unless specified elsewhere. The Levene test rejects the hypothesis that the variances are homogeneous if $W > F_{(1-\alpha,k-1,N-1)}$ where $F_{(1-\alpha,k-1,N-1)}$ is the upper critical value of the F distribution with k - 1 and N - 1 degrees of freedom at a significance level of α

7.5.2. ARCH Type Models And The Second Moment

A number of papers in the literature employ statistical methods that allow for deviation from the OLS assumptions. These papers fall into two families: adjusting the statistical procedures and adjusting the estimated equation. Those that adjust the equation to be estimated typically employ GARCH specifications (for example Connolly (1989),Clare, Ibrahaim and Thomas (1998) or Lucey (2000a)). The advantages of a GARCH specification are many. In addition to parsimoniously capturing the autocorrelation dynamics of a stock return series, they allow for time varying volatility and are robust to underlying non-normality. Expanded versions of the GARCH model allow for non normal distribution of the conditional errors, and allow for examination of whether the abnormally fat-tailed distribution of stock returns is due to a combination of time varying volatility and non-normality of the returns, or simply due to the time varying volatility. IGARCH models are part of a set of statistical models that exhibit persistence in variance, where the current information remains important as an element of future estimates of volatility for all time – this contrasts sharply with the ideas of efficient capital markets, especially the view that nothing is really forecastable. Crucially, the use of an ARCH type model allows us not only to investigate the existence of seasonal patterns in the second moment but also to pinpoint the source of these regularities.

ARCH Models also allow the incorporation of a number of residual dynamics. The most important of these is the ability to adjust for a particular form of autocorrelation. This is required for two reasons. From a statistical perspective the presence of autocorrelation in the series will cause difficulties in interpreting the estimated parameters and their economic significance. From an economic perspective the presence of autocorrelation in asset returns can be attributed to thin trading. Thin trading implies that the daily return to an asset may in fact be a statistical artefact and as such this should be taken into account in any investigation of seasonal factors. This is well summarised in Atchinson, Butler and Simonds (1987), who state (p111)

> *"Market index autocorrelation by itself is of limited interest. However, knowledge concerning the source of price-adjustment delays causing this is very significant for a better understanding of the price formation process"*

Thin trading gives rise to autocorrelation in an equity returns series due to the induced averaging which it imparts. The knowledge of this dates back at least to Working (1960)If we consider an index composed of a number of shares, one of which is thinly traded. Thus on the close of Friday the index consists of an average of those shares traded on Friday and on Monday, at least one share not having traded since Monday. The normal practice in the construction of indices is to pad data series where this occurs – the price of the asset at the last trade is deemed to be the price of the asset on all subsequent trading sessions until a new price is set. The index then is an average of some sort not over all occurrences on Friday but over the period Monday-Friday. Therefore it is tautological that there will be some degree of positive serial correlation between the index and itself. This can easily occur not simply at daily frequencies, but depending on the extent and duration of thin trading can manifest itself over higher, weekly and monthly, frequencies. Further details and examples can be found in Officer (1975).

Standard ARCH models (Engle (1982)) rely on the assumption that the conditional variances of residuals from a regression are themselves an AR(q) process. Typically the assumption modelled is that the squared residuals are denoted as an AR(q) process. This system can be denoted as

EQ. 26:
$$
\begin{aligned}
y_t &= a_0 + a_1 y_{t-1} + \varepsilon_t \\
VAR(y_t | y_{t-1}) &= E_{t-1}\left[(y_t - a_0 + a_1 y_{t-1} + \varepsilon_t)^2\right] \\
&= E_{t-1}\hat{\varepsilon}_t^2 \\
\hat{\varepsilon}_t^2 &= \alpha_0 + \sum_{i=1}^{q} \alpha_i \hat{\varepsilon}_{t-i}^2
\end{aligned}
$$

A finding of ARCH type errors in the residuals of a day of the week equation indicates that time varying hetroskedasticity may indeed be a problem. It is a relatively simple task to add exogenous elements to the ARCH model.

GARCH methods (deriving from the works of Bollerslev (1986)) can assist in dealing with volatility in returns as they generalise the process above to allow the conditional variance to be an ARMA process. Consider the specification common to Beller and Nofsinger (1998), Clare, Ibrahaim and Thomas (1998) and Lucey (2000b). The mean equation is given as

Eq. 27 $R_r = \alpha_0 + \alpha_1 h_t^{0.5} + \alpha_2 R_{t-1} + \sum_{i=1}^{n} \mu_i D_i + \xi$, where h_t refers to the conditional variance , D_d is a dummy variable corresponding to a particular calendar event such as the day preceding holidays, weekdays or months of the year, while the conditional variance itself is given by the representation

Eq. 28 $h_t = \gamma_0 + \sum_{d=i}^{n} \mu_i^* D_i + \sum_{j=1}^{p} \gamma_j h_{t-j} + \sum_{i=1}^{q} \gamma_i \xi_{t-i}^2$

Here both the mean equation Eq. 27 and the equation for the conditional variance Eq. 28 contain dummy variables to take account of the interrelationship between risk, return and these calendar events. There is no agreement in the literature as to which dummy variables should be included. Clare, Ibrahaim and Thomas (1998) and Lucey (2000a) include daily dummies for those days that have been shown, from a standard OLS regression, to have significant coefficients. Glosten, Jagannathan and Runkle (1993) include dummies for January and October, on similar justification. Beller and Nofsinger (1998) test all calendar variables.

Another issue is the mode of propagation of calendar effects. As Beller and Nofsinger (1998) points out, there are of course three places where such dummies can go. The equations above make the implicit assumption that the effect on the conditional variance of calendar effects is through the intercept terms, in effect assuming that there is a different form of conditional variance for each day of the week etc. Alternatively, it could be the case that the relationship is propagated through the variance itself (Eq. 29) or through the unexpected returns (residuals) (Eq. 30).

EQ. 29 $h_t = \gamma_0 + \sum_{d=i}^{n} \mu_i^* D_i \sum_{j=1}^{p} \gamma_j h_{t-j} + + \sum_{i=1}^{q} \gamma_i \xi_{t-i}^2$

EQ. 30 $h_t = \gamma_0 + \sum_{j=1}^{p} \gamma_j h_{t-j} + \sum_{d=i}^{n} \mu_i^* D_i \sum_{i=1}^{q} \gamma_i \xi_{t-i}^2$

Indeed, it is possible that the effects could propagate through more than one channel. However, the number of parameters to estimate rises rapidly as more terms are added, and may make convergence towards a solution difficult. Interpretation of the equations is relatively straightforward: If the dummies included in the mean equation are significant, despite the inclusion of the conditional volatility terms, then we may conclude that seasonality is not due to calendar variation in equity risk as proxied by the conditional variance term. If the dummies are insignificant in the mean equation but significant in the conditional variance equation, we can conclude that there is seasonality in market risk.

Clearly the ARCH type methods allow for a considerable amount of investigation as to the source of potential seasonalities. However, they cannot in themselves provide evidence of these seasonalities, rather playing a part when seasonalities are suspected

One problem with the standard ARCH/GARCH models is that there is a symmetry imposed on the conditional variance. Nelson (1991) showed that the EGARCH, or Exponential GARCH model overcame this. In this parameterisation, as shown in Eq. 31, the EGARCH model is given as below, with $\delta\sqrt{h_t}$ representing the ARCH in Mean Term, and **X** and **V** represent vectors of potential explanatory variables, such as calendar or other dummies, for the mean and variance equations respectively. The λ coefficient is referred to as the leverage coefficient and shows the degree of asymmetric response of the conditional variance to negative versus positive innovations. More details of this element of the EGARCH model can be found in Henry (1998).

EQ. 31:

$$Y_t = \alpha_0 + \sum \beta_i Y_{t-i} + \sum \varphi_j u_{t-j} + \sum \chi_k X_k + \delta\sqrt{h_t} + u_{t-i}$$

$$\log(h_t) = c + \sum \theta_p \left(\left| \frac{u_{t-p}}{\sqrt{h_{t-p}}} \right| - \sqrt{2/\Pi} \right) + \sum \psi_q \log(h_{t-q}) + \sum \lambda_\iota \frac{u_{t-\iota}}{\sqrt{h_{t-\iota}}} + \sum \xi_\zeta V_\zeta$$

7.5.3. STOCHASTIC DOMINANCE TESTS FOR THE SECOND MOMENT

An alternative non-parametric technique, potentially promising but little used, is the technique of Stochastic Dominance. Few papers have used this technique; Wingender and Groff (1989) examined the daily seasonal, while Sehun (1993) investigated the monthly seasonal.

Stochastic dominance is a non-parametric method to compare sets of returns. It allows simple choice among risky alternatives. As an example, consider two risky assets, A & B. Disregarding the actual distribution of (per money unit) returns, we can say that if the returns to A always exceed those to B, non-satiated investors will always choose A over B. This is a particular case of first order stochastic dominance (FSD). In general, first order stochastic dominance would be the instance where the probability that returns less than or equal to x is greater for B than A for any return x, in which case A FSD B. In terms of cumulative density functions (CDF) the CDF of A must not cross that of B, at any stage and must always lie to the right of B. Second order stochastic dominance (SSD) refers to the areas under the CDF of the two distributions of the assets returns. If the area under the CDF of A is greater than that of B then A SSD B. Note that unlike FSD, SSD allows that the CDF intersect, so long as the areas differ. Also note that FSD implies SSD, while the reverse is not the case.

More formally, given two distributions, the condition that $F_1(x) \leq F_2(x), \forall x$ is described as the first order stochastic dominance (FSD) of $F_1(x)$ over $F_2(x)$. Applied to the case of return distributions of equity assets, a return distribution that first order dominates another is preferred by any wealth maximisers regardless of their utility function. A less stringent condition then is second order stochastic dominance (SSD), with $F_1(x)$ said to dominate $F_3(x)$ by SSD if and only if $\int_{-\infty}^{x} F_1(y)dy \leq \int_{-\infty}^{x} F_3(y)dy, \forall x$

Stochastic dominance allows us to answer the question: is the higher (lower) return to this asset (or day) due to higher (lower) risk? If so, then the higher risk is expected to manifest itself in the form of more outliers, and so the higher (lower) return asset will not dominate the other.

Plotting, followed by visual inspection, of the realised CDF's is an easily implemented but informal operationalisation of stochastic dominance tests, although a two-sample Kolmogorov-Smirnoff test can also be applied. Sehun (1993) provides a good example of this approach within the context of searching for an explanation of monthly seasonality. For more complex situations there are a number of algorithms available to formally investigate stochastic dominance, such as that of Aboudi and Thon (1994)

Wingender and Groff (1989) find that Wednesday FSD Monday, while all other days SSD Monday. In other words, there is an unambiguous, non-parametric, statistical reason for investors with reasonable preferences to avoid Monday: the negative return generated on average cannot be explained by increased risk.

One criticism that can be levied against stochastic dominance analysis is that a single larger negative outlier (such perhaps as that associated with either of the stock market crashes of 1929 or 1987) can result in the prevention of dominance by a distribution everywhere else dominant. Trimming the distribution of outliers allows a simple check on the robustness of the results. When this is done, even with a trim discarding of the top and bottom 25% of the distribution, Wingender and Groff (1989) find that their results are robust to outliers. This provides strong, non-parametric evidence of the significance of negative Monday returns and also some evidence of an important Wednesday effect.

7.6. INVESTIGATING HIGHER MOMENTS#

The testing procedures described above all involve testing, either singly or as a pair, the distributional characteristics of the first two moments of the return distribution. Testing the two higher moments is more problematic however. In the absence of knowledge of the sample distribution of skewness or kurtosis no parametric test is possible.

Tang (1997) proposes a solution, although using his proposed approach; it is not possible to distinguish between seasonality in skewness and that of kurtosis. Relying on the fact that the standard scores of a variable preserve skewness and kurtosis he proposes the use of the Kolmogorov-Smirnov test to compare whether the distribution, of standard scores, as between each day of the week and each other, is equal. Testing involves partitioning each index according to the day of the week and standardizing on this day. The KS test tests the maximum vertical difference between the two observed cumulative distributions (standard scores of day I and standard scores of day j).

EQ. 32 $KS = \underset{1 \le i \le N}{MAX} \left| SCD_m(i) - SCD_n(j) \right|$

Part of this section appears in *Lucey, B. M. "Market Direction and Moment Seasonality", Evidence from Irish Equities" Applied Financial Economics 2002 (Forthcoming)*

The asymptotic test statistic is KSvn.

7.7. ROBUST INVESTIGATION: INCORPORATING DISTRIBUTIONAL KNOWLEDGE

One major difficulty with OLS lies in the manner in which it treats outliers. By its nature OLS deals with squared deviations from the mean. Thus large deviations become squared to even larger deviations. Outliers are not problems with the data- they represent realisations of the data generation process that must in some way be accounted for. The difficulty with OLS in the presence of outliers is that, at the limit, a single large enough outlier can render the estimates unreliable. Alternative approaches exist to dealing with this. Two approaches are the estimation of the first moment by means of Least Absolute Deviation and by Trimmed Least Squares (TLS). As shown in Koenker (1982), TLS is essentially the same as censoring the data and running OLS on the censored sample. A detailed discussion of Least Absolute Deviation regression is contained in Connolly (1989, Section IV).It is also discussed in Doan (2000,Section 5.7). In brief, if we consider the standard equation $y = \beta X + \varepsilon$, the LAD estimator is $\hat{\beta} = \underset{\beta}{Minimize} \sum |y - \beta X|$. This however is computationally complex. An approach, implemented in the RATS programming language, uses the fact that $min \sum \left(c^2 + \varepsilon(\beta)^2\right)^{0.5}$ approaches LAD as c→ 0. This can be estimated with consistency using iterative weighted least squares. This approach is used here.

A series of papers that employ adjusted methods of estimation include those by Connolly (1989) ,Chang, Pinegar and Ravichandran (1993),Easton and Faff

(1994),Mills and Coutts (1995) and Peiro (1994). These papers use estimation methods such as Trimmed Least Squares, Mean Absolute Deviation Estimation and also proceed by adjusting the estimated parameters by means of Whites procedure for hetroskedastic disturbances. These 'robust' estimates are presented alongside simpler 'non robust' estimates, in Connolly, Easton and Faff, and Chang, Pinegar and Ravichandran, again allowing for direct analysis of the benefits of triangulation. Like the studies that utilise both parametric and non-parametric methods to test the statistical significance of equations, these papers provide results on the daily anomalies using methods that differ fundamentally in how they treat the non-normality of the asset returns series. Connolly finds that, using robust estimators, the negative Monday average returns found in the US, while still present into the 1980's are no longer statistically significant. This is in contrast to the work of the other two sets of authors, who find that the anomalous daily seasonality survives in Australia and in seven European countries (including the UK but not Ireland). Mills and Coutts and Peiro find mixed results across time periods. Relatively little work in the area of monthly seasonality has used these approaches. More detailed discussion on the various approaches can be found in Connolly (1989).

7.8. BAYESIAN INFERENCE

The interpretation of classical statistics is to compare the computed F or t value against a table showing the critical values at various levels of significance, usually 0.05 or 5%. While this is customary and convenient, it has no well-founded economic or statistical justification over any other significance level. Bayesian analysis on the other hand incorporates directly into the critical values the fact that as the sample size rises there is a need to adjust downward the critical values (whose initial choice is still perhaps arbitrary). This problem has been recognised since Lindley (1957).

For example, consider a simple test (t-test), where the question (or null hypothesis) is: is the mean of the population under investigation equal to k.

More formally, the test is

$H_0: \mu = k$ and the alternative hypothesis of $H_1: \mu$? k, where k is an arbitrary constant.

Hence, the simple test is $t = \left(\frac{\bar{x}-k}{S}\right)\sqrt{n-1}$ where $\bar{x}$ is the mean, S is the Standard deviation, and n is the sample size. Hence, t can be increased (and hence the associated P-value decreased) by increasing either $\bar{x}-k$-or $\sqrt{n-1}$. But as n increases, then $\bar{x}-k$ and S will tend to constants - their true values. Hence, a large value of n directly translates into a large value of t, and hence a small value of P. More formally, as $n \to \infty, \bar{x}-k \to \text{constant}, S \to \text{constant}, t \to \infty, P \to 0$ Hence, it can be stated that P has a strong dependence on the sample size, and its value is almost independent of the existence, or not, of an effect, when the sample size is large.

Chang, Pinegar and Ravichandran (1993), in addition to the use of robust estimators, employ explicit Bayesian adjustments, in the spirit of Connolly (1991) and French (1980). Their paper is noteworthy for apparently being the only paper that combines Bayesian methods with robust estimation procedures. This is especially interesting as it allows the relative 'robustness' of the results to the various alternative estimation procedures, adjustments to the classical error term, and Bayesian inferences to be seen.

As pointed out, the use of Bayesian inference in this area is not new, having been adopted by French. While both he and Connolly (1991)used a posterior odds approach, Connolly (1989) and Chang, Pinegar and Ravichandran (1993) utilise the fact that one can adjust the standard F and t tests to incorporate the effect of increased amounts of data.

The interpretation of classical statistics is to compare the computed F or t value against a table showing the critical values at various levels of significance, usually 0.05 or 5%. While this is customary and convenient, it has no well-founded economic or statistical justification over any other significance level. Bayesian analysis on the other hand incorporates directly into the critical values the fact that as the sample size rises there is a need to adjust downward the critical values (whose initial choice is still perhaps arbitrary) Connolly (1991) discusses the Bayesian approach to daily seasonality in detail while Connolly (1989) (p 140)provides formulae for adjusted, or Bayesian , t and F statistics. These are easily calculated from the classical OLS F and t statistics being

$$\text{EQ. 33: } F^{\text{bayes}} = \left[\left(\frac{T-k_i}{k_0-k_i}\right)*\left(T^{k_0-k_i/T}-1\right)\right]$$

and

$$\text{EQ. 34: } t^{\text{bayes}} = \left[(T-k)*\left(T^{1/T}-1\right)\right]^{0.5}$$

where k = number of parameters to be estimated, subscripted 0 and 1 for the alternative and null hypotheses and T is the number of observations. Clearly, these are simply calculated, and thus a Bayesian t and F statistic calculated. As the number of observations in the sample size increases so too do the Bayesian t and f statistics

7.9. RESAMPLING ANALYSIS

A radically different approach to statistical inference has more recently become available, taking the older concept of Monte Carlo Simulation and using the power of modern computing to allow it be used for inference.

A wide variety of introductions to the resampling methodology exist; not surprisingly, given the computer intensive nature of these approaches, many of these are web based. Two in particular which this section draws heavily upon are Yu (2002) and Simon (1997).

In classical statistics, including here the Bayesian families, the mode of inference is to compare observed to theoretical. In financial economics the vast majority of theoretical distributions that are used for inference purposes are, whether consciously or unconsciously, normal distributions Using the resampling approach allows one to dispense with the need to assume either that a particular distribution is the one that the series should follow in theory or is the most likely candidate to describe the actual distribution. Inference is based on the observed sample itself, using a large number of reshufflings, permutations, and resampling from the data. It is important to realize that in this respect the resampling school shares a key assumption or commonality with the classical school. Both rely on the observed sample for inference. If the observed sample is truly a poor reflection or sample of reality then both schools of analysis will return poor inferences about the population. Resampling is closely tied to Monte Carlo simulation. In the latter the data that are under investigation (for example the power of a test for heteroskedasticity under non-linearity) could equally validly be real or constructed. The same is not the case for resampling, which properly is only used in real world datasets.

A number of types of resampling can be identified.

- **Randomization Exact Tests**. Developed by R A Fisher, this approach involves taking all possible permutations of observations from the data. Take a case where we have 3000 daily observations of stock returns and are interested in the first moment of the daily distributions. There are approximately 600 Monday, Tuesday etc observations in the sample (ignoring for the moment days for which returns are missing due to exchange closings etc). In reality there is one vector of 600 Monday returns. A RET would require taking all possible combinations of 600 days from the 3000, calculating their first moment and thus having a distribution of means against which the observed mean of the Monday returns can then be calculated. This is an immense number of vectors, and a full analysis of daily seasonality in the first moment would require 5 of these analyses. Not surprisingly this approach is not commonly used in cases with large numbers as above. More detail on exact tests can be found in Edgington (1995).

- **Jacknife**. Also known as the Quenouille-Tukey Jacknife, Tukey considered it to be a useful tool in all circumstances, hence the name. Developed initially by Quenouille (1949) and modified by Tukey (1958), it is also known as **Leave-one-out**. Jacknife can be seen as a step further from cross validation. In Jacknife, the same test is repeated by leaving one subject out each time. This procedure is especially useful when the dispersion of the distribution is wide or extreme values are present in the data set.

- **Bootstrap**: Using the analogy of 'pulling oneself up by one's own bootstrap', this approach was introduced and refined by Efron and Tibshirani (1993). The key difference between the bootstrap and other methods noted above is that the sample is duplicated many times and the parameter estimates from this are used as an empirical sampling distribution. Thus instead of drawing all possible combinations of 600 days from the 3000 in the example above we might instead draw, at random, 1000, or 10000 samples of 600 days. A distinction can be drawn between permutation bootstrapping (more commonly called randomization analysis) and bootstrapping. With bootstrapping there is typically replacement of each data point drawn into the larger sample, while with randomisation analysis there is no replacement. The rationale for this is that each observation has a unitary probability of appearing in reality (there is only one day every day) and so this should be reflected in the virtual populations.

Resampling and bootstrapping has been advocated in a number of situations, some of which are relevant to this study. These include

- **Population uncertainty**: where we are not sure of the exact extent of the population or the population is itself ill-defined then Diaconis and Efron (1983) and Peterson (1991) advocate resampling. In the case of financial economics, for the most part we are fairly sure as to the extent of the population. For example, this work is concerned with the distribution of equity returns in the Irish market across calendar periods. To that extent the population is precise. However, we may often find ourselves in a situation in finance where the entire population of price changes in an asset is not known, either through investigator uncertainty or lack of adequate recording of such data.

- **Small Samples**: Finance does not typically suffer from small sample sizes, except in cases of either new series (a new asset or a new market) or in historical investigations. Where there are small datasets and/or these do not conform to the theoretical distributions Diaconis and Efron (1983) suggest resampling.

- **Non-random sample**: Classical procedures require random sampling to validate the inference from a sample to a population. Resampling is valid for any kind of data, including random and non-random data, as discussed in Edgington (1995). In finance, this is important, as often the analysis of data is of a national or regional or industrial sample of data from an overall universe of asset returns.

- **Large sample size**: Although resampling is a remedy for small sample size, it can also be applied to the situation of overpowering. Given a very large sample size, one can reject virtually any null hypothesis. A very large sample can be subdivided into smaller samples allowing cross validation, and also allowing resampling to act as a check on the 'population' inferences.

- **Replications**: Classical procedures do not inform researchers how likely the results can be replicated. Repeated experiments in resampling such as cross-validation and bootstrap can be used as **internal replications** (Thompson and Snyder (1997))

Resampling is not without its criticisms however. Some of these include:

- **Generalization**: Some critics (Ludbrook and Dudley (1998)) argue that resampling is based on one sample and therefore the generalization cannot go beyond that particular sample.

- **Bad data**: Some critic's challenge that when the collected data are biased, resampling repeats and magnifies the same mistake. Rodgers (1999) admitted that the potential magnification of unusual features of the sample is certainly one of the major threats to validity of conclusion derived from resampling procedure.

Although increasingly being used in biomedical, engineering and general statistical literature the use of randomization in analysis of calendar regularities is negligible. An analysis of EconLit and ABI-Inform databases reveals that only Larsen and Resnick (1995), Sullivan, Timmerman and White (1999) and Sullivan, Timmermann and White (2002) have incorporated bootstrapping or randomization into their works.

8. Data To Be Analysed

This section of the work describes the data sources and provides basic information regarding the distribution of the moments of the data.

8.1. DATA TO BE ANALYSED

The dataset consists of a variety of indices, of varying constructions and covering various time periods, covering the Irish equity market. To overcome the problem of a significant outlier, such as the 1987 market crash, distorting the results the data are trimmed. This operates by discarding the extreme 2.5% positive and negative changes, giving a 5% trim. In addition, as discussed, this allows a robust analysis to be carried out of the first moment by means of Trimmed Least Squares.

8.2. THE IRISH STOCK EXCHANGE OFFICIAL INDICES

8.2.1. PRICE AND RETURN INDICES

Wholly reliable, daily, consistent stock indices are available in Ireland only from the start of January 1988 with the start of publication of the ISEQ index by the Irish Stock Exchange. Longer run monthly indices do exist, calculated by the Central Statistic Office, providing a monthly share price index back to the early 1930's. However, these are available only on a monthly basis and as such are unsuited to the analysis of daily seasonality. The Stock Exchange subsequently back calculated the ISEQ data to January 1983. This index is available both as a price index and as a total return index, with dividends included. Other indices available from the stock exchange consist of the stock exchange general and financial series of indices. The availability of the dividend inclusive index is auspicious, as it allows the hypotheses of the Phillips-Patrick and Schneeweis (1988) contention that adjusting for dividends reduces any daily seasonal effects. All ISEQ indices are market capitalization weighted indices. More detail is available on http://www.ise.ie/marketinfo/iseqcalculation.pdf.

The stock exchange data thus gives eight indices: the official market index, ISEQ and its 5% trimmed version, TISEQ; the stock exchange official index with dividends included, ISEQR and its 5% trimmed version, TISEQR; the stock exchange financial sector index, ISEFIN and its 5% trimmed version TISEFIN; the stock exchange general market index, ISEGEN and its 5% trimmed version, TISEGEN.

8.2.2. VOLUME AND TURNOVER DATA

One of the difficulties facing those who would investigate equity market activities in the Irish stock exchange is the lack of volume data. Communication with the stock exchange ascertained that only after 1997 was a consistent electronic recording of volume on a stock-by-stock basis established. Prior to this, stock level transactions data is available only from hardcopy records issued daily. In all cases this is total daily net trade however, rather than total daily trade overall.

8.3. AUTHOR CREATED INDICES

This set of data consists of indices created by the author, in response to the non-existence of a series of indices that would permit comparison between the dynamics of returns for small and large firms over the time period under investigation.

Gibbons and Hess (1981), Rogalski (1984) and Kohers and Kohers (1995) for the USA and Theobald and Price (1984) for the UK find size effects in various indices. Since

January 1999, the Irish stock exchange has compiled and published an official index of small capitalisation stocks, defined as stocks with a market capitalisation of less than £400m. However, they have not made available any back-calculated data for this index and there are, it appears, no plans by the stock exchange to so do. In addition, as noted earlier, this work examines the period between the breaking of the link between the Irish pound with sterling, in 1979, and entry to EMU in 1999.

The numbers of firms on the Irish stock market have varied between 80 and 130 over the period of analysis. Thus, the formation of value-weighted deciles would have resulted in small numbers of firms in each decile, carrying with it the probability that the smallest deciles might have extremely thin trading. The Stock Exchange and Riada Stockbrokers provided the author with a dataset consisting of the monetary amount of each stock's aggregate daily transactions, market value and daily closing price, for the years 1993-1998. From this dataset were then excluded three sets of stocks. I first excluded those with their primary listing in the UK and with only a secondary listing on the Dublin exchange (companies such as Tesco or Ashquay, who list on the exchange but in whose shares no trading takes place on the Irish market). The second set of excluded data consisted of the equities of companies engaged in oil or gas exploration (such as Pan-Andean Resources or Glencar Holdings). The final set consisted of the equities of government owned companies, where those companies held an exchange listing but in which trading was not possible (such as ICC Bank).

While the rationale for the first and last are self evident, the reasoning behind the exclusion of the petrochemical exploration companies perhaps requires more explanation. We have seen that throughout the 1970's and 80's a large number of such companies obtained full or partial listings on the exchange. Many of these have been characterised by very small volumes of trade, very low capitalisation, and very volatile price histories. I therefore decided, mainly on pragmatic grounds, to exclude these from the analysis. Certain of these firms were, at times, highly valued and highly capitalised, and attained a full official listing on the exchange. Thus, *inter alia* they would have been included in the ISEQ index.

I ranked the firms according to the December 31 market value. I then divided them into quartiles based on these market values. Firms hold their place, in terms of the quartile in which they place based on the 31 December market value, during the subsequent year, regardless of how the market value evolves. For each quartile, I then calculate equal- and value- weighted daily price indices, as well as an overall equal or value weighted index. The process is repeated each 31 December.

20 indices arise from this: for each quartile an equal weighted index (EWQi) and a value weighted price index (VWQi), an overall equal or value weighted index (EQUAL WEIGHTED TOTAL & VALUE WEIGHTED TOTAL), as well as trimmed indices (EQUAL WEIGHTED TOTAL TRIMMEDi, VALUE WEIGHTED TOTAL TRIMMEDi, etc.). Table 10 shows the numbers of companies per quartile per annum, quartile 1 containing those firms ranked in the lowest quartile by market capitalisation, quartile 4 those ranked in the largest.

TABLE 10: NUMBER OF FIRMS IN EACH QUARTILE BY YEAR.

Quartile	93	94	95	96	97	98
1	16	17	19	19	17	19
2	15	15	13	14	13	12
3	13	11	11	12	11	12
4	15	15	16	15	15	17

8.4. DATASTREAM INTERNATIONAL INDICES

Datastream international produce other sets of indices, and they represent the longest consistent daily series available for the Irish market. They comprise indices for the market as a whole in price and total return forms; Datastream have also calculated four sectoral indices. As noted, the Irish market has been characterised by a high level of speculative issues, chiefly related to exploration stocks. While the market indices include these, the sectoral indices, as do the authors own constructions, exclude them. These Datastream indices are for the market as a whole; for financial services companies, useful in the light of the high weighting of financial firms in the Irish stock market; for industrial firms defined as the market less financial and less resource extractive firms) and; the market excluding resource extraction firms. All data are value-weighted indices. The availability of sectoral indices allows in principle replication of the work of Pena (1995)and Kamath, Chakornpipat and Chatrath (1998) on sectoral indices and daily seasonality.

A major problem with these indices exists however. The construction method of the indices is such as to induce a considerable, but unknown, amount of survivor bias. Firms that existed on the market at 1 January 1988 formed the basis for back calculation of the indices. From 1 January 1988, firms that obtained listings on the market, either in full or in part are included in the appropriate sectoral index. This issue in the Irish case has been analysed by Ryan and Donnelly (1998) who carried out an analysis of such survivor bias and concluded that the effects were potentially serious, and accordingly I have therefore decided not to use them. Table 11 provides summary details of the indices on which I carry out preliminary analyses. From these, as discussed in the next chapter, a sample set is chosen for more detailed examination.

8.5. INDICES FOR MONTHLY ANALYSES

Analysis of monthly seasonality requires different considerations to that of daily seasonality. In particular, the frequency of data collected imposes limits on the statistical techniques that are deployable. For example, when daily data are collected (such as for the ISEQ) then there are, on average, 20+ data points in each month and therefore even a few years of data will yield well over 100 data points for reach of the 12 months in the year. Consequently, partitioning the data on these months will still leave enough usable data in each 'bin'. By contrast, if data are available only on higher frequencies correspondingly longer runs of data are needed to obtain enough data points to allow any meaningful analysis.

As noted earlier (section 8.2) the longest run of daily data for the Irish market extends only to 1988. However, this provides over 10 years an average of in excess of 200 data points in each month, more than enough for any statistical analyses. Longer run data does exist however. From January 1934 to the mid-1980s the Irish Central Statistics Office (CSO) compiled a capital return index of Irish companies, *the CSO Price Index of Ordinary Stocks and Shares of Companies incorporated in Ireland (except Railways)* (the CSO Index). Details on the construction of the index are rather scant with, for instance, official sources such as the CSO itself, the annual *Statistical Abstract of Ireland* or its forerunner, the *Irish Trade Journal,* providing minimal descriptions. However, Geary (1944) describes it as an arithmetic, market-capitalisation weighted index with (at that time) complete coverage of the 88 non-railway Irish registered stocks listed on the two Irish exchanges of Dublin and Cork. This method of construction, was unusual for that time with, for instance, the Dow Jones Industrial Average being a unweighted arithmetic average of 30 share prices or the British FT Ordinary Share Index being an unweighted geometric average of again just 30 share prices.

The CSO Index was calculated from share prices quoted on the Irish Stock Exchange on the first trading day of each month. There have been a few changes in its method of construction since 1934. Each January beginning in January 1958, the index was adjusted to include only those shares that had been dealt in the previous twelve months. This entailed a reduction of the number of companies covered from 118 in January 1957 to 101 in January 1958 (Murray (1960)). In 1967 the index was again adjusted to include only companies with a market capitalisation in excess of IR£0.5 million (Kirwan and Mcgilvray (1983)). Finally, the index was later superseded in the January 1988 (Statistical Abstract 1988) by the more comprehensive Irish Stock Exchange Equity (ISEQ) series of indices. The statistical properties and monthly seasonal pattern of the CSO index is discussed in a number of publications, notably Whelan (1999) and Lucey and Whelan (2002).

8.6. Index Selection

In total the indices above represent 40 indices, a considerable amount of data for analysis. To achieve focus on the moments of the distribution, the main aim of this work, I choose a reduced sample of the 40 indices. With rare exceptions, all the indices are highly correlated with one another across the time periods under investigation. In particular, all of the Datastream and Irish stock exchange indices are highly correlated with each other, and as the segmentation of the market represented by the indices is similar, I decided that only the Irish stock exchange indices should be retained. The quartile indices are not highly correlated (although many still retaining statistical significance) with the Irish Stock Exchange indices, nor with one another. Accordingly, these represent a set of data whose movements are not mirrored in other indices. The final selection of data therefore comprises the following;

- The Irish Stock Exchange Official Index, ISEQ and its total returns variant, ISEQR;
- The Irish stock exchange Financial index ISEFIN
- The Irish stock Exchange general industrial companies index ISEGEN and
- The quartile indices created by the author

Graphs of the data are appended to the end of this chapter.

TABLE 11: INDICES ANALYSED

Index Type	Description	Mnemonic	Construction Method	Coverage	Sample Period
Own Indices					
	Equal Weighted Quartile 1	EWP1	Equal Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Quartile 1 Trimmed	TEW1	Equal Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Quartile 2	EWP2	Equal Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Quartile 2 Trimmed	TEW2	Equal Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Quartile 3	EWP3	Equal Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Quartile 3 Trimmed	TEW3	Equal Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Quartile 4	EWP4	Equal Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Quartile 4 Trimmed	TEW4	Equal Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Total	EWP	Equal Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Equal Weighted Total Trimmed	TEW	Equal Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value Weighted Quartile 1	VWP1	Value Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value Weighted Quartile 1 Trimmed	TVW1	Value Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value Weighted Quartile 2	VWP2	Value Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value Weighted Quartile 2 Trimmed	TVW2	Value Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value Weighted Quartile 3	VWP3	Value Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998

Index Type	Description	Mnemonic	Construction Method	Coverage	Sample Period
	Value Weighted Quartile 3 Trimmed	TVW3	Value Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value weighted quartile 4	VWP4	Value Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value weighted quartile 4 trimmed	TVW	Value Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value Weighted Total	VWP	Value Weighted	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
	Value Weighted Total Trimmed	TVW	Value Weighted, Trimmed	All stocks with the exception of NI and UK stocks	Jan 1 1993 – Dec 31 1998
Official Irish Stock Market Indices					
	ISEQ	ISEQ	Value Weighted	All Stocks	Jan 1 1988- Dec 31 1998
	ISEQ Trimmed	TISEQ	Value Weighted, Trimmed	All Stocks	Jan 1 1988- Dec 31 1998
	ISEQ Total Returns	ISEQR	Value Weighted, Dividend Inclusive	All Stocks	Jan 1 1988- Dec 31 1998
	ISEQ Total Returns Trimmed	TISEQR	Value Weighted, Trimmed, Dividend Inclusive	All Stocks	Jan 1 1988- Dec 31 1998
	ISE Financial Sector Index	ISEFIN	Value Weighted	All Financial Stocks	Feb 17 1989 – Dec 31 1998
	ISE Financial Sector Trimmed	TISEFIN	Value Weighted, Trimmed	All Financial Stocks	Feb 17 1989 – Dec 31 1998
	ISE Industrial Companies	ISEGEN	Value Weighted	All Stocks less Financial	Feb 17 1989 – Dec 31 1998
	ISE Industrial Companies Trimmed	TISEGEN	Value Weighted, Trimmed	All Stocks less Financial	Feb 17 1989 – Dec 31 1998

8.7. Lower Moments

Details of the daily and monthly moments of the indices are contained in Table 12 & Table 13. Concentrating initially on the daily distribution, certain patterns are evident. First, there appears, at least in the indices from the Irish stock exchange, to be a Wednesday effect. The literature internationally demonstrates a Monday or occasionally a Tuesday minimum with a Friday maximum, while the previous Irish literature offers contradictory results. For the ISEQ, ISEQ total returns, Irish stock exchange financial and general indices, and for the trimmed variants of the ISEQ and the ISEQ total returns index, a Wednesday maximum occurs when the data are looked at in aggregate, while for the ISE Financial and general indices, in their trimmed variants, the maximum occurs on Tuesday. A Monday minimum is also observed in 6 of these 8 indices, with only the ISEQ Total Returns index showing, both in trimmed and original versions, a Friday minimum.

The situation is much more confused in the quartile indices. Recall however that these are not highly correlated with the Irish stock exchange indices. Each day is, at least once, the day on which the highest mean return occurs, and the lowest. The pattern of maximum-minimum days also shifts considerably from the original to the trimmed indices, in contrast to the situation found in the stock exchange indices. The most stable set of relationships is in the value weighted indices, for the largest companies and overall, where both in the original and trimmed indices the pattern of Tuesday being the maximum and Thursday the minimum is maintained. The only other sets of common daily duos are for the small companies indices where both the value and equal weighted indices show a Tuesday maximum and Friday minimum, and for micro companies where the trimmed indices show a Monday-Wednesday paring. Such regularity as does appear therefore is minimal.

Second, this pattern of returns seems not to be related to risk patterns. Examination of the relationship between the days on which the maximum and minimum means occur versus those for standard deviation reveals little empirical support for the contention of the standard paradigm that high returns accompany higher risk. In only a very small number of cases does the day on which the highest, or lowest, mean return occur, match that of the days on which the highest or lowest standard deviation. For the stock market indices the ISEQ and ISEQ Total return index, trimmed, shows a match between the highest mean return and standard deviation on a Wednesday, while the ISEQ total return shows a match for the lowest on a Friday. In the equal weighted indices only the medium companies index provides a match between the highest mean and standard deviation on a Friday, while the matches are for the lowest on the equal weighted all companies index, for Thursday, and also for a lowest Thursday on the value weighted largest and all companies indices.

An analysis of the mean and standard deviation of the returns by year also displays a number of interesting patterns that help refine the results above. For the Irish stock exchange indices, the pattern that they display overall, in terms of the days on which the highest and lowest mean returns occur, is not entirely stable across the 10 years of observations. Thus, the ISEQ shows the overall pattern in only 4 individual years, the total returns index only in 2 years and the financial index in only 1 of the years. However, while the pattern of the two days taken as a pair may be less stable, the frequency with which that day, which, overall, provides the highest or lowest mean return, is greater.

Thus the ISEQ total return has 3 Wednesdays (they being the highest) and 5 Fridays (they being the lowest), the general index 4 Wednesdays and 5 Fridays, and so forth. This general tendency is also evident in the quartile indices, again, the particular pattern of days that, overall, are maximal or minimal, being rare, but the frequency of such days individually being high. Certain 'islands of stability' are apparent however. For the trimmed equal weighted indices, for the smaller capitalization portfolios the minimum return days tend to be Monday through Wednesday, while the lowest return days for the largest capitalisation portfolios tend to be Thursday and Friday. An examination of the pattern of standard deviations by year yields similar results. Regardless, this indicates that the stability of the daily seasonal relationship is not immediately obvious.

In terms of the monthly data, a number of patterns are also evident. January mean return is typically high, being the highest in three of four ISEQ indices (the exception being the ISEFIN, the highest month being December followed by February and then January. There is some difference however in the pattern as between the equal and value weighted indices; while the value weighted indices typically show January as being the highest (save for the value weighed quartile 1 index, the smallest), this is not the case for the equal weighed indices. In the trimmed indices this pattern is changed somewhat. January is typically the highest mean return for the smaller quartile portfolio indices across the equal and value weighed indices. In general there does not appear to be a relationship across months between risk and return; the rank correlation coefficients of the mean-standard deviation set of data are negative for the ISEQ, ISEQR, ISEGEN, EWP2, EWP3, EWP, and VWP indices, and is below 0.5 for the majority of the trimmed indices, the clear exception being the TISEFIN. Thus on a risk-return basis the pattern is not as predicted.

Using the Levene test for equality of variance, we can see that, in general and with few exceptions, it is not possible to reject conclusively the hypothesis of equality of variances. At the 5% significance level the Value weighted large companies, trimmed, value weighted all companies, trimmed, and the ISEQ Trimmed indices reject the hypothesis. For the ISEQ itself the acceptance or rejection of the hypothesis varies across time-periods. A number of other indices at other times reject the hypothesis of variance equality, but at lower significance levels. The results in Table 12 show that the ISEQ indices, when analysed on a year-by-year basis, typically cannot reject the hypothesis of equality of variance.

Finally, significant departure from normality is the norm for the indices under investigation. Under all the measures provided, only for the trimmed variants of the ISEQ indices do we seem to have some evidence of normality of the indices. Shown in Appendix I are the histograms of the data with normal curves superimposed.

TABLE 12: MOMENTS OF THE DISTRIBUTION FOR ALL INDICES, BY DAY.

		N	Mean	Median	Std. Deviation	Skewness	Kurtosis
ISEQ	Monday	511	0.002	-0.010	0.450	0.045	10.445
	Tuesday	565	0.031	0.020	0.411	-0.957	10.992
	Wednesday	568	0.052	0.020	0.385	0.420	2.538
	Thursday	568	0.032	0.030	0.369	-1.014	8.495
	Friday	567	0.008	0.010	0.353	0.019	3.444
	Total	2779	0.025	0.010	0.394	-0.301	8.170
ISEQR	Monday	510	0.033	0.010	0.449	0.154	10.365
	Tuesday	565	0.032	0.020	0.414	-0.906	10.168
	Wednesday	568	0.051	0.010	0.378	0.462	2.499
	Thursday	568	0.031	0.030	0.370	-1.033	8.524
	Friday	567	0.006	0.010	0.354	0.068	3.256
	Total	2778	0.030	0.020	0.393	-0.247	8.028
ISEFIN	Monday	462	-0.011	-0.040	0.575	0.763	5.871
	Tuesday	512	0.054	0.025	0.551	-0.570	7.636
	Wednesday	514	0.057	0.010	0.538	-0.088	2.860
	Thursday	515	0.044	0.030	0.569	-0.761	7.093
	Friday	513	0.008	0.010	0.494	-0.254	5.130
	Total	2516	0.031	0.000	0.546	-0.186	5.779
ISEGEN	Monday	462	0.004	0.000	0.429	-1.235	25.160
	Tuesday	512	0.009	0.000	0.400	-0.394	12.629
	Wednesday	514	0.035	0.010	0.371	0.396	2.857
	Thursday	515	0.016	0.020	0.328	-0.798	7.010
	Friday	513	0.013	0.020	0.330	0.229	2.637
	Total	2516	0.016	0.000	0.372	-0.450	13.364
EWP1	Monday	274	0.008	0.000	0.490	-2.028	14.313
	Tuesday	309	-0.054	0.000	1.301	-7.811	97.872
	Wednesday	310	0.045	0.000	0.592	2.658	33.973
	Thursday	309	0.041	0.000	1.072	13.011	211.738
	Friday	309	0.071	0.000	0.573	4.759	39.676
	Total	1511	0.022	0.000	0.874	-0.062	200.091
EWP2	Monday	274	0.003	0.000	0.349	-5.844	64.389
	Tuesday	309	0.055	0.010	0.728	3.364	52.897
	Wednesday	310	0.019	0.020	0.245	-3.919	35.895
	Thursday	309	0.036	0.010	0.202	1.208	9.204
	Friday	309	-0.018	0.000	1.063	-15.751	268.121
	Total	1511	0.020	0.010	0.618	-15.428	500.479
EWP3	Monday	274	-0.025	0.000	0.744	-14.324	225.543
	Tuesday	309	0.038	0.010	0.601	2.604	96.292
	Wednesday	310	0.036	0.010	0.223	0.847	5.316
	Thursday	309	0.023	0.010	0.223	0.797	10.683

		N	Mean	Median	Std. Deviation	Skewness	Kurtosis
	Friday	309	0.054	0.000	1.132	12.637	218.022
	Total	1511	0.026	0.000	0.675	9.036	422.509
EWP4	Monday	274	0.093	0.000	0.667	8.359	98.669
	Tuesday	309	0.020	0.030	0.459	-3.150	22.190
	Wednesday	310	0.061	0.040	0.484	1.680	16.751
	Thursday	309	0.024	0.030	0.511	-4.044	38.324
	Friday	309	0.024	0.000	0.538	-0.375	39.395
	Total	1511	0.043	0.020	0.533	2.014	63.731
EWP	Monday	274	0.033	0.030	0.424	-3.865	84.882
	Tuesday	309	0.029	0.030	0.245	-3.056	27.625
	Wednesday	310	0.044	0.040	0.229	0.872	6.477
	Thursday	309	0.028	0.030	0.220	-2.477	24.017
	Friday	309	0.030	0.020	0.221	-1.549	17.787
	Total	1511	0.033	0.030	0.274	-3.320	94.707
VWP1	Monday	274	0.077	0.000	0.618	1.760	12.423
	Tuesday	309	0.056	0.000	1.098	-6.050	102.742
	Wednesday	310	0.020	0.000	0.589	3.753	39.307
	Thursday	309	0.272	0.000	3.772	16.974	294.597
	Friday	309	-0.217	0.000	4.097	-17.150	299.041
	Total	1511	0.041	0.000	2.596	-3.235	650.223
VWP2	Monday	274	0.032	0.010	0.358	-3.193	43.561
	Tuesday	309	0.098	0.030	0.733	8.059	83.970
	Wednesday	310	0.045	0.010	0.267	2.424	25.799
	Thursday	309	0.020	0.010	0.551	-12.186	191.924
	Friday	309	-0.004	0.000	0.426	-5.943	55.369
	Total	1511	0.038	0.010	0.497	1.070	150.460
VWP3	Monday	274	0.008	0.000	0.270	-0.965	6.926
	Tuesday	309	0.079	0.030	0.424	4.270	36.356
	Wednesday	310	0.035	0.025	0.257	0.836	12.511
	Thursday	309	-0.001	0.000	0.905	-6.847	143.052
	Friday	309	0.108	0.030	1.140	13.757	212.134
	Total	1511	0.047	0.020	0.705	9.123	377.960
VWP4	Monday	274	0.051	0.040	0.400	0.135	20.575
	Tuesday	309	0.067	0.040	0.399	0.783	4.021
	Wednesday	310	0.050	0.035	0.394	-0.970	7.997
	Thursday	309	0.007	0.010	0.390	-2.332	16.865
	Friday	309	0.056	0.010	0.396	2.022	14.664
	Total	1511	0.046	0.030	0.396	-0.044	12.615
VWP	Monday	274	0.046	0.040	0.345	-0.156	18.717
	Tuesday	309	0.069	0.050	0.347	0.635	3.746
	Wednesday	310	0.048	0.050	0.338	-1.199	9.203
	Thursday	309	0.013	0.010	0.327	-1.815	13.481
	Friday	309	0.054	0.010	0.359	2.574	19.950
	Total	1511	0.046	0.030	0.344	0.157	13.149
TISEQ	Monday	454	0.007	0.000	0.253	0.344	0.078

		N	Mean	Median	Std. Deviation	Skewness	Kurtosis
	Tuesday	516	0.034	0.000	0.255	0.150	-0.312
	Wednesday	519	0.048	0.000	0.278	0.164	-0.500
	Thursday	525	0.037	0.010	0.239	-0.033	-0.179
	Friday	526	0.015	0.000	0.252	0.040	-0.149
	Total	2540	0.029	0.000	0.256	0.142	-0.231
TISEQR	Monday	446	0.020	0.000	0.243	0.123	-0.120
	Tuesday	506	0.034	0.000	0.245	0.169	-0.399
	Wednesday	509	0.042	0.000	0.262	0.151	-0.546
	Thursday	523	0.039	0.010	0.238	0.008	-0.281
	Friday	516	0.011	0.000	0.241	0.004	-0.334
	Total	2500	0.029	0.000	0.246	0.099	-0.342
TISEFIN	Monday	412	-0.020	0.000	0.347	0.370	-0.104
	Tuesday	460	0.056	0.000	0.337	0.119	-0.384
	Wednesday	456	0.051	0.000	0.362	0.158	-0.497
	Thursday	463	0.051	0.000	0.326	0.064	-0.152
	Friday	473	0.018	0.000	0.337	0.127	-0.267
	Total	2264	0.032	0.000	0.343	0.163	-0.316
TISEGEN	Monday	413	-0.001	0.000	0.220	0.069	-0.060
	Tuesday	460	0.025	0.000	0.234	0.083	-0.462
	Wednesday	454	0.011	0.000	0.241	0.055	-0.462
	Thursday	476	0.025	0.000	0.230	0.096	-0.413
	Friday	461	0.015	0.000	0.221	-0.059	-0.375
	Total	2264	0.015	0.000	0.230	0.054	-0.366
TEW1	Monday	250	0.040	0.000	0.196	0.598	0.836
	Tuesday	274	0.030	0.000	0.218	0.506	0.855
	Wednesday	278	0.016	0.000	0.195	0.162	1.056
	Thursday	277	0.017	0.000	0.192	0.581	1.447
	Friday	280	0.022	0.000	0.171	0.254	1.859
	Total	1359	0.025	0.000	0.195	0.442	1.206
TEW2	Monday	246	0.017	0.000	0.119	0.631	0.805
	Tuesday	272	0.023	0.000	0.117	0.210	0.307
	Wednesday	282	0.039	0.000	0.130	0.160	0.219
	Thursday	281	0.027	0.000	0.119	0.255	0.320
	Friday	278	0.026	0.000	0.119	0.511	0.650
	Total	1359	0.027	0.000	0.121	0.347	0.408
TEW3	Monday	244	0.020	0.000	0.130	0.490	0.493
	Tuesday	273	0.021	0.000	0.143	0.198	0.093
	Wednesday	280	0.029	0.000	0.129	0.529	0.338
	Thursday	287	0.024	0.000	0.140	0.189	0.253
	Friday	275	0.021	0.000	0.132	0.270	0.278
	Total	1359	0.023	0.000	0.135	0.313	0.275
TEW4	Monday	251	0.030	0.000	0.200	0.420	0.248
	Tuesday	277	0.058	0.010	0.217	0.124	-0.471
	Wednesday	269	0.042	0.000	0.214	0.163	-0.478
	Thursday	280	0.033	0.000	0.201	0.210	-0.081

		N	Mean	Median	Std. Deviation	Skewness	Kurtosis
	Friday	282	0.025	0.000	0.213	0.360	0.073
	Total	1359	0.038	0.000	0.209	0.252	-0.192
TEW	Monday	242	0.031	0.010	0.112	-0.022	0.472
	Tuesday	280	0.041	0.020	0.126	0.091	-0.321
	Wednesday	274	0.040	0.015	0.123	-0.009	-0.333
	Thursday	283	0.028	0.010	0.118	0.078	-0.424
	Friday	280	0.027	0.000	0.122	0.175	-0.371
	Total	1359	0.033	0.010	0.121	0.075	-0.253
TVW1	Monday	238	0.047	0.000	0.266	0.540	0.756
	Tuesday	272	0.039	0.000	0.269	0.254	0.547
	Wednesday	284	0.006	0.000	0.262	0.450	0.906
	Thursday	281	0.012	0.000	0.262	0.426	1.093
	Friday	284	0.016	0.000	0.255	0.332	0.478
	Total	1359	0.023	0.000	0.263	0.398	0.732
TVW2	Monday	247	0.048	0.000	0.141	0.267	-0.221
	Tuesday	277	0.040	0.000	0.135	0.221	0.199
	Wednesday	278	0.036	0.000	0.150	0.399	-0.047
	Thursday	277	0.030	0.000	0.142	0.414	0.283
	Friday	280	0.028	0.000	0.147	0.479	0.225
	Total	1359	0.036	0.000	0.143	0.360	0.066
TVW3	Monday	250	0.008	0.000	0.173	0.188	-0.326
	Tuesday	272	0.039	0.000	0.162	0.262	-0.139
	Wednesday	282	0.032	0.000	0.153	0.189	-0.007
	Thursday	271	0.026	0.000	0.169	0.214	-0.205
	Friday	284	0.041	0.020	0.157	0.158	-0.106
	Total	1359	0.030	0.000	0.163	0.185	-0.163
TVW4	Monday	249	0.047	0.000	0.221	0.151	-0.314
	Tuesday	268	0.054	0.000	0.233	0.174	-0.551
	Wednesday	278	0.048	0.010	0.233	0.091	-0.421
	Thursday	284	0.033	0.000	0.238	0.136	-0.570
	Friday	280	0.035	0.000	0.204	0.307	-0.127
	Total	1359	0.043	0.000	0.226	0.166	-0.413
TVW	Monday	251	0.047	0.010	0.196	0.190	-0.290
	Tuesday	269	0.054	0.010	0.207	0.118	-0.614
	Wednesday	276	0.052	0.015	0.198	0.129	-0.427
	Thursday	282	0.029	0.000	0.202	0.107	-0.559
	Friday	281	0.037	0.000	0.174	0.403	-0.092
	Total	1359	0.044	0.000	0.195	0.178	-0.414

TABLE 13: MOMENTS OF THE DISTRIBUTION FOR ALL INDICES, BY MONTH

		N	Mean	Std. Deviation	Skewness	Kurtosis
ISEQ	January	233	0.108	0.441	0.879	1.579
	February	222	0.064	0.393	0.917	7.882
	March	231	0.042	0.365	0.107	0.464
	April	228	0.029	0.319	-0.320	1.976
	May	239	0.015	0.307	0.975	6.672
	June	225	0.005	0.264	0.471	1.103
	July	243	0.042	0.312	-0.764	1.958
	August	233	-0.056	0.484	-0.939	5.226
	September	236	-0.019	0.420	-0.110	5.198
	October	232	0.015	0.592	-1.129	10.231
	November	236	-0.005	0.350	0.066	3.386
	December	221	0.066	0.344	0.112	2.069
	Total	2779	0.025	0.394	-0.301	8.170
ISEQR	January	232	0.112	0.437	0.814	1.391
	February	222	0.068	0.393	0.972	8.332
	March	231	0.049	0.365	0.114	0.448
	April	228	0.035	0.319	-0.145	1.806
	May	239	0.028	0.304	0.913	6.853
	June	225	0.011	0.269	0.447	1.127
	July	243	0.039	0.322	-0.494	2.222
	August	233	-0.048	0.472	-0.900	5.206
	September	236	-0.013	0.422	-0.076	4.639
	October	232	0.017	0.595	-1.005	9.977
	November	236	0.005	0.352	0.058	3.294
	December	221	0.067	0.341	0.095	2.098
	Total	2778	0.030	0.393	-0.247	8.028
ISEFIN	January	203	0.084	0.604	0.378	3.445
	February	201	0.091	0.540	0.772	5.586
	March	209	0.030	0.467	-0.056	0.563
	April	208	0.045	0.446	0.008	2.647
	May	217	-0.016	0.415	0.031	1.446
	June	204	0.004	0.347	0.833	2.810
	July	222	0.059	0.488	-0.566	2.514
	August	211	-0.097	0.636	-0.617	4.617
	September	214	-0.004	0.588	-0.216	4.535
	October	212	0.061	0.787	-0.800	5.736
	November	214	0.032	0.502	-0.472	3.333
	December	201	0.095	0.576	0.621	6.154
	Total	2516	0.031	0.546	-0.186	5.779

		N	Mean	Std. Deviation	Skewness	Kurtosis
ISEGEN	January	203	0.101	0.432	0.735	1.977
	February	201	0.056	0.347	0.915	7.930
	March	209	0.038	0.361	0.323	1.131
	April	208	0.022	0.305	-0.033	1.087
	May	217	-0.001	0.251	-0.502	1.932
	June	204	-0.019	0.270	-0.365	2.351
	July	222	0.028	0.288	-0.689	2.232
	August	211	-0.023	0.468	-0.376	7.082
	September	214	-0.045	0.372	-0.377	4.285
	October	212	-0.011	0.593	-1.485	17.427
	November	214	0.000	0.314	0.755	2.716
	December	201	0.048	0.309	0.109	-0.142
	Total	2516	0.016	0.372	-0.450	13.364
EWP1	January	125	0.096	2.425	-0.290	39.321
	February	121	-0.044	0.581	-1.175	12.617
	March	126	0.068	0.526	3.524	22.920
	April	124	-0.020	0.291	-1.699	8.101
	May	127	0.024	0.218	-0.004	3.995
	June	123	0.039	0.895	1.023	24.622
	July	133	0.032	0.698	2.917	37.870
	August	126	-0.051	0.585	-2.206	11.465
	September	130	-0.018	0.449	-1.409	6.762
	October	126	-0.026	0.514	-1.440	13.629
	November	128	0.090	0.599	4.236	42.910
	December	122	0.076	0.399	2.201	15.141
	Total	1511	0.022	0.874	-0.062	200.091
EWP2	January	125	-0.003	1.883	-6.679	70.317
	February	121	0.063	0.423	8.317	80.367
	March	126	-0.000	0.436	-6.805	57.306
	April	124	0.059	0.277	-1.763	11.493
	May	127	0.073	0.185	2.848	13.780
	June	123	0.015	0.204	0.030	7.720
	July	133	0.039	0.244	2.644	19.582
	August	126	-0.035	0.248	-2.542	16.254
	September	130	-0.011	0.416	1.815	36.662
	October	126	-0.020	0.446	-3.589	46.544
	November	128	0.024	0.179	0.141	2.493
	December	122	0.035	0.195	0.531	2.712
	Total	1511	0.020	0.618	-15.428	500.479
EWP3	January	125	0.319	1.850	7.475	72.831
	February	121	-0.001	0.250	-0.547	5.553
	March	126	-0.059	1.058	-10.875	120.738
	April	124	0.060	0.200	0.626	4.151
	May	127	0.031	0.176	-0.559	1.685
	June	123	0.018	0.198	-0.129	1.640

		N	Mean	Std. Deviation	Skewness	Kurtosis
	July	133	-0.008	0.214	0.192	6.876
	August	126	-0.036	0.257	-1.125	6.503
	September	130	-0.047	0.243	-1.671	7.499
	October	126	-0.002	0.226	-1.396	8.511
	November	128	0.034	0.666	-8.522	88.625
	December	122	0.009	0.213	-0.137	2.240
	Total	1511	0.026	0.675	9.036	422.509
EWP4	January	125	0.042	1.010	3.576	45.882
	February	121	0.046	0.511	-1.003	18.980
	March	126	0.057	0.431	3.978	27.888
	April	124	0.064	0.351	0.851	4.648
	May	127	0.020	0.323	-0.582	5.216
	June	123	0.076	0.381	2.794	15.781
	July	133	0.029	0.367	-0.229	2.537
	August	126	-0.045	0.349	-1.909	10.864
	September	130	-0.000	0.569	-2.286	20.537
	October	126	0.101	0.714	0.309	10.173
	November	128	0.063	0.638	0.339	44.087
	December	122	0.069	0.290	-0.082	1.254
	Total	1511	0.043	0.533	2.014	63.731
EWP	January	125	0.122	0.366	6.248	55.897
	February	121	0.034	0.220	1.133	7.910
	March	126	0.008	0.484	-8.499	88.920
	April	124	0.052	0.177	0.594	2.912
	May	127	0.035	0.172	-1.223	5.848
	June	123	0.045	0.187	1.104	6.947
	July	133	0.020	0.173	-0.196	1.419
	August	126	-0.040	0.229	-2.399	11.885
	September	130	-0.017	0.299	-3.579	27.024
	October	126	0.039	0.344	-0.526	8.921
	November	128	0.051	0.246	-3.091	28.656
	December	122	0.047	0.168	-0.360	2.221
	Total	1511	0.033	0.274	-3.320	94.707
VWP1	January	125	0.050	8.841	-1.026	58.694
	February	121	0.019	0.548	0.339	2.912
	March	126	0.051	0.597	1.853	21.278
	April	124	0.007	0.379	-0.793	6.280
	May	127	0.002	0.310	-0.914	4.948
	June	123	0.068	0.406	1.888	8.294
	July	133	-0.005	0.421	0.542	3.018
	August	126	-0.067	0.427	-0.705	4.583
	September	130	0.073	0.873	4.367	30.525
	October	126	-0.030	0.576	-1.680	12.564
	November	128	0.170	0.833	4.102	24.563
	December	122	0.151	0.755	4.187	26.058

		N	Mean	Std. Deviation	Skewness	Kurtosis
	Total	1511	0.041	2.596	-3.235	650.223
VWP2	January	125	0.114	1.313	0.801	33.154
	February	121	0.015	0.503	-3.149	25.593
	March	126	0.062	0.196	1.107	2.092
	April	124	0.065	0.229	0.752	3.665
	May	127	0.064	0.203	0.557	2.121
	June	123	0.027	0.214	0.398	2.734
	July	133	0.035	0.227	0.400	2.412
	August	126	-0.032	0.246	-2.784	19.156
	September	130	-0.022	0.424	-4.644	38.882
	October	126	-0.020	0.475	-6.512	60.625
	November	128	0.104	0.515	6.603	54.377
	December	122	0.049	0.202	0.723	3.412
	Total	1511	0.038	0.497	1.070	150.460
VWP3	January	125	0.299	1.014	5.894	39.629
	February	121	0.006	0.405	-1.288	17.578
	March	126	0.032	0.184	-0.342	0.525
	April	124	0.068	0.217	1.062	4.166
	May	127	0.041	0.216	0.408	3.134
	June	123	-0.001	0.205	-0.334	0.773
	July	133	0.012	0.252	0.324	5.885
	August	126	0.149	1.702	9.811	103.819
	September	130	-0.042	0.245	-0.894	6.342
	October	126	-0.072	1.169	-10.152	109.896
	November	128	0.041.	0.343	-2.274	18.918
	December	122	0.033	0.221	0.468	2.381
	Total	1511	0.047	0.705	9.123	377.960
VWP4	January	125	0.104	0.554	1.614	13.881
	February	121	0.037	0.325	0.436	2.749
	March	126	0.019	0.302	0.123	1.352
	April	124	0.072	0.292	0.322	0.756
	May	127	0.023	0.301	-0.298	1.708
	June	123	0.050	0.282	0.853	1.997
	July	133	0.036	0.423	-1.127	11.100
	August	126	-0.071	0.444	-2.015	10.159
	September	130	0.040	0.396	-0.007	5.149
	October	126	0.084	0.624	-0.482	7.528
	November	128	0.063	0.309	-0.308	0.518
	December	122	0.099	0.292	1.057	2.192
	Total	1511	0.046	0.396	-0.044	12.615
VWP	January	125	0.126	0.399	2.437	11.901
	February	121	0.032	0.290	0.125	2.797
	March	126	0.023	0.256	0.102	1.571
	April	124	0.070	0.253	0.298	0.655
	May	127	0.027	0.259	-0.430	1.968

		N	Mean	Std. Deviation	Skewness	Kurtosis
	June	123	0.043	0.240	0.652	1.500
	July	133	0.031	0.354	-1.168	10.904
	August	126	-0.041	0.485	0.770	17.624
	September	130	0.029	0.340	-0.103	5.034
	October	126	0.060	0.538	-0.682	6.227
	November	128	0.064	0.274	-0.326	1.189
	December	122	0.092	0.257	1.012	2.333
	Total	1511	0.046	0.344	0.157	13.149
TISEQ	January	202	0.050	0.294	0.176	-0.609
	February	202	0.044	0.252	0.096	-0.188
	March	211	0.053	0.285	0.159	-0.367
	April	211	0.054	0.238	0.232	-0.024
	May	228	0.018	0.234	0.198	0.064
	June	216	-0.007	0.221	0.133	-0.271
	July	232	0.064	0.254	-0.160	-0.114
	August	204	-0.010	0.256	0.202	0.035
	September	211	-0.008	0.256	0.089	-0.473
	October	199	0.028	0.257	0.199	-0.402
	November	217	0.006	0.243	0.163	-0.016
	December	207	0.050	0.266	0.009	-0.390
	Total	2540	0.029	0.256	0.142	-0.231
TISEQR	January	192	0.033	0.270	0.084	-0.707
	February	199	0.038	0.239	-0.054	-0.311
	March	204	0.057	0.266	0.146	-0.376
	April	210	0.043	0.233	0.152	-0.235
	May	228	0.031	0.229	0.119	0.096
	June	215	0.001	0.222	0.113	-0.247
	July	227	0.056	0.244	-0.181	-0.187
	August	202	-0.005	0.247	0.154	-0.263
	September	207	0.008	0.248	0.199	-0.487
	October	196	0.020	0.254	0.204	-0.598
	November	214	0.014	0.235	0.120	-0.044
	December	206	0.054	0.261	0.023	-0.451
	Total	2500	0.029	0.246	0.099	-0.342
TISEFIN	January	174	0.042	0.361	0.161	-0.754
	February	184	0.035	0.369	0.023	-0.502
	March	190	0.054	0.355	0.136	-0.232
	April	194	0.027	0.335	0.161	-0.189
	May	201	-0.009	0.312	0.176	0.120
	June	197	-0.015	0.277	0.388	0.151
	July	202	0.087	0.345	0.064	-0.441
	August	181	-0.023	0.328	0.398	0.401
	September	188	0.011	0.345	0.045	-0.514
	October	181	0.091	0.376	0.003	-0.729
	November	194	0.037	0.347	0.159	-0.345

		N	Mean	Std. Deviation	Skewness	Kurtosis
	December	178	0.049	0.345	0.106	-0.128
	Total	2264	0.032	0.343	0.163	-0.316
TISEGEN	January	171	0.047	0.254	-0.066	-0.707
	February	183	0.040	0.220	0.086	-0.208
	March	183	0.026	0.246	0.058	-0.472
	April	189	0.025	0.218	-0.109	0.055
	May	208	0.012	0.203	0.017	-0.062
	June	194	-0.011	0.217	0.147	-0.410
	July	209	0.048	0.223	-0.045	-0.583
	August	182	0.017	0.243	0.173	-0.431
	September	195	-0.038	0.235	0.197	-0.314
	October	175	-0.004	0.226	0.163	-0.231
	November	194	-0.006	0.215	-0.039	-0.236
	December	181	0.029	0.246	-0.040	-0.459
	Total	2264	0.015	0.230	0.054	-0.366
TEW1	January	102	0.080	0.212	0.565	0.523
	February	104	0.008	0.185	0.355	1.011
	March	117	0.016	0.202	0.398	1.619
	April	117	0.019	0.183	0.294	1.560
	May	122	0.029	0.165	0.456	2.241
	June	112	0.038	0.201	0.547	1.057
	July	122	0.003	0.180	0.546	0.984
	August	109	0.006	0.203	0.340	1.670
	September	113	0.027	0.204	0.363	0.777
	October	113	-0.004	0.183	0.112	1.001
	November	117	0.037	0.206	0.594	0.820
	December	111	0.041	0.205	0.433	1.578
	Total	1359	0.025	0.195	0.442	1.206
TEW2	January	102	0.051	0.121	0.286	0.129
	February	115	0.013	0.114	0.204	0.781
	March	115	0.020	0.116	0.254	0.600
	April	109	0.044	0.123	0.827	0.722
	May	120	0.047	0.112	0.446	0.767
	June	114	0.026	0.127	0.015	0.153
	July	122	0.038	0.143	0.318	-0.458
	August	113	0.001	0.118	0.285	0.631
	September	113	0.016	0.111	0.177	0.245
	October	112	0.008	0.110	0.355	0.206
	November	118	0.029	0.127	0.607	0.890
	December	106	0.031	0.116	0.177	0.496
	Total	1359	0.027	0.121	0.347	0.408
TEW3	January	99	0.058	0.148	0.148	-0.245
	February	108	0.005	0.147	0.472	0.151
	March	121	0.037	0.131	0.223	0.069
	April	114	0.037	0.129	0.184	0.048

		N	Mean	Std. Deviation	Skewness	Kurtosis
	May	120	0.051	0.140	0.270	0.271
	June	113	0.032	0.142	0.243	- 0.063
	July	120	0.008	0.116	0.626	0.767
	August	113	- 0.006	0.120	0.235	- 0.005
	September	116	- 0.010	0.138	0.201	0.627
	October	117	0.017	0.138	0.297	0.640
	November	113	0.036	0.143	0.378	0.451
	December	105	0.015	0.111	0.318	1.051
	Total	1359	0.023	0.135	0.313	0.275
TEW4	January	113	0.053	0.224	0.207	- 0.600
	February	112	0.039	0.214	0.532	0.018
	March	116	0.022	0.206	0.174	0.142
	April	112	0.041	0.213	0.158	- 0.060
	May	117	0.047	0.212	0.294	- 0.296
	June	112	0.045	0.194	0.057	- 0.054
	July	112	0.045	0.208	0.249	- 0.220
	August	115	0.005	0.207	0.031	- 0.509
	September	116	0.019	0.213	0.411	0.042
	October	102	0.030	0.200	- 0.025	- 0.547
	November	122	0.052	0.209	0.285	- 0.130
	December	110	0.055	0.211	0.539	0.025
	Total	1359	0.038	0.209	0.252	- 0.192
TEW	January	110	0.063	0.138	- 0.151	- 0.874
	February	109	0.020	0.122	0.316	0.147
	March	117	0.035	0.115	0.004	- 0.099
	April	110	0.043	0.115	- 0.180	- 0.038
	May	120	0.044	0.120	0.047	- 0.343
	June	112	0.035	0.113	0.130	- 0.000
	July	118	0.028	0.119	0.063	- 0.354
	August	111	0.008	0.120	0.130	- 0.336
	September	116	0.014	0.119	0.210	- 0.277
	October	106	0.030	0.119	0.387	0.321
	November	117	0.035	0.114	- 0.220	0.024
	December	113	0.046	0.128	0.019	- 0.067
	Total	1359	0.033	0.121	0.075	- 0.253
TVW1	January	106	0.064	0.285	0.283	- 0.026
	February	104	0.024	0.298	0.279	0.545
	March	116	0.045	0.292	0.487	0.745
	April	116	0.023	0.253	0.027	0.094
	May	122	0.029	0.236	0.442	1.411
	June	114	0.026	0.253	0.341	0.469
	July	121	0.011	0.273	0.605	0.719
	August	114	- 0.030	0.234	0.057	0.168
	September	112	- 0.014	0.225	- 0.246	0.257
	October	114	0.002	0.260	0.535	1.109

		N	Mean	Std. Deviation	Skewness	Kurtosis
	November	113	0.053	0.283	0.613	0.968
	December	107	0.048	0.251	0.643	1.344
	Total	1359	0.023	0.263	0.398	0.732
TVW2	January	109	0.062	0.147	0.176	0.049
	February	109	0.049	0.151	0.503	0.004
	March	118	0.042	0.151	0.488	-0.241
	April	111	0.052	0.147	0.470	-0.146
	May	116	0.049	0.140	0.149	0.257
	June	109	0.028	0.129	0.378	0.030
	July	118	0.028	0.142	0.295	-0.306
	August	114	-0.009	0.133	0.409	0.379
	September	117	0.025	0.137	0.124	0.703
	October	111	0.023	0.137	0.435	0.255
	November	113	0.050	0.145	0.402	0.105
	December	114	0.033	0.150	0.318	0.196
	Total	1359	0.036	0.143	0.360	0.066
TVW3	January	99	0.073	0.188	-0.152	-0.614
	February	102	0.010	0.182	0.231	-0.718
	March	123	0.045	0.167	0.071	-0.299
	April	119	0.058	0.170	0.208	-0.554
	May	116	0.035	0.147	0.201	0.002
	June	114	0.025	0.161	0.015	-0.332
	July	121	0.010	0.149	-0.041	-0.061
	August	107	0.017	0.168	0.368	0.138
	September	118	-0.008	0.143	0.298	0.577
	October	113	0.036	0.146	0.186	0.228
	November	115	0.031	0.168	0.257	0.063
	December	112	0.028	0.155	0.351	0.590
	Total	1359	0.030	0.163	0.185	-0.163
TVW4	January	111	0.062	0.248	0.233	-0.631
	February	113	0.042	0.244	0.337	-0.473
	March	117	0.032	0.228	0.178	-0.234
	April	115	0.054	0.229	0.191	-0.011
	May	117	0.046	0.217	0.097	-0.576
	June	116	0.025	0.213	0.085	-0.585
	July	115	0.060	0.214	0.207	-0.706
	August	107	0.008	0.235	0.309	-0.256
	September	116	0.026	0.225	0.249	-0.135
	October	102	0.059	0.206	0.063	0.051
	November	119	0.062	0.256	-0.105	-0.855
	December	111	0.043	0.193	0.116	-0.273
	Total	1359	0.043	0.226	0.166	-0.413
TVW	January	109	0.058	0.207	0.112	-0.569
	February	113	0.040	0.213	0.319	-0.401
	March	117	0.035	0.190	0.211	-0.241

	N	Mean	Std. Deviation	Skewness	Kurtosis
April	112	0.059	0.187	0.284	- 0.084
May	118	0.044	0.190	0.013	- 0.600
June	116	0.023	0.184	0.037	- 0.617
July	120	0.049	0.203	0.161	- 0.372
August	107	0.015	0.209	0.358	- 0.330
September	116	0.034	0.192	0.326	- 0.316
October	101	0.055	0.175	0.176	- 0.308
November	118	0.066	0.217	- 0.052	- 0.776
December	112	0.047	0.174	0.233	0.053
Total	1359	0.044	0.195	0.178	- 0.414

TABLE 14: NORMALITY TESTS OF INDICES

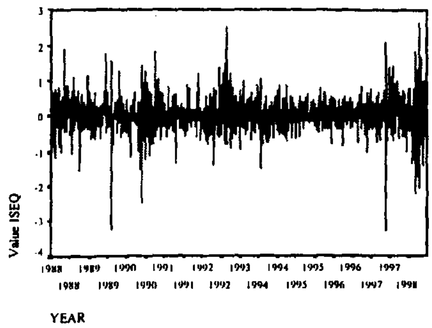
	N	Z[a]	Sig	JB[b]	Sig	Ep[c]	Sig
ISEQ	2778	4.050	.000	8.51	0.01	1292.843	.000
ISEQR	2778	3.951	.000	8.85	0.01	1249.293	.000
ISEFIN	2516	3.843	.000	9.18	0.01	1002.496	.000
ISEGEN	2516	3.888	.000	9.51	0.01	1077.967	.000
EWP1	1512	10.592	.000	6.89	0.00	3.098	.000
EWP2	1512	11.086	.000	5.66	0.00	1.825	.000
EWP3	1512	11.088	.000	5.86	0.05	1.694	.000
EWP4	1512	6.558	.000	6.19	0.04	8548.315	.000
EWP	1512	5.926	.000	6.52	0.04	8662.134	.000
VWP1	1512	13.619	.000	6.85	0.03	1.1080	.000
VWP2	1512	8.834	.000	7.18	0.03	2.599	.000
VWP3	1512	10.016	.000	7.52	0.02	1.0713	.000
VWP4	1512	3.669	.000	7.85	0.02	2057.138	.000
VWP	1512	3.737	.000	8.18	0.01	2243.924	.000
TISEQ	2454	1.197	.114	17.17	0.00	1.961	.37
TISEQR	2430	1.223	.100	17.50	0.00	1.304	.52
TISEFIN	2192	1.577	.014	17.84	0.00	4.260	.12
TISEGEN	2172	1.218	.103	18.17	0.00	1.685	.43
TEW1	1033	2.196	.000	13.84	0.00	95.891	.000
TEW2	1173	2.001	.001	14.17	0.00	37.603	.000
TEW3	1244	1.907	.001	14.51	0.00	26.509	.000
TEW4	1303	1.363	.049	14.84	0.00	25.443	.000
TEW	1284	1.108	.172	15.17	0.00	6.781	.000
TVW1	1103	1.151	.141	15.51	0.00	62.611	.000
TVW2	1180	1.430	.034	15.84	0.00	49.441	.000
TVW3	1272	1.459	.028	16.17	0.00	16.043	.000
TVW4	1306	1.102	.176	16.50	0.00	17.708	.000
TVW	1301	1.285	.074	16.84	0.00	22.568	.000

a: Kolmogorov-Smirnoff Z Statistic; b: Jarque-Bera Statistic; c: Doornik-Hansen Ep Statistic:

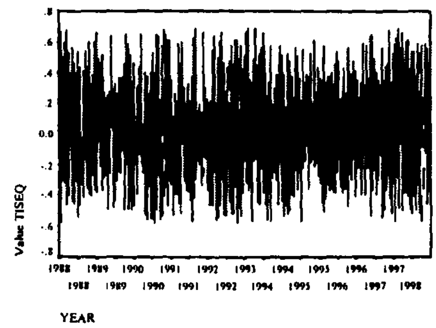
In all cases Ho = Normality

The graphs below show the various indices. What is immediately obvious is that, not unexpectedly, the trimming introduces a much less volatile pattern to the data, and that the portfolio indices are more volatile than the more complete indices. In all cases the y-axis is percentage change and the x-axis is time.

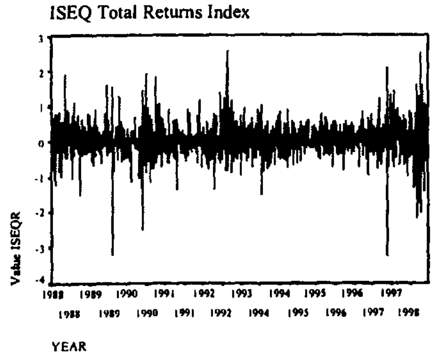
ISEQ Index



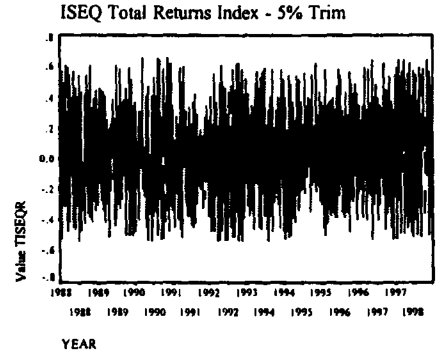
ISEQ Index - 5% Trim



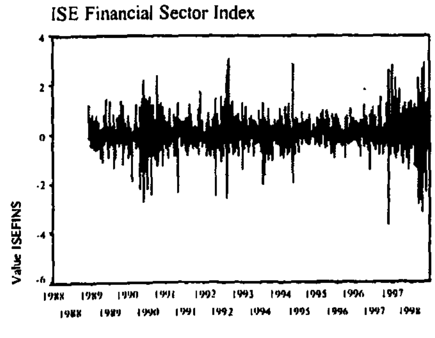
ISEQ Total Returns Index



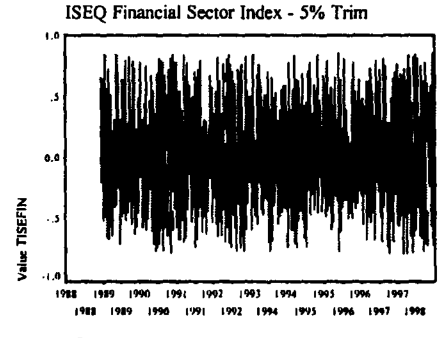
ISEQ Total Returns Index - 5% Trim



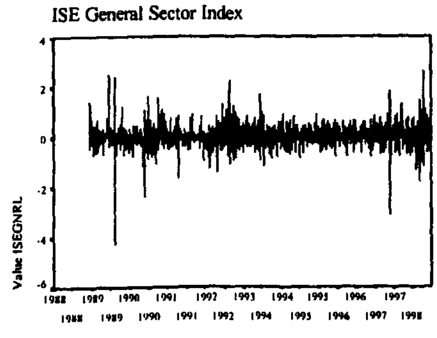
ISE Financial Sector Index



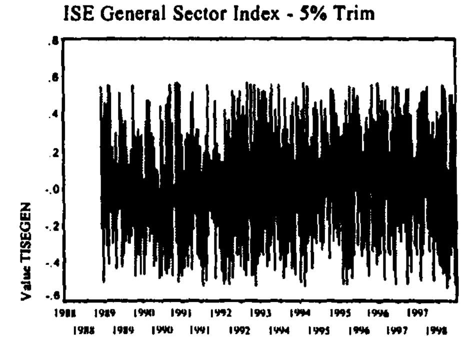
ISEQ Financial Sector Index - 5% Trim



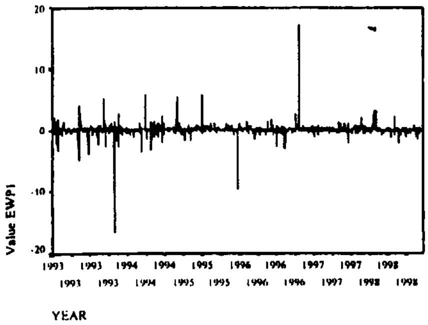
ISE General Sector Index



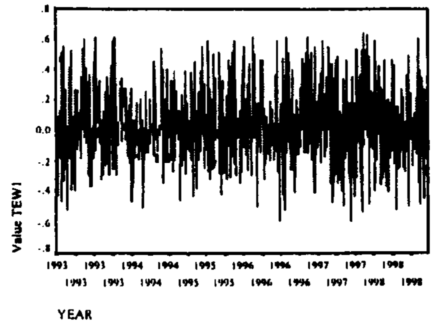
ISE General Sector Index - 5% Trim



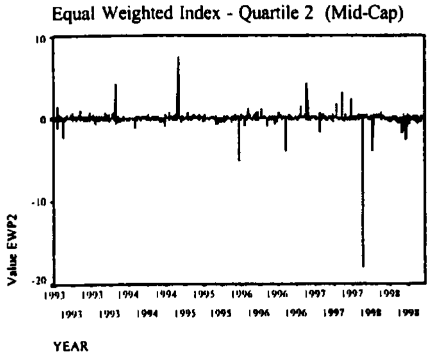
Equal Weighted Index - Quartile 1 (Smallest)



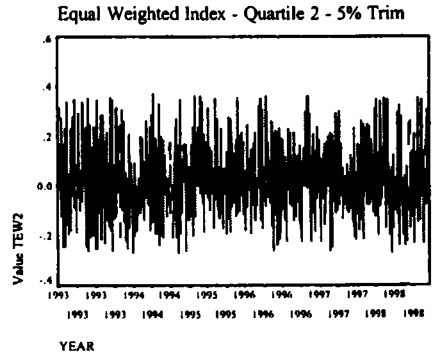
Equal Weighted Index - Quartile 1 - 5% Trim



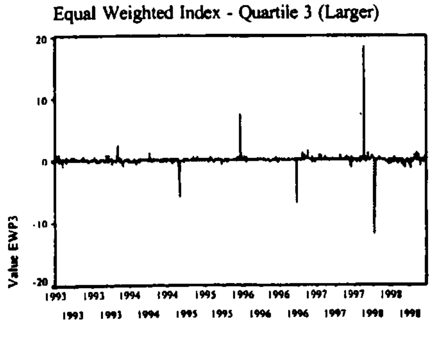
Equal Weighted Index - Quartile 2 (Mid-Cap)



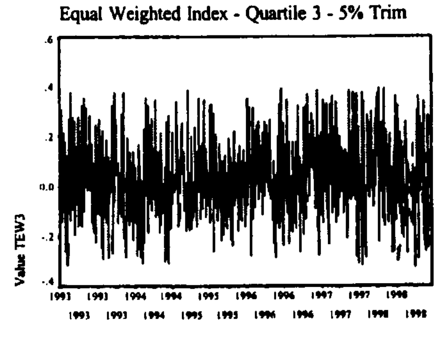
Equal Weighted Index - Quartile 2 - 5% Trim



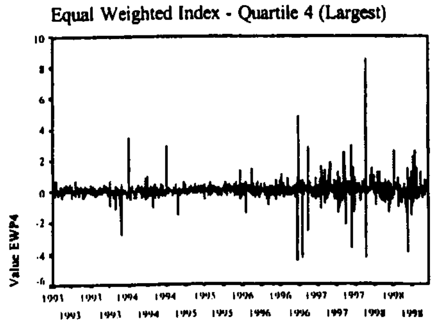
Equal Weighted Index - Quartile 3 (Larger)



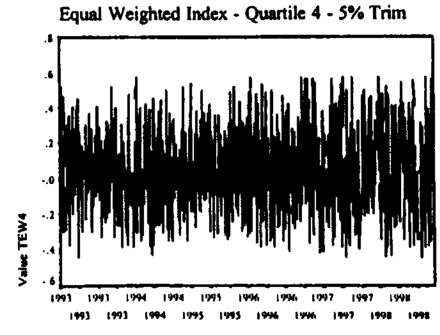
Equal Weighted Index - Quartile 3 - 5% Trim



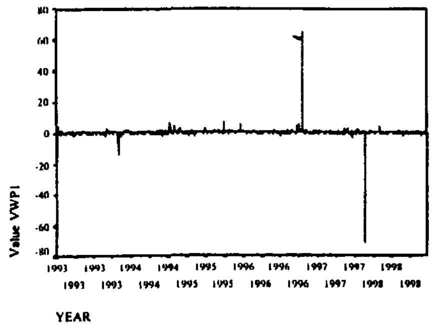
Equal Weighted Index - Quartile 4 (Largest)



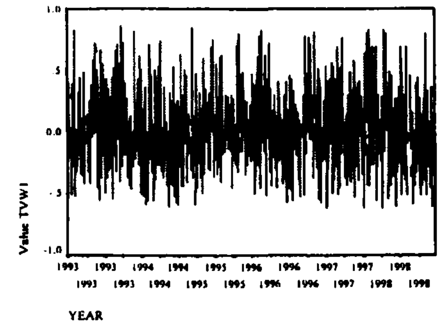
Equal Weighted Index - Quartile 4 - 5% Trim



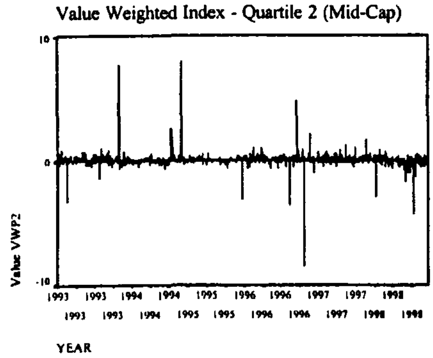
Value Weighted Index - Quartile 1 (Smallest)



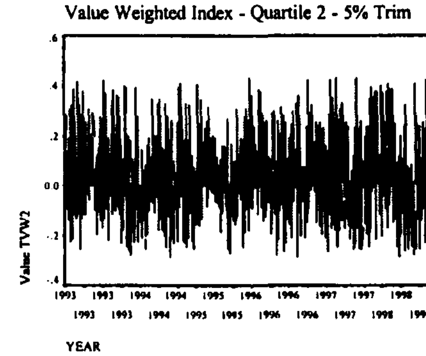
Value Weighted Index - Quartile 1 - 5% Trim



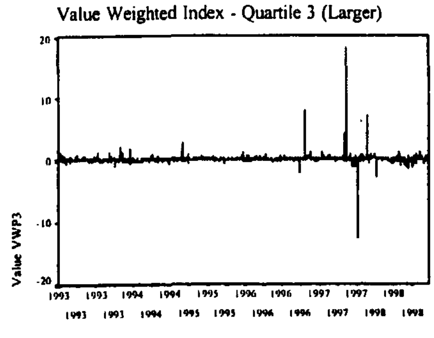
Value Weighted Index - Quartile 2 (Mid-Cap)



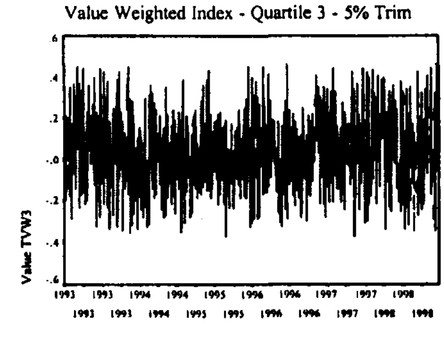
Value Weighted Index - Quartile 2 - 5% Trim



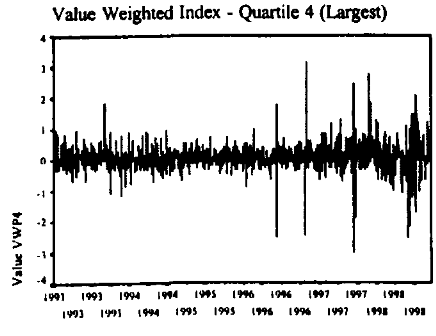
Value Weighted Index - Quartile 3 (Larger)



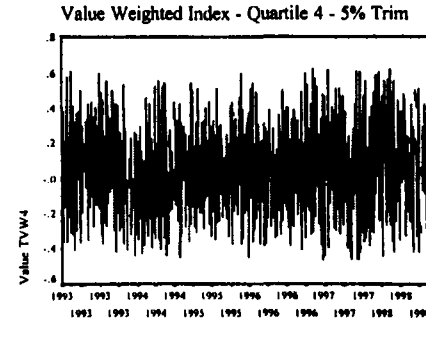
Value Weighted Index - Quartile 3 - 5% Trim



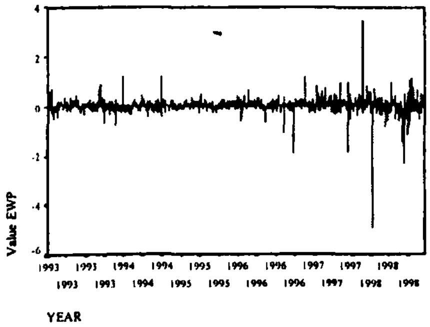
Value Weighted Index - Quartile 4 (Largest)



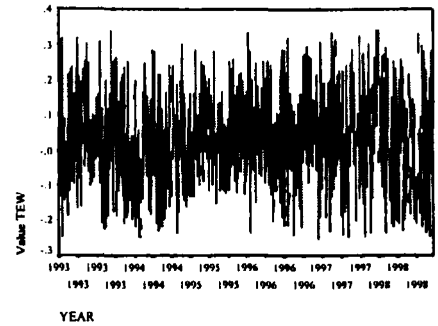
Value Weighted Index - Quartile 4 - 5% Trim



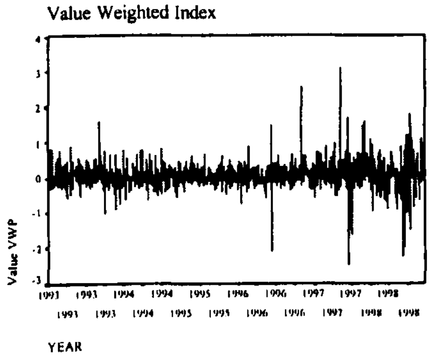
Equal Weighted Index



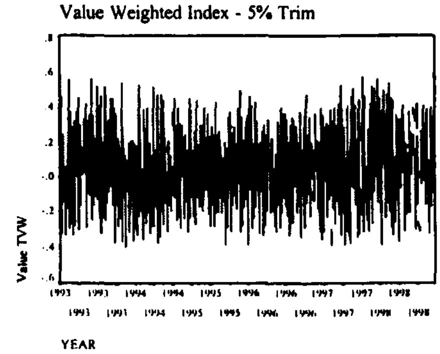
Equal Weighted Index - 5% Trim



Value Weighted Index



Value Weighted Index - 5% Trim



9. Is Daily Seasonality Present In Irish Equity Indices[#]?

9.1. Parametric Investigation Of The First Moment

From the tables above, it would seem prima facia, that there exists a possible daily seasonal. Wednesday returns appear high, with no obvious relationship to risk. We have seen that the parametric examination of such a seasonal takes two main threads. The first is a testing for the significance of individual daily dummy coefficients, the second the testing of the overall significance of a regression, via an F test or its equivalent.

Table 15 shows the results of an OLS analysis of the first moment.

[#] An abridged version of this chapter appears in *Lucey, B. M. (2002). "How Robust was the daily seasonal in the Irish equity market 1988-1998." Revise and Resubmit* Economic and Social Review *2002*

TABLE 15: INITIAL ESTIMATES OF DAILY SEASONALITY IN THE IRISH MARKET

	Variable	Coeff	t-stat	Sig
ISEQ	Monday	0.00	0.11	0.95
	Tuesday	0.03	1.85	0.06
	Wednesday	0.05	3.11	0.00
	Thursday	0.03	1.91	0.06
	Friday	0.01	0.49	0.00
#	2,778			
	F(4,2773)	6.11		0.00
ISEQR	Monday	0.03	1.88	0.06
	Tuesday	0.03	1.96	0.05
	Wednesday	0.05	3.07	0.00
	Thursday	0.03	1.87	0.06
	Friday	0.01	0.35	0.73
#	2,778			
	F(4,2773)	0.95		0.44
ISEFIN	Monday	-0.01	-0.42	0.67
	Tuesday	0.05	2.25	0.03
	Wednesday	0.06	2.36	0.02
	Thursday	0.04	1.82	0.07
	Friday	0.01	0.35	0.73
#	2,516			
	F(4,2511)	1.49		0.20
ISEGEN	Monday	0.00	0.23	0.82
	Tuesday	0.01	0.57	0.57
	Wednesday	0.04	2.10	0.04
	Thursday	0.02	0.99	0.33
	Friday	0.01	0.79	0.43
#	2,516			
	F(4,2511)	0.49		0.74
EWP1	Monday	0.01	0.15	0.89
	Tuesday	-0.05	-1.09	0.28
	Wednesday	0.05	0.91	0.36
	Thursday	0.04	0.82	0.41

	Variable	Coeff	t-stat	Sig
	Friday	0.07	1.42	0.16
#	1,511			
	F(4,1506)	0.94		0.44
EWP2	Monday	0.00	0.09	0.93
	Tuesday	0.06	1.57	0.12
	Wednesday	0.02	0.55	0.58
	Thursday	0.04	1.04	0.30
	Friday	-0.02	-0.51	0.61
#	1,511			
	F(4,1506)	0.65		0.63
EWP3	Monday	-0.03	-0.62	0.54
	Tuesday	0.04	0.98	0.33
	Wednesday	0.04	0.93	0.35
	Thursday	0.02	0.60	0.55
	Friday	0.05	1.41	0.16
#	1511			
	F(4,1506)	0.57		0.69
EWP4	Monday	0.09	2.88	0.00
	Tuesday	0.02	0.65	0.52
	Wednesday	0.06	2.02	0.04
	Thursday	0.02	0.79	0.43
	Friday	0.02	0.79	0.43
#	1,511			
	F(4,1506)	1.03		0.39
EWP	Monday	0.03	1.97	0.05
	Tuesday	0.03	1.83	0.07
	Wednesday	0.04	2.81	0.01
	Thursday	0.03	1.80	0.07
	Friday	0.03	1.92	0.06
	1,511			
#	F(4,1506)	0.17		0.95
VWP1	Monday	0.08	0.49	0.62
	Tuesday	0.06	0.38	0.71
	Wednesday	0.02	0.14	0.89
	Thursday	0.27	1.84	0.07
	Friday	-0.22	-1.47	0.14
#	1,511			

	Variable	Coeff	t-stat	Sig
	F(4,1506)	1.39		0.23
VWP2	Monday	0.03	1.05	0.29
	Tuesday	0.10	3.47	0.00
	Wednesday	0.05	1.60	0.11
	Thursday	0.02	0.70	0.48
	Friday	0.00	-0.13	0.90
#	1,511			
	F(4,1506)	1.80		0.13
VWP3	Monday	0.01	0.19	0.85
	Tuesday	0.08	1.98	0.05
	Wednesday	0.04	0.86	0.39
	Thursday	0.00	-0.02	0.99
	Friday	0.11	2.70	0.01
#	1,511			
	F(4,1506)	1.33		0.26
VWP4	Monday	0.05	2.13	0.03
	Tuesday	0.07	3.00	0.00
	Wednesday	0.05	2.24	0.03
	Thursday	0.01	0.31	0.76
	Friday	0.06	2.48	0.01
#	1,511			
	F(4,1506)	1.05		0.38
VWP	Monday	0.05	2.22	0.03
	Tuesday	0.07	3.52	0.00
	Wednesday	0.05	2.44	0.02
	Thursday	0.01	0.67	0.50
	Friday	0.05	2.79	0.01
#	1,511			
	F(4,1506)	1.10		0.36

From this we can see a number of interesting facts emerge.

It would seem to be the case that daily seasonality does not pose a major issue, as only for the ISEQ index can we see a significant F statistic, indicating overall seasonality. There would also appear not to be a Monday effect: Monday returns are positive in all indices although rarely significant. Instead we seem to find here a midweek seasonal, with Wednesday and / or Tuesday having significant t-statistics.

However, the equation is not well specified, as shown by the results of a number of regression diagnostic procedures detailed in Table 16.

TABLE 16: REGRESSION RESIDUAL DIAGNOSTICS FOR DAY OF THE WEEK OLS MODEL

	Autocorrelation Tests	Heteroskedasticity Tests						Normality
	Q[b]	ARCH1[c]	ARCH2	ARCH3	ARCH4	ARCH5	White's	Jarque-Bera
ISEQ	182.10	120.36	54.02	46.86	26.99	27.86	8.29	24.17
	0.00[f]	0.00	0.00	0.00	0.00	0.00	1.00	0.00
ISEQR	168.23	125.98	64.73	29.23	23.36	21.86	8.53	24.18
	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
ISEFIN	116.84	125.98	64.73	29.23	23.36	21.86	3.31	24.50
	0.00	0.00	0.00	0.00	0.00	0.00	0.65	0.00
ISEGEN	146.02	129.75	14.38	3.28	0.49	1.65	7.17	24.56
	0.00	0.00	0.01	0.66	0.99	0.90	0.72	0.00
EWP1	2.82	0.01	0.02	0.02	0.00	0.02	4.11	34.83
	0.80	1.00	1.00	1.00	1.00	1.00	1.00	0.00
EWP2	4.21	0.00	0.00	0.00	0.01	0.00	3.22	35.70
	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00
EWP3	21.40	0.01	0.00	0.01	0.00	0.01	3.35	33.50
	0.75	1.00	1.00	1.00	1.00	1.00	1.00	0.00
EWP4	82.00	95.82	0.00	0.16	0.04	0.04	2.54	24.51
	0.36	0.00	1.00	1.00	1.00	1.00	1.00	0.00
EWP	150.00	0.18	0.00	0.31	0.00	0.00	8.77	34.83
	0.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00
VWP1	6.74	0.00	0.00	0.00	0.00	0.00	2.78	36.50
	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00
VWP2	34.01	0.04	0.02	0.05	0.04	0.05	3.65	36.83
	0.56	1.00	1.00	1.00	1.00	1.00	1.00	0.00
VWP3	44.21	0.00	0.00	0.01	0.00	0.01	3.63	37.11
	0.16	1.00	1.00	1.00	1.00	1.00	1.00	0.00
VWP4	94.16	69.89	2.99	23.18	3.94	0.88	0.03	36.83
	0.00	0.00	0.70	0.00	0.56	0.97	1.00	0.00
VWP	130.18	34.47	3.49	36.61	4.86	0.79	0.38	37.50
	0.00	0.00	0.63	0.00	0.43	0.98	1.00	0.00

a: Regression Durbin Watson Statistic ; b: Ljung-Box Q statistic for serial correlation of up to 36 lags with Ho: No serial Correlation ; c: ARCH model of specified lag length;

d: Whites test for general heteroskedasticity with Ho: No Hetroskedasticity; e Ep Statistic for Univariate normality from Doornik and Hansen (1994); f: Marginal Significance of statistic

9.1.1. RE-ESTIMATION OF THE FIRST MOMENT

Regression residual diagnostics for the initial regression of the day of the week model of Table 15, are show in Table 16. A number of problems emerge which cast some doubt on the appropriateness of the OLS procedure.

Heteroskedasticity: Whites test indicates that in no case is there generalized heteroskedasticity. To compute the ARCH Tests, the squared residuals from the OLS model are used to compute an autoregression of order n. The test statistic is then calculated for each ARCH level as R^2N; the test statistic is distributed as a χ^2 with n degrees of freedom. A number of points are evident. The null of no ARCH Effects is rejected for the ISEQ, The ISEQ total returns and the ISE Financial Index, with rejection at certain lags for the ISE General index, the ISEQ total returns index, the Equal weighted–Largest companies at lag 5, Value Weighted Largest companies at lags 1 and 3, and also at lags 1 and 3 for the Value Weighted Total index. Apart from this there appears to be no evidence of ARCH-form heteroskedasticity. Thus what hetroskedastic disturbances exist are ARCH form and are thus amenable to direct modelling.

Serial Correlation: There is however substantial evidence of serial correlation in the residuals of almost all the regressions, with the exception of the Equal Weighted portfolio indices, and the value weighted Micro-Small-Medium indices. This evidence on regression correlation is almost identical in pattern with that from the Q statistics for the indices themselves. Accordingly, following the lead of Chang, Pinegar and Ravichandran (1993), Easton and Faff (1994),Mills and Coutts (1995) Peiro (1994), the data are adjusted where appropriate for autocorrelation. Whites correction for disturbances in the error terms was used. This is discussed in more detail in Hansen (1982). In brief, given the regression model $\mathbf{Y} = \mathbf{X}\beta + \mathbf{u}$ the standard assumption regarding the distribution of the errors is $\mathbf{V} = E(\mathbf{uu}') = \sigma^2\mathbf{I}$. This however is violated in the presence of hetroskedastic or autocorrelated disturbances. We can achieve consistent estimators of the coefficients, but the estimate $s^2\mathbf{X}'\mathbf{X}^{-1}$ of the variance of these coefficients is not consistent. Accordingly, inference based on these estimates will be incorrect. Hansen (1982) shows that an estimate of the variance of the form $(\mathbf{X}'\mathbf{X})^{-1}\sum_{k=-\ell}^{\ell}\sum_t u_t X_t' X_{t-k} u_{t-k}(\mathbf{X}'\mathbf{X})^{-1}$, where ϑ is the number of serially correlated lags, is consistent. This is implemented in RATS by invoking the *ROBUSTERRORS* option on regression procedures. The degree of serial correlation to be corrected for is estimated by an examination of the partial autocorrelation functions of the residuals. These partial autocorrelation coefficients are reproduced in Appendix II. The indicated autocorrelation lags are: ISEQ 1-3, ISEQ Total Returns 1-4, ISE Financial 1-4, ISE General 1-4, Equal Weighted Largest Companies 1-3, Equal Weighted All Companies 1-4, Value Weighted Largest Companies 1-4. The results of this process are presented in Table 17 as the column AR. All other indices had single lag autocorrelation adjustments.

Normality of Residuals: Finally, based on both the Jarque-Bera and Doornik-Hansen tests there is clear evidence of non-normality in the residuals.

A number of alternative specifications of the regression are presented in Table 17, two of which are robust to deviations from normality; the initial OLS estimates are also presented in order to facilitate comparison, AR are estimates incorporating adjustments for autoregression, MAD estimates are from Minimum (Least) Absolute Deviation estimates and TLS are estimates of Trimmed Least Squares; both of these are robust estimators in the presence of non-normality. As discussed, TLS can be estimated simply by running OLS on trimmed datasets. In additio n, a further 'robustness' adjustment is also applied. Following the lead of Chang, Pinegar and Ravichandran (1993),Connolly (1991) and French (1980), as well as the methods discussed in 7.8, the significance levels of the various test statistics are adjusted to allow for Bayesian inference given the large number of datapoints being investigated

While White's procedure allows correction of the covariance matrix for heteroskedasticity of an unknown form, we do have evidence as to the particular form of ARCH in the error terms. Therefore, Table 18 shows results of an ARCH modelling, for those indices for which ARCH heteroskedasticity was indicated, while the regression diagnostics for these models are contained in Table 19. In all cases the number of autoregression parameters was determined by reference to the partial autocorrelations, as noted above, while the number of ARCH terms is determined by the regression diagnostics of Table 16. The ARCH models fit the data reasonably well, and can be deemed moderately successful, as indicated both by the regression diagnostics and the significance of the coefficients[67]. In all cases the ARCH and Volatility terms are significant, and the values of the daily coefficients, relative to the non-ARCH models, are mostly unchanged. Examination of the regression diagnostics indicates that the major remaining problem is the non-normality of the residuals. Thus while the ARCH models are useful they do not fully take account of the distributional characteristics of the data.

[67] Appended to the end of this chapter are graphs of the Partial Autocorrelation Function of ISEQ, ISEQR, ISEFIN and ISEGEN. Examination of the residual diagnostics of ARCH(1,q) models, where q is the indicated number of ARCH terms, did not show any significant change. Parsimony indicates therefore that in the GARCH models for examination of the variance a single lag will be used.

TABLE 17: ROBUST ESTIMATES OF DAILY SEASONALITY IN THE IRISH MARKET

			OLS			AR			LAD			TLS			
	Variable	Bayesian t / F	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Bayesian t/ F	Coeff	t-stat	Sig
ISEQ	Monday	2.82	0.00	0.11	0.95	0.00	0.02	0.53	0.00	0.50	0.62	2.80	0.01	0.53	0.59
	Tuesday	2.82	0.03	1.85	0.06	0.03	0.02	0.69	0.02	2.02	0.04	2.80	0.03	3.01	0.00
	Wednesday	2.82	0.05	3.11	0.00	0.05	0.02	0.00	0.07	4.39	0.00	2.80	0.04	4.26	0.00
	Thursday	2.82	0.03	1.91	0.06	0.03	0.01	0.10	0.02	3.02	0.00	2.80	0.03	3.33	0.00
	Friday	2.82	0.01	0.49	0.00	0.01	0.01	0.36	0.01	1.31	0.18	2.80	0.01	1.36	0.17
#	2,778														
	F(4,2773)	7.97	6.11		0.00	22.70		0.00	34.29		0.00	7.87	3.57		0.01
ISEQR	Monday	2.82	0.03	1.88	0.06	0.03	0.02	0.10	0.02	2.34	0.02	2.80	0.02	1.68	0.09
	Tuesday	2.82	0.03	1.96	0.05	0.03	0.02	0.06	0.03	3.56	0.00	2.80	0.03	3.10	0.00
	Wednesday	2.82	0.05	3.07	0.00	0.05	0.02	0.00	0.04	2.58	0.01	2.80	0.04	3.81	0.00
	Thursday	2.82	0.03	1.87	0.06	0.03	0.02	0.05	0.04	4.42	0.00	2.80	0.04	3.61	0.00
	Friday	2.82	0.01	0.35	0.73	0.01	0.02	0.70	0.00	0.81	0.41	2.80	0.01	1.05	0.29
#	2,778														
	F(4,2773)	7.97	0.95		0.44	20.53		0.00	45.18		0.00	7.87	1.41		0.23
ISEFIN	Monday	2.80	-0.01	-0.42	0.67	-0.01	0.03	0.69	-0.03	-2.91	0.00	2.78	-0.02	-1.18	0.24

			OLS			AR			LAD			TLS			
	Variable	Bayesian t / F	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Bayesian t/ F	Coeff	t-stat	Sig
	Tuesday	2.80	0.05	2.25	0.03	0.05	0.02	0.03	0.05	4.65	0.00	2.78	0.06	3.50	0.00
	Wednesday	2.80	0.06	2.36	0.02	0.06	0.02	0.02	0.05	2.56	0.01	2.78	0.05	3.17	0.00
	Thursday	2.80	0.04	1.82	0.07	0.04	0.03	0.08	0.05	4.48	0.00	2.78	0.05	3.20	0.00
	Friday	2.80	0.01	0.35	0.73	0.01	0.02	0.70	0.01	0.86	0.38	2.78	0.02	1.12	0.26
#	2,516														
	F(4,2511)	7.88	1.49		0.20	14.09		0.02	57.05		0.00	7.77	3.83		0.00
ISEGEN	Monday	2.80	0.00	0.23	0.82	0.00	0.02	0.84	0.00	-0.09	0.92	2.78	0.00	-0.10	0.92
	Tuesday	2.80	0.01	0.57	0.57	0.01	0.02	0.60	0.01	1.71	0.08	2.78	0.03	2.32	0.02
	Wednesday	2.80	0.04	2.10	0.04	0.04	0.02	0.04	0.00	1.58	0.11	2.78	0.01	0.98	0.33
	Thursday	2.80	0.02	0.99	0.33	0.02	0.01	0.26	0.00	2.44	0.01	2.78	0.03	2.35	0.02
	Friday	2.80	0.01	0.79	0.43	0.01	0.02	0.37	0.00	1.63	0.09	2.78	0.02	1.39	0.16
#	2,516														
	F(4,2511)	7.88	0.49		0.74	6.84		0.23	14.18		0.01	7.77	0.98		0.42
EWP1	Monday	2.70	0.01	0.15	0.89	0.008	0.030	0.80	0.03	2.65	0.00	2.69	0.04	3.21	0.00
	Tuesday	2.70	-0.05	-1.09	0.28	(0.054)	0.074	0.46	0.02	1.71	0.09	2.69	0.03	2.56	0.01
	Wednesday	2.70	0.05	0.91	0.36	0.045	0.034	0.18	0.03	1.77	0.08	2.69	0.02	1.35	0.18
	Thursday	2.70	0.04	0.82	0.41	0.041	0.061	0.50	0.00	0.61	0.53	2.69	0.02	1.48	0.14
	Friday	2.70	0.07	1.42	0.16	0.071	0.033	0.03	0.03	3.54	0.00	2.69	0.02	1.85	0.07
#	1,511														

			OLS			AR			LAD			TLS			
	Variable	Bayesian t / F	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Bayesian t/ F	Coeff	t-stat	Sig
	F(4,1506)	7.39	0.94		0.44	7.574		0.18	26.09		0.00	7.29	0.68		0.60
EWP2	Monday	2.70	0.00	0.09	0.93	0.003	0.021	0.87	0.02	1.91	0.05	2.69	0.02	2.27	0.02
	Tuesday	2.70	0.06	1.57	0.12	0.055	0.041	0.18	0.03	3.52	0.00	2.69	0.02	3.18	0.00
	Wednesday	2.70	0.02	0.55	0.58	0.019	0.014	0.16	0.03	2.12	0.03	2.69	0.04	5.43	0.00
	Thursday	2.70	0.04	1.04	0.30	0.036	0.011	0.00	0.03	4.50	0.00	2.69	0.03	3.79	0.00
	Friday	2.70	-0.02	-0.51	0.61	(0.018)	0.060	0.77	0.03	3.73	0.00	2.69	0.03	3.65	0.00
#	1,511														
	F(4,1506)	7.39	0.65		0.63	13.919		0.02	54.90		0.00	7.29	1.15		0.33
EWP3	Monday	2.70	-0.03	-0.62	0.54	(0.025)	0.045	0.57	0.02	1.93	0.05	2.69	0.02	2.26	0.02
	Tuesday	2.70	0.04	0.98	0.33	0.038	0.034	0.27	0.03	3.37	0.00	2.69	0.02	2.57	0.01
	Wednesday	2.70	0.04	0.93	0.35	0.036	0.013	0.00	0.03	2.20	0.02	2.69	0.03	3.63	0.00
	Thursday	2.70	0.02	0.60	0.55	0.023	0.013	0.07	0.02	2.66	0.00	2.69	0.02	3.02	0.00
	Friday	2.70	0.05	1.41	0.16	0.054	0.064	0.40	0.02	2.24	0.02	2.69	0.02	2.54	0.01
#	1511														
	F(4,1506)	7.39	0.57		0.69	13.485		0.02	32.13		0.00	7.29	0.23		0.92
EWP4	Monday	2.70	0.09	2.88	0.00	0.09	0.04	0.02	0.03	3.74	0.00	2.69	0.03	2.27	0.02
	Tuesday	2.70	0.02	0.65	0.52	0.02	0.03	0.45	0.05	5.27	0.00	2.69	0.06	4.59	0.00
	Wednesday	2.70	0.06	2.02	0.04	0.06	0.03	0.03	0.04	2.69	0.00	2.69	0.04	3.31	0.00

			OLS			AR			LAD			TLS			
	Variable	Bayesian t / F	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Bayesian t/ F	Coeff	t-stat	Sig
	Thursday	2.70	0.02	0.79	0.43	0.02	0.03	0.41	0.03	4.16	0.00	2.69	0.03	2.63	0.01
	Friday	2.70	0.02	0.79	0.43	0.02	0.03	0.44	0.02	2.90	0.00	2.69	0.03	2.01	0.05
#	1,511														
	F(4,1506)	7.39	1.03		0.39	12.15		0.03	74.95		0.00	7.29	1.05		0.38
EWP	Monday	2.70	0.03	1.97	0.05	0.03	0.03	0.20	0.03	4.99	0.00	2.69	0.03	4.03	0.00
	Tuesday	2.70	0.03	1.83	0.07	0.03	0.01	0.04	0.04	5.97	0.00	2.69	0.04	5.67	0.00
	Wednesday	2.70	0.04	2.81	0.01	0.04	0.01	0.00	0.04	3.46	0.00	2.69	0.04	5.54	0.00
	Thursday	2.70	0.03	1.80	0.07	0.03	0.01	0.02	0.03	5.06	0.00	2.69	0.03	3.94	0.00
	Friday	2.70	0.03	1.92	0.06	0.03	0.01	0.02	0.03	4.90	0.00	2.69	0.03	3.70	0.00
	1,511														
#	F(4,1506)	7.39	0.17		0.95	3.21		0.01	122.57		0.00	7.29	0.86		0.49
VWP1	Monday	2.70	0.08	0.49	0.62	0.077	0.037	0.04	0.06	4.07	0.00	2.69	0.05	2.78	0.01
	Tuesday	2.70	0.06	0.38	0.71	0.056	0.062	0.37	0.06	4.02	0.00	2.69	0.04	2.45	0.01
	Wednesday	2.70	0.02	0.14	0.89	0.020	0.033	0.55	0.00	0.27	0.78	2.69	0.01	0.39	0.69
	Thursday	2.70	0.27	1.84	0.07	0.272	0.214	0.20	0.05	4.01	0.00	2.69	0.01	0.76	0.45
	Friday	2.70	-0.22	-1.47	0.14	(0.217)	0.233	0.35	0.00	-0.01	0.99	2.69	0.02	1.00	0.32
#	1,511														
	F(4,1506)	7.39	1.39		0.23	7.930		0.16	48.97		0.00	7.29	1.24		0.29

			OLS			AR			LAD			TLS			
	Variable	Bayesian t / F	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Bayesian t/ F	Coeff	t-stat	Sig
VWP2	Monday	2.70	0.03	1.05	0.29	0.032	0.022	0.14	0.04	4.75	0.00	2.69	0.05	5.24	0.00
	Tuesday	2.70	0.10	3.47	0.00	0.098	0.042	0.02	0.05	6.13	0.00	2.69	0.04	4.65	0.00
	Wednesday	2.70	0.05	1.60	0.11	0.045	0.015	0.00	0.04	2.80	0.00	2.69	0.04	4.18	0.00
	Thursday	2.70	0.02	0.70	0.48	0.020	0.031	0.53	0.03	4.61	0.00	2.69	0.03	3.51	0.00
	Friday	2.70	0.00	-0.13	0.90	(0.004)	0.024	0.88	0.02	2.92	0.00	2.69	0.03	3.23	0.00
#	1,511														
	F(4,1506)	7.39	1.80		0.13	16.970		0.00	98.01		0.00	7.29	0.83		0.51
VWP3	Monday	2.70	0.01	0.19	0.85	0.008	0.016	0.62	0.01	1.19	0.23	2.69	0.01	0.82	0.41
	Tuesday	2.70	0.08	1.98	0.05	0.079	0.024	0.00	0.05	6.00	0.00	2.69	0.04	4.00	0.00
	Wednesday	2.70	0.04	0.86	0.39	0.035	0.015	0.02	0.03	2.21	0.03	2.69	0.03	3.28	0.00
	Thursday	2.70	0.00	-0.02	0.99	(0.001)	0.051	0.99	0.02	2.02	0.04	2.69	0.03	2.65	0.01
	Friday	2.70	0.11	2.70	0.01	0.108	0.065	0.09	0.04	4.97	0.00	2.69	0.04	4.25	0.00
#	1,511														
	F(4,1506)	7.39	1.33		0.26	19.514		0.00	71.22		0.00	7.29	1.70		0.15
VWP4	Monday	2.70	0.05	2.13	0.03	0.05	0.02	0.04	0.05	5.71	0.00	2.69	0.05	3.31	0.00
	Tuesday	2.70	0.07	3.00	0.00	0.07	0.02	0.00	0.05	6.13	0.00	2.69	0.05	3.89	0.00
	Wednesday	2.70	0.05	2.24	0.03	0.05	0.02	0.02	0.05	3.50	0.00	2.69	0.05	3.56	0.00
	Thursday	2.70	0.01	0.31	0.76	0.01	0.02	0.75	0.02	2.31	0.02	2.69	0.03	2.45	0.01
	Friday	2.70	0.06	2.48	0.01	0.06	0.02	0.01	0.03	4.32	0.00	2.69	0.04	2.59	0.01

			OLS			AR			LAD			TLS			
		Bayesian										Bayesian			
	Variable	t / F	Coeff	t-stat	Sig	Coeff	t-stat	Sig	Coeff	t-stat	Sig	t/ F	Coeff	t-stat	Sig
#	1,511														
	F(4,1506)	7.39	1.05		0.38	24.64		0.00	106.64		0.00	7.29	0.45		0.78
VWP	Monday	2.70	0.05	2.22	0.03	0.05	0.02	0.03	0.05	5.75	0.00	2.69	0.05	3.84	0.00
	Tuesday	2.70	0.07	3.52	0.00	0.07	0.02	0.00	0.06	7.30	0.00	2.69	0.05	4.57	0.00
	Wednesday	2.70	0.05	2.44	0.02	0.05	0.02	0.01	0.05	3.69	0.00	2.69	0.05	4.40	0.00
	Thursday	2.70	0.01	0.67	0.50	0.01	0.02	0.48	0.02	2.67	0.00	2.69	0.03	2.46	0.01
	Friday	2.70	0.05	2.79	0.01	0.05	0.02	0.01	0.03	4.76	0.00	2.69	0.04	3.18	0.00
#	1,511														
	F(4,1506)	7.39	1.10		0.36	30.87		0.00	129.92		0.00	7.29	70.90		0.00

TABLE 18: ARCH MODELLING OF DAY OF THE WEEK EFFECT.

	ISEQ			ISEQR			ISEGEN		
Variable	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig
AR(1)	0.228	11.562	0.000	0.242	12.333	0.000	0.198	8.456	0.000
AR(2)	0.012	0.551	0.581	0.014	0.709	0.478	0.046	1.896	0.058
AR(3)	0.035	1.599	0.110	0.024	1.115	0.265	0.019	1.111	0.267
AR(4)				0.030	1.364	0.173	0.041	2.199	0.028
Monday	-0.010	-0.746	0.456	0.018	1.388	0.165	-0.005	-0.311	0.755
Tuesday	0.036	2.698	0.007	0.039	3.648	0.000	0.007	0.457	0.647
Wednesday	0.044	3.396	0.001	0.035	2.938	0.003	0.024	1.589	0.112
Thursday	0.044	2.874	0.004	0.033	2.154	0.031	0.019	1.161	0.246
Friday	0.007	0.471	0.638	0.007 s	0.489	0.625	0.019	1.365	0.172
Constant (Volatility)	0.073	34.397	0.000	0.064	28.366	0.000	0.093	64.280	0.000
ARCH1	0.112	5.777	0.000	0.129	6.214	0.000	0.162	6.715	0.000
ARCH2	0.104	6.339	0.000	0.069	3.521	0.000	0.135	10.198	0.000
ARCH3	0.131	7.876	0.000	0.170	10.407	0.000			
ARCH4	0.167	8.650	0.000	0.244	13.332	0.000			

	ISEFIN			VW4			VEW		
Variable	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig
AR(1)	0.145	6.654	0.000	0.168	7.813	0.000	0.200	9.710	0.000
AR(2)	0.009	0.441	0.659						
AR(3)	0.006	0.309	0.757						
AR(4)	0.008	0.335	0.738						
Monday	-0.016	-0.825	0.410	0.059	3.010	0.003	0.056	3.202	0.001
Tuesday	0.059	3.179	0.001	0.062	4.038	0.000	0.052	3.486	0.000
Wednesday	0.040	2.336	0.020	0.064	4.063	0.000	0.062	4.487	0.000
Thursday	0.045	2.347	0.019	0.001	0.038	0.970	0.032	2.770	0.006
Friday	-0.001	-0.035	0.972	0.026	1.871	0.061	0.035	2.755	0.006
Constant (Volatility)	0.122	26.533	0.000	0.095	39.100	0.000	0.072	34.660	0.000
ARCH1	0.180	8.929	0.000	0.442	15.275	0.000	0.470	11.875	0.000
ARCH2	0.144	9.335	0.000						
ARCH3	0.132	8.495	0.000						
ARCH4	0.155	7.587	0.000						

TABLE 19: REGRESSION DIAGNOSTICS FOR ARCH MODELLING OF DAY OF THE WEEK

	ISEQ		ISEQR		ISEGEN		ISEFIN		VW4		VWT	
	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.
Ljung-Box Q Test for Serial Correlation of Residuals[a]												
LB(4)	2.39	0.12							16.45	0.00	24.07	0.00
LB(8)	4.79	0.44	4.59	0.33	4.37	0.36	5.20	0.27	20.61	0.00	27.09	0.00
LB(12)	12.16	0.20							23.91	0.01	30.28	0.00
LB(16)	16.27	0.23	15.88	0.20	18.04	0.11	11.60	0.48	24.51	0.06	31.33	0.01
LB(20)	20.04	0.27							27.05	0.10	34.74	0.02
LB(24)	25.94	0.21	26.29	0.16	31.05	0.05	20.05	0.45	38.06	0.03	40.75	0.01
Jarque-Bera Test for Normality of Residuals[b]												
	Sig:	0.00	Sig:	0.00	Sig:	0.00	Sig:	0.00	Sig:	0.00	Sig:	0.00
ARCH Test for ARCH Effects in Residuals[c]												
ARCH(4)	0.57	0.68	0.56	0.69	0.16	0.96	1.03	0.39	1.18	0.32	0.78	0.54
ARCH(8)	0.36	0.94	0.32	0.96	0.12	1.00	1.11	0.35	13.38	0.00	0.89	0.52
ARCH(12)	0.36	0.98	0.53	0.90	0.11	1.00	1.28	0.22	10.09	0.00	0.90	0.55
ARCH(16)	0.28	1.00	0.43	0.97	0.08	1.00	1.26	0.22	8.13	0.00	0.90	0.57
ARCH(20)	0.26	1.00	0.38	0.99	0.09	1.00	1.57	0.05	7.02	0.00	0.79	0.73
ARCH(24)	0.24	1.00	0.35	1.00	0.09	1.00	1.61	0.03	5.96	0.00	0.74	0.81

	ISEQ		ISEQR		ISEGEN		ISEFIN		VW4		VWT	
	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.	Stat.	Sig.
Ljung-Box Q Test for Serial Correlation of Squared Residuals[a]												
LB(4)	2.26	0.13							4.74	0.19	3.13	0.37
LB(8)	2.93	0.71	2.62	0.62	0.99	0.91	9.44	0.05	103.51	0.00	7.47	0.38
LB(12)	4.28	0.89							119.19	0.00	11.56	0.40
LB(16)	4.58	0.98	6.94	0.86	1.40	1.00	20.22	0.06	125.14	0.00	16.37	0.36
LB(20)	5.46	1.00							128.81	0.00	17.87	0.53
LB(24)	6.04	1.00	8.87	0.98	2.30	1.00	40.16	0.00	132.10	0.00	20.67	0.60

a: Ho=no serial correlation ; b:Ho=normality, c:Ho = ARCH effects

9.1.2. OVERALL SIGNIFICANCE AS A TEST OF DAILY SEASONALITY

Examination of the results of Table 17 indicates that we cannot with certainty say that daily seasonality is a persistent and consistent feature of the Irish stock market.

First, the issue of whether or not we find the existence overall of daily seasonality is dependent on the estimation procedure used. Standard OLS estimation indicates by means of the regression F test that the only index that exhibits daily seasonality is the ISEQ. Correcting for autocorrelation makes a substantial difference, resulting in almost all the indices, with the exception of the ISEQ General index and the smaller equal weighted indices showing daily seasonality. However, with correction for the non-normality of the data by means of a robust estimator this changes – while the LAD estimator indicates that all indices are seasonal at the daily level this is not the case for the TLS estimator.

The ISEQ appears to have a daily seasonal under all the estimators, the ISEQ total return under adjustment for autocorrelation and LAD, the ISE Financial index under all except the initial OLS, and the ISE General index only under LAD estimation Apart from this set a number of indices show daily seasonality under correction for autocorrelation and under LAD, these being Value Weighted Quartiles 2-4 and Total and Equal Weighted Quartiles 2-4 and Total. Thus, at least an initial assessment that there may be daily seasonality in the Irish stock market indices is possible, but this appears to be confined to larger indices and to those for which we have a longer run of data. That we have found no strong evidence of seasonality in the smaller capitalization stocks is unusual, and in contrast to the theoretical findings of Theobald and Price (1984), and to numerous empirical results since.

Correcting for the number of observations we find that in the majority of cases where the overall significance was evident that this is also the case with adjustment. The exceptions are Equal Weighted Total index (under autocorrelated correction) and the ISEQ and ISE Financial under TLS, and the ISEQ under OLS.

If we place more subjective weight on the 'corrected' indices and the LAD estimator we therefore find that daily seasonality appears to be significant and widespread. However, this tells us little as to the actual pattern of this seasonality

9.1.3. STATISTICALLY SIGNIFICANT DAYS

As noted above the tests of overall significance are joint tests that the daily coefficients are jointly and severally equal to zero. Finding that they are not so leads to a requirement to examine which days, if any are non-zero.

There are two alternative parametric approaches to this. The simplest approach relies on the interpretation of the individual t-statistics from the regressions reported in Table 17. Under this approach we find that there appears to be two sets of daily coefficients the significance of which differs markedly from previous results reported in the literature.

Examining Monday for example, we find that only in three indices, Equal weighted Quartile 4, Value Weighted Quartile 4 and Value Weighted Total, does it appear as statistically significant regardless of the method of estimation. In general these are also only significant when no account is taken of the number of data points used in the investigation. For two indices, the ISEQ and the Value Weighted Quartile 2 index, Monday is not significant under any form of adjustment or estimation. For the other indices there is some tendency for Monday returns to be more significant under robust (TLS/LAD) estimation than otherwise, but this appears to be dependent on the number of observations, significance declining under adjustment for data points. Monday is however significant when we account for ARCH disturbances in the Value Weighted Quartile 4 and Value Weighted Total indices.

By contrast, Wednesday appears significant in all bar the Equal and Value Weighted Quartile 1 indices. For the ISEQ it is significant across all estimation methods and , with the exception of LAD estimation, this does not appear to be an artefact of the number of data points. For the ISEQ total returns and the Financial index it is also significant across all estimators, although more so under classical than Bayesian assumptions. The ISE general index does not have a significant Wednesday effect under robust estimation, nor under Bayesian assumptions in the non-robust estimates. For the quartile indices (bar the quartile 1 indices as noted) as the size of the firms increases the significance of Wednesday remains, and emerges not only under classical but also under Bayesian adjustment. This holds more under robust estimation than non-robust. Tuesday is the only day for which, under at least one estimator and under at least one of classical or Bayesian assumptions, the coefficient is statistically significant for all indices. However, in many indices this is a result that only emerges from the robust estimators, showing the importance of adjusting the data for non-normalities. A pattern similar to that of Tuesday also holds for Thursday, although weaker. Wednesday's significance disappears however when we account for ARCH type heteroskedasticity in the ISEQ General index.

Given that the significance of Wednesday extends across estimation methods, indices, and adjustments for data points, it seems reasonable to conclude that there is a Wednesday effect in the Irish stock market. It also seems reasonable to conclude that there is not a Monday effect. This is in marked contrast to the international literature.

An alternative to the standard t-test for differences between means that allows for a detailed examination of whether differences do in fact exist between individual mean daily returns is given by Tukey's Honestly Significant Difference (HSD) test. However, while Steeley (2001) uses this test, with a finding that no significant difference in means exists in the FTSE 100 index, it has the potential drawback that it incorporates the assumption of equality of variances across the categories. As we will see in section 9.5, this is not tenable in the data for a small number of indices. An alternative, which does not assume such equality, is Tamhane's (Adjusted) T^2 statistic.[68] This is the statistic applied to the indices, ISEQ, ISEQR, TVW4 and TVW, which display a second moment effect. Table 20 shows the results of these tests.

[68] A difficulty with these tests is that they arise as post-hoc restrictions on an ANOVA model. We have seen that OLS estimates alone are not reliable and require at a minimum a robust estimator such as TLS. There are no robust analogs of the T^2 statistic or Tukeys' HSD test. A partial solution to this problem can be found by applying these tests to the Trimmed data rather than the original data.

TABLE 20: DIFFERENCES IN MEANS BY DAY OF THE WEEK: TAMHANE'S T^2 TESTS

Tamhane		ISEQ		TISEQ		TVW4		TVW	
		Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.
Monday	Tuesday	-0.029	0.960	-0.028	0.652	-0.005	1.000	-0.005	1.000
	Wednesday	-0.050	0.423	-0.043	0.150	0.001	1.000	-0.003	1.000
	Thursday	-0.030	0.936	-0.031	0.442	0.016	0.997	0.021	0.947
	Friday	-0.006	1.000	-0.009	1.000	0.013	0.999	0.010	1.000
Tuesday	Wednesday	-0.021	0.991	-0.015	0.992	0.006	1.000	0.002	1.000
	Thursday	-0.001	1.000	-0.004	1.000	0.021	0.979	0.026	0.793
	Friday	0.023	0.979	0.019	0.941	0.017	0.990	0.016	0.987
Wednesday	Thursday	0.020	0.991	0.011	0.999	0.015	0.998	0.024	0.857
	Friday	0.043	0.387	0.034	0.394	0.012	1.000	0.013	0.996
Thursday	Friday	0.023	0.959	0.022	0.816	-0.003	1.000	-0.010	1.000

TABLE 21: DIFFERENCES IN MEANS BY DAY OF THE WEEK: TUKEY'S HONESTLY SIGNIFICANT DIFFFERENCE TESTS

		ISEQR		ISEF		ISEGEN		TISEQR		TISEFIN		TISEGEN	
		Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.
Monday	Tuesday	0.000	1.000	-0.065'	0.334	-0.005	0.999	-0.014	0.911	-0.078	0.009	-0.027	0.454
	Wednesday	-0.018	0.946	-0.068	0.296	-0.031	0.702	-0.023	0.647	-0.073	0.019	-0.012	0.946
	Thursday	0.002	1.000	-0.055	0.515	-0.012	0.986	-0.020	0.743	-0.073	0.019	-0.027	0.448
	Friday	0.027	0.797	-0.020	0.981	-0.009	0.996	0.008	0.987	-0.040	0.462	-0.017	0.846
Tuesday	Wednesday	-0.018	0.936	-0.002	1.000	-0.025	0.817	-0.008	0.984	0.005	1.000	0.015	0.879
	Thursday	0.001	1.000	0.010	0.998	-0.007	0.998	-0.006	0.996	0.005	0.999	0.000	1.000
	Friday	0.026	0.789	0.046	0.662	-0.003	1.000	0.022	0.621	0.039	0.451	0.010	0.965
Wednesday	Thursday	0.020	0.917	0.013	0.996	0.018	0.934	0.003	1.000	0.000	1.000	-0.015	0.877
	Friday	0.045	0.309	0.048	0.616	0.022	0.880	0.031	0.299	0.034	0.592	-0.005	0.999
Thursday	Friday	0.025	0.821	0.035	0.836	0.004	1.000	0.028	0.386	0.033	0.597	0.010	0.965

		EWP1		EWP2		EWP3				EWP	
		Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.
Monday	Tuesday	0.062	0.914	-0.052	0.850	-0.063	0.797	0.073	0.465	0.004	1.000
	Wednesday	-0.037	0.986	-0.016	0.998	-0.061	0.814	0.031	0.955	-0.011	0.988
	Thursday	-0.033	0.991	-0.033	0.966	-0.049	0.909	0.068	0.536	0.005	1.000
	Friday	-0.063	0.908	0.021	0.994	-0.079	0.617	0.068	0.534	0.003	1.000
Tuesday	Wednesday	-0.099	0.621	0.036	0.952	0.002	1.000	-0.042	0.866	-0.015	0.956
	Thursday	-0.095	0.660	0.019	0.996	0.014	0.999	-0.005	1.000	0.000	1.000
	Friday	-0.125	0.390	0.073	0.581	-0.017	0.998	-0.005	1.000	-0.002	1.000
Wednesday	Thursday	0.004	1.000	-0.017	0.997	0.012	0.999	0.037	0.911	0.016	0.954

	Friday	-0.026	0.996	0.037	0.944	-0.019	0.997	0.037	0.910	0.014	0.970
Thursday	Friday	-0.030	0.993	0.055	0.807	-0.031	0.980	0.000	1.000	-0.002	1.000
		TEW1		TEW2		TEW3		TEW4		TEW	
		Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.
Monday	Tuesday	0.010	0.991	-0.006	0.989	-0.001	1.000	-0.026	0.661	-0.007	0.964
	Wednesday	0.029	0.676	-0.024	0.272	-0.009	0.961	-0.010	0.986	-0.007	0.972
	Thursday	0.026	0.764	-0.011	0.903	-0.004	0.998	-0.001	1.000	0.005	0.990
	Friday	0.020	0.899	-0.010	0.925	-0.001	1.000	0.006	0.998	0.007	0.971
Tuesday	Wednesday	0.019	0.905	-0.018	0.527	-0.008	0.965	0.016	0.912	0.000	1.000
	Thursday	0.016	0.949	-0.005	0.994	-0.004	0.998	0.025	0.649	0.013	0.753
	Friday	0.010	0.992	-0.004	0.997	-0.000	1.000	0.032	0.419	0.015	0.651
Wednesday	Thursday	-0.003	1.000	0.014	0.777	0.005	0.996	0.009	0.988	0.012	0.780
	Friday	-0.009	0.993	0.014	0.748	0.008	0.970	0.016	0.912	0.014	0.682
Thursday	Friday	-0.006	0.999	0.001	1.000	0.003	0.999	0.007	0.996	0.002	1.000
		VWP1		VWP2		VWP3		VWP4		VWP	
		Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.	Difference	Sig.
Monday	Tuesday	0.021	1.000	-0.066	0.491	-0.071	0.738	-0.017	0.986	-0.023	0.929
	Wednesday	0.057	0.999	-0.014	0.997	-0.027	0.991	0.000	1.000	-0.002	1.000
	Thursday	-0.195	0.895	0.012	0.999	0.009	1.000	0.043	0.675	0.033	0.778
	Friday	0.294	0.650	0.035	0.914	-0.100	0.425	-0.005	1.000	-0.009	0.998
Tuesday	Wednesday	0.035	1.000	0.053	0.682	0.045	0.933	0.017	0.983	0.021	0.939
	Thursday	-0.216	0.839	0.078	0.291	0.080	0.621	0.060	0.318	0.056	0.258
	Friday	0.272	0.688	0.101	0.083	-0.029	0.987	0.012	0.996	0.014	0.986
Wednesday	Thursday	-0.252	0.747	0.025	0.969	0.035	0.972	0.043	0.655	0.034	0.723
	Friday	0.237	0.788	0.049	0.738	-0.074	0.692	-0.006	1.000	-0.007	0.999
Thursday	Friday	0.488	0.132	0.023	0.977	-0.109	0.308	-0.049	0.540	-0.042	0.561

		TVW1		TVW2		TVW3	
		Difference	Sig.	Difference	Sig.	Difference	Sig.
Monday	Tuesday	0.010	0.997	0.010	0.956	-0.032	0.214
	Wednesday	0.051	0.377	0.016	0.803	-0.025	0.470
	Thursday	0.044	0.544	0.023	0.506	-0.019	0.719
	Friday	0.040	0.609	0.024	0.470	-0.035	0.137
Tuesday	Wednesday	0.041	0.571	0.006	0.994	0.007	0.988
	Thursday	0.034	0.745	0.013	0.894	0.013	0.908
	Friday	0.030	0.804	0.014	0.868	-0.003	1.000
Wednesday	Thursday	-0.007	0.999	0.007	0.987	0.006	0.996
	Friday	-0.011	0.994	0.008	0.979	-0.010	0.954
Thursday	Friday	-0.003	1.000	0.001	1.000	-0.016	0.815

Little evidence is present from these tests of statistically significant daily differences. Only for the ISE Financial index do we find some, between Monday and Tuesday-Wednesday-Thursday. This generalised rejection, under a more robust parametric statistical approach, of significant daily differences in returns, echoes the findings of Steeley (1999).

9.2. NON-PARAMETRIC ANALYSIS OF THE FIRST MOMENT

We have already seen that non-parametric approaches exist to allow testing of daily seasonality, but that surprisingly little use has been made of these in the published literature. This is despite the evidence of significant non-normality in stock returns and stock indices. The results in Table 22 show non-parametric analyses as to the day of the week effect. The effect of the day of the week on the indices were analysed by means of a Kruskal-Wallis H test, which is the non-parametric equivalent to one-way ANOVA. It tests whether several independent samples, in this case the individual daily returns are from the same population. It is distributed as a chi-squared statistic with n-1 degrees of freedom, where n is the number of possible distributions from which the sample can be drawn. The null hypothesis, which can be rejected of the significance level is below a pre-set critical value, is that the data are from the same distributions.

In this case, the null therefore is that the data, the indices, do not differ as to the day of the week. A finding of a low significance therefore would indicate a rejection of the null, and an indication that a day of the week effect is present, the distributions of the index differing by the day of the week. The Kruskal-Wallis test therefore allows the parametric F tests to be augmented. Testing for a day of the week effect using both the regression F and Kruskal-Wallis test, Elyasiani, Perera and Puri (1996) in their examination of Sri Lankan data found that the two tests were in agreement, indicating no day of the week effect. This agreement between the two forms of tests was also found in Arsad and Coutts (1997) and Steeley (1999).

TABLE 22: NON-PARAMETRIC TEST FOR DAY OF THE WEEK EFFECT; KRUSKAL-WALLIS H TEST.

	Chi-Square	Significance.		Chi-Square	Significance.
ISEQ	14.222	.007	TISEQ	9.978	.041
ISEQR	4.105	.392	TISEQR	4.052	.399
ISEFIN	15.337	.004	TISEFIN	16.648	.002
ISEGEN	1.993	.737	TISEGEN	3.606	.462
EWP1	1.804	.772	TEW1	1.281	.865
EWP2	3.419	.490	TEW2	6.236	.182
EWP3	.515	.972	TEW3	.584	.965
EWP4	1.735	.784	TEW4	4.280	.369
EWT	1.392	.846	TEW	3.680	.451
VWP1	4.568	.335	TVW1	4.532	.339
VWP2	4.061	.398	TVW2	4.831	.305
VWP3	5.750	.219	TVW3	6.848	.144
VWP4	2.992	.559	TVW4	1.827	.767
VWT	4.150	.386	TVW	3.214	.523

From this analysis the evidence in favour of daily seasonality found under parametric analyses is weakened considerably. While the majority of indices show such a seasonal under parametric analyses, under non-parametric analysis this does not hold. Only for the ISEQ and the ISE financial index, trimmed and original, would a non-parametric test hold out the possibility of a daily seasonal. The ISEQ and ISEFIN indices are the only indices from Table 12 that showed negative medians for any day of the week.

While the ISEQ index displayed overall seasonality under all forms of estimation the ISE Financial index did not so display under OLS (analogous to a

H test on the original series) but did under the TLS estimator (analogous to a H test on the trimmed series).

9.3. STOCHASTIC DOMINANCE ANALYSIS

Table 23 shows the results of another non-parametric method of analysis, that of stochastic dominance. In order to implement the stochastic dominance algorithm of Aboudi and Thon (1994), only those weeks wherein each day was represented could be chosen. Thus, weeks with a holiday are necessarily excluded from the analysis as the number of days taken as holidays need not be 1 in all cases.

TABLE 23: STOCHASTIC DOMINANCE ANALYSIS

Index	Second Order Stochastic Dominance
EWP1	Friday dominates Thursday
EWP2	Friday dominates Wednesday
TEW2	Friday dominates Thursday
EWP3	Friday dominates Wednesday
EWP	Friday dominates Thursday
VWP2	Friday dominates Thursday
TVW2	Friday dominates Thursday
TVW4	Friday dominates Thursday
ISEFIN	Friday dominates Thursday
ISEGEN	Friday dominates Thursday
ISEQR	Friday dominates Thursday

Clearly, there is no significant evidence of widespread day of the week effects from a stochastic dominance perspective. This is in significant contrast to the findings of the regression results presented above, regardless of the particular methodology used. What is also evident is that the results that are achieved are, unlike those of Wingender & Groff, not robust to trimming – thus the issue of normality of the indices arises again.

Only for the equally and value weighted indices for the second smallest quartile of firms does the stochastic dominance of Friday over Thursday returns hold after trimming. In all other cases the results are eliminated on a 5% trim. Fridays are the most common days to achieve dominance, usually being dominant over Wednesday. In none of the indices does first order stochastic dominance arise. The stochastic dominance analysis seemingly contradicts the other evidence, with for example the ISEQ index, which demonstrates a daily seasonal both from parametric and non-parametric tests showing no stochastically dominant pairs. This result is strikingly at variance with the other results. The implication is that there is no universal preference, from a risk-return perspective, to avoid Mondays or to prefer any other day of the week. In consequence, we can infer that the Stochastic Dominance results indicate a widespread lack of presence of day of the week effects in the Irish market.

9.4. RESAMPLING ANALYSES

Shown in Table-24 are the results of a series of resampling analyses.

In all cases 1000 random draws were made from the actual data, the daily returns to the index in question, each of N, where N equalled the number of actual occurrences of the day in question. For each day which was identified as being highest or lowest, for both the first and second moment, the table shows the percentage of drawings where the moment of the random draw exceeded or was lower than the moment of the empirical distribution.

TABLE 24: RESAMPLING ANALYSIS OF DAILY SEASONALITY

	ISEQ	ISEQR	ISEFIN	ISEGEN	
Maximum Mean	Wednesday	Wednesday	Wednesday	Wednesday	
% Above Mean	6.3%	6.3%	15.3%	12.4%	
Maximum St Dev	Monday	Monday	Monday	Monday	
% Above St Dev	1.8%	2.0%	19.0%	5.5%	
Minimum Mean	Monday	Friday	Monday	Monday	
% Below Mean	9.7%	13.9%	4.3%	22.6%	
Minimum St Dev	Friday	Friday	Friday	Thursday	
% Below St Dev	6.2%	6.7%	5.3%	6.4%	
	EWP1	EWP2	EWP3	EWP4	EWP
Maximum Mean	Friday	Tuesday	Friday	Monday	Wednesday
% Above Mean	15.1%	12.4%	17.6%	5.9%	22.7%
Maximum St Dev	Tuesday	Friday	Friday	Monday	Monday
% Above St Dev	6.1%	14.5%	8.7%	14.5%	3.0%
Minimum Mean	Tuesday	Friday	Monday	Tuesday	Thursday
% Below Mean	4.4%	12.0%	7.2%	20.8%	36.1%
Minimum St Dev	Monday	Thursday	Wednesday	Thursday	Thursday
% Below St Dev	13.4%	2.6%	10.2%	31.3%	33.1%
	VWP1	VWP2	VWP3	VWP4	VWP
Maximum Mean	Thursday	Tuesday	Friday	Tguesday	Tuesday
% Above Mean	6.1%	2.6%	9.1%	17.5%	12.0%
Maximum St Dev	Friday	Tuesday	Friday	Monday	Friday
% Above St Dev	18.0%	6.8%	9.7%	42.7%	30.7%
Minimum Mean	Friday	Friday	Thursday	Thursday	Thursday
% Below Mean	4.7%	6.5%	8.3%	4.7%	4.6%
Minimum St Dev	Wednesday	Wednesday	Wednesday	Thursday	Thursday
% Below St Dev	26.1%	11.3%	5.9%	49.8%	30.9%

Take the ISEQ as an example. There are 510 Mondays in the sample. Monday is the day that has the highest standard deviation but also has the lowest mean – contrary to the predictions of the mean-variance framework. Thus 1000 drawings each of 510 data points were made and the average and standard deviation calculated for each of the 1000 sets of 510 points. In only 97 cases out of 1000 random drawings each of 510 returns from the ISEQ was a mean found which was lower than the mean Monday return of the ISEQ.

It is not strictly possible to interpret the percentages here as marginal probabilities. This arises as a result of the fact that to do so we would be required to know the precise sampling distribution of the resampled statistic. If the distribution of these statistics, the means for example, were to be of a recognised distribution, normal, binomial, Poisson or whatever, then we would be able indeed to estimate the probability of observing a particular value. However, in general the histograms of the resampled statistics are non-normal, by inspection. Thus a t- or Z- test is not possible. In the absence of this we are therefore reduced to stating the percentage of trials in which a particular statistic of interest is exceeded or not.

Thus we can conclude that the low mean return on Monday is probably not, at a level of around 9%, an artefact or due to chance alone. Similarly, for Wednesday the ISEQ high mean return is also probably not an artefact, at a significance level of around 6%. For the second moment we find that only in 18 drawings, 1.8%, do we find a standard deviation above that of Monday, the highest observed, and only in 62, 6.2%, cases is there a standard deviation less than that of Friday. From the table it seems possible to conclude that the pattern of maximum first and second, and minimum second moments, is not attributable to chance in the case of the ISEQ.

Less certainty can be attributed to the measured moments of the ISEFIN and ISEGEN indices. The evidence for a Wednesday seasonal is weakened considerably, although the evidence indicates that the low Monday mean return in ISEFIN is not as a result of chance. ISEGEN Wednesday mean results are considerably out of line with the other ISE indices, but this was also the case with regard to the ISEGEN under robust and under Bayesian estimation. In general the results are similar to other non-parametric approaches. The evidence tends also to be stronger for the minimum than the maximum. The evidence also seems stronger for the value than the equal weighted indices

9.5. Analysis Of The Second Moment

The evidence presented in Table 20 results in part from the analyses in this section. The results of a Levene test are displayed in Table 25.

TABLE 25: TEST OF HOMOGENEITY OF VARIANCE BY DAY OF THE WEEK.

	Levene Statistic	df1	df2	Sig.		Levene Statistic	df1	df2	Sig.
ISEQ	2.404	4	2773	0.048	TISEQ	3.97	4	2449	0.003
ISEQR	2.145	4	2773	0.073	TISEQR	2.286	4	2425	0.058
ISEFIN	1.083	4	2511	0.363	TISEFIN	1.785	4	2187	0.129
ISEGEN	1.782	4	2511	0.13	TISEGEN	1.355	4	2167	0.247
EWP1	1.725	4	1507	0.142	TEW1	2.348	4	1028	0.053
EWP2	1.949	4	1507	0.100	TEW2	0.657	4	1168	0.622
EWP3	1.376	4	1507	0.24	TEW3	0.744	4	1239	0.562
EWP4	0.165	4	1507	0.956	TEW4	0.93	4	1298	0.446
EWT	0.582	4	1507	0.676	TEW	1.153	4	1279	0.33
VWP1	0.946	4	1507	0.436	TVW1	0.118	4	1098	0.976
VWP2	0.837	4	1507	0.502	TVW2	0.929	4	1175	0.446
VWP3	1.363	4	1507	0.244	TVW3	2.103	4	1267	0.078
VWP4	0.88	4	1507	0.475	TVW4	2.409	4	1301	0.048
VWT	0.891	4	1507	0.469	TVW	2.527	4	1296	0.039

H_0: $\sigma_i = \sigma_j \forall i, j$. Calculated with SPSS for Windows Analyze Means: ANOVA procedure

The evidence from Table 25 is that only in a small number of indices can we reject the null of equality of variance across the day of the week. These indices are the ISEQ and indices in both trimmed and original forms, and the trimmed value weighted indices for largest and all companies. This is not surprising, as for the untrimmed ISEQ ARCH effects were detected in the residuals of the parametric regression. As noted earlier, a GARCH type model specification allows for the simultaneous estimation of the mean and conditional variance of a series. Thus, it allows us in principle to focus in on those days that have a significant influence on the variance. However, there is no justification for testing a series, using EGARCH or other specifications, which has not demonstrated ARCH effects. Bollerslev (1986) indicates that for the majority of financial series a GARCH(1,1) specification , indicating that the variance equation has an ARMA(1,1) process, is sufficient. However, it is clear from Table 18 that the ARCH lags specification is appropriate. Therefore the final GARCH models are of the form GARCH(p,q,r) where p=number of AR terms in the mean equation decided according to an examination of the PACF function in Appendix II, ,q=number of AR terms in the variance equation and r=number of MA terms in the variance equation (always here 1). The finals specification therefore is: ISEQ(3,1,4). Following the lead from Beller and Nofsinger (1998) to reduce the probability of non-convergence only 4 of the 5 daily dummies are included in the variance equation (Monday through Thursday). Thus the constant in the variance equation can be seen as the effect of Friday on volatility and the individual daily dummies then become the differential effect from Friday on volatility of the individual days. An ARCH-In Mean term (Engle, Lilien and

Robins (1987)) is also included to allow the returns to depend on their own conditional variance, reflecting the presupposition in financial economics that investors are risk averse and require compensation for risk. To ensure that the conditional variance is strictly positive, and also to allow for potential asymmetries in the volatility transmission mechanism, an EGARCH specification is used.

Results for these analyses are contained in Table 26 and regression diagnostics in Table 27. The regression diagnostics indicate that the residuals are non-normally distributed and that the variance is non-explosive, the coefficients of the ARCH terms in the variance equation summing to less than 1. However, unlike the results of the ARCH models presented earlier there still exists serial correlation in the normalised residuals, although not in the squared residuals. No ARCH effects are present. As all daily dummies in the variance equation are significant (indicating that the daily risk pattern represented by each differs from that of Friday), we are no further in attributing variation in volatility to individual days of the week. The ARCH-in-Mean term is not statistically significant, indicating that there is not a trade-off between risk and returns at the daily frequency.

TABLE 26: EGARCH ESTIMATION OF DAY OF THE WEEK EFFECTS IN VARIANCE OF SELECTED INDICES

Variable	Coeff	T-Stat	Signif
AR(1)	0.02	1.17	0.24
AR(2)	-0.00	0.00	1.00
AR(3)	0.00	0.00	1.00
Constant Va riance	-1.19	-21.28	0.00
ARCH1	0.33	10.89	0.00
ARCH2	-0.08	-1.99	0.05
ARCH3	-0.16	-5.33	0.00
ARCH4	0.71	22.78	0.00
AR-Variance	0.72	63.18	0.00
Leverage Term	0.22	7.53	0.00
Monday	1.19	13.83	0.00
Tuesday	0.87	10.84	0.00
Wednesday	3.42	39.25	0.00
Thursday	-1.03	-11.28	0.00
ARCH-in-Mean	0.00	0.00	1.00

TABLE 27: REGRESSION DIAGNOSTICS FOR EGARCH MODELLING OF THE DAY OF THE WEEK EFFECT ON VARIANCE

	Stat	Sig
The Ljung-Box Q-Test for Serial Correlation in Normalized Residuals [a]		
LB(4)	34.65	0.00
LB(8)	46.33	0.00
LB(12)	70.03	0.00
LB(16)	77.92	0.00
LB(20)	78.50	0.00
LB(24)	83.07	0.00
The Ljung-Box Q-Test for Serial Correlation in Squared Normalized Residuals [a]		
LB(4)	3.57	0.06
LB(8)	3.70	0.59
LB(12)	10.15	0.34
LB(16)	18.02	0.16
LB(20)	19.93	0.28
LB(24)	20.89	0.47
The Jarque-Bera Normality Test for Normalized Residuals [b]		
	22,860.82	0.00
F-Test of no ARCH vs. ARCH in Normalized Residuals [c]		
ARCH(4)	0.91	0.46
ARCH(8)	0.47	0.88
ARCH(12)	0.82	0.62
ARCH(16)	1.11	0.34
ARCH(20)	0.97	0.50
ARCH(24)	0.84	0.69

a: Ho: No Serial Correlation ; b: Ho: Normality ; c: Ho: No ARCH

9.6. Testing Higher Moments

The evidence presented in Table 28 regarding higher moments is clear; for the trimmed indices there is no evidence of daily seasonality, while significant evidence exists in the untrimmed data. There is almost always a difference between Wednesday and Friday, and also as between Monday and Wednesday, further reinforcing the hypothesised Wednesday effect seen already in the other moments. These results are not surprising.

TABLE 28: DAY OF THE WEEK EFFECTS IN HIGHER MOMENTS

Pairs of Days		ISEQ	ISEQR	ISEFIN	ISEGEN	EW1	EW2	EW3	EW4	EW	VW1	VW2	VW3	VW4	VW
Monday-Tuesday	K-S Stat[a]	0.781	0.782	0.787	1.021	3.529	2.792	3.21	2.906	2.291	3.261	2.702	1.505	0.798	1.006
	Sig	0.576	0.574	0.566	0.248	0	0	0	0	0	0	0	0.022	0.548	0.264
Monday-Wednesday	K-S Stat	1.408	1.302	1.041	1.452	2.532	1.432	4.3	1.908	2.157	2.186	2.338	0.652	0.549	0.522
	Sig	0.038	0.067	0.228	0.029	0	0.033	0	0.001	0	0	0	0.789	0.923	0.948
Monday-Thursday	K-S Stat	0.878	1.062	0.948	1.398	2.846	2.868	3.687	2.282	2.072	4.081	1.735	2.806	0.74	0.862
	Sig	0.424	0.21	0.33	0.04	0	0	0	0	0	0	0.005	0	0.644	0.448
Monday-Friday	K-S Stat	1.24	1.401	1.166	1.376	3.509	2.693	3.865	2.178	2.189	6.325	2.164	3.596	1.37	1.399
	Sig	0.092	0.04	0.132	0.045	0	0	0	0	0	0	0	0	0.047	0.04
Tuesday-Wednesday	K-S Stat	1.284	1.314	0.832	1.105	4.928	2.926	2.523	1.395	0.873	1.788	2.482	1.553	0.611	0.787
	Sig	0.074	0.063	0.493	0.174	0	0	0	0.041	0.431	0.003	0	0.016	0.849	0.566
Tuesday-Thursday	K-S Stat	0.712	0.623	0.81	0.915	4.706	3.178	1.931	1.167	0.845	3.54	2.856	3.741	0.965	0.724
	Sig	0.69	0.832	0.528	0.372	0	0	0	0.131	0.473	0	0	0	0.309	0.671
Tuesday-Friday	K-S Stat	1.046	1.055	1.202	0.994	5.27	4.626	1.81	1.529	1.046	5.873	3.821	3.339	1.126	1.167
	Sig	0.223	0.216	0.111	0.277	0	0	0.003	0.019	0.224	0	0	0	0.158	0.131
Wednesday-Thursday	K-S Stat	1.305	1.216	1.065	0.919	3.077	2.832	1.228	1.636	0.639	3.6	3.201	3.001	0.705	0.773
	Sig	0.066	0.104	0.206	0.367	0	0	0.098	0.009	0.808	0	0	0	0.704	0.588
Wednesday-Friday	K-S Stat	1.559	1.589	1.358	1.514	2.832	4.047	4.049	1.475	0.639	6.055	2.919	3.768	1.633	1.754
	Sig	0.015	0.013	0.05	0.02	0	0	0	0.026	0.808	0	0	0	0.01	0.004
Thursday-Friday	K-S Stat	0.928	1.016	1.232	0.907	3.982	5.39	3.459	1.006	0.764	7.965	1.689	2.936	1.529	1.609
	Sig	0.356	0.253	0.096	0.383	0	0	0	0.264	0.603	0	0.007	0	0.019	0.011

		TISEQ	TISEQR	TISEFIN	TISEGEN	TEW1	TEW2	TEW3	TEW4	TEW	TVW1	TVW2	TVW3	TVW4	TVW
Monday-Tuesday	K-S Stat	0.758	0.624	0.626	0.651	0.965	0.851	0.689	0.876	0.84	0.784	0.674	0.565	0.482	0.412
	Sig	0.614	0.831	0.827	0.79	0.31	0.464	0.73	0.427	0.481	0.571	0.754	0.907	0.974	0.996
Monday-Wednesday	K-S Stat	0.746	0.628	0.624	0.7	1.165	0.739	0.766	0.735	0.869	1.126	0.79	0.614	0.432	0.465
	Sig	0.634	0.825	0.832	0.711	0.133	0.646	0.6	0.653	0.437	0.158	0.56	0.846	0.992	0.982
Monday-Thursday	K-S Stat	0.876	0.611	0.6	0.722	0.94	0.78	0.567	0.607	0.83	0.943	0.61	0.56	0.445	0.447
	Sig	0.426	0.849	0.864	0.675	0.34	0.577	0.905	0.856	0.496	0.336	0.851	0.912	0.989	0.988
Monday-Friday	K-S Stat	1.021	0.756	1.148	1.101	1.499	0.872	0.557	0.448	1.013	1.197	0.647	0.737	1.027	0.828
	Sig	0.249	0.616	0.143	0.177	0.022	0.433	0.915	0.988	0.256	0.114	0.797	0.649	0.242	0.499
Tuesday-Wednesday	K-S Stat	0.639	0.746	0.529	0.597	1.117	0.539	0.998	0.46	0.593	0.644	0.919	0.783	0.516	0.467
	Sig	0.809	0.634	0.942	0.868	0.165	0.934	0.272	0.984	0.873	0.801	0.368	0.572	0.953	0.981
Tuesday-Thursday	K-S Stat	0.608	0.472	0.55	0.618	0.5	0.844	0.644	0.687	0.672	0.56	0.742	0.606	0.491	0.468
	Sig	0.854	0.979	0.922	0.84	0.964	0.474	0.801	0.732	0.757	0.913	0.64	0.856	0.969	0.981
Tuesday-Friday	K-S Stat	0.918	1.079	0.743	1.204	1.123	0.944	0.749	0.803	0.709	0.733	1.028	0.997	0.828	0.728
	Sig	0.368	0.195	0.64	0.11	0.16	0.335	0.629	0.539	0.696	0.656	0.241	0.273	0.499	0.664
Wednesday-Thursday	K-S Stat	0.704	0.844	0.524	0.574	0.74	0.564	0.894	0.906	0.724	0.518	0.494	0.606	0.599	0.636
	Sig	0.704	0.474	0.946	0.897	0.644	0.908	0.401	0.385	0.672	0.951	0.968	0.856	0.865	0.814
Wednesday-Friday	K-S Stat	1.025	1.082	0.948	0.81	0.701	0.719	0.61	0.696	0.974	0.468	0.462	0.6	1.019	1.107
	Sig	0.244	0.193	0.329	0.528	0.71	0.68	0.851	0.717	0.299	0.981	0.983	0.864	0.25	0.172
Thursday-Friday	K-S Stat	0.614	0.69	0.839	0.779	0.679	0.621	0.681	0.531	0.637	0.551	0.578	1.085	1.024	0.854
	Sig	0.845	0.728	0.483	0.579	0.746	0.835	0.743	0.941	0.812	0.922	0.892	0.19	0.245	0.46

a: Kolmogorov-Smirnoff Test statistic.

9.7. ECONOMIC VS STATISTICAL SIGNIFICANCE

It is perhaps worth reminding ourselves of the difference between statistical and economic significance. This is best summed up in the words of Jensen (1978) who summarizes the issue as

" a market is efficient with respect to an information set Ω if it is impossible to make economic profits by trading on the basis of Ω By economic profits we mean the risk adjusted rate of return, net of all costs"

Thus, while there is some statistical evidence presented above that the Irish market, in particular the ISEQ and the ISE Financial index show daily seasonality in their first second and higher moments, there is no guarantee that this provides a profitable trading opportunity. This issue was examined in a number of papers. French (1980) and Kim (1988) , Mills and Coutts (1995)and Arsad and Coutts (1997) among others have concluded that there is little profit to be gained, after trading costs, from a weekday trading strategy. One problem with the Irish indices that does not appear in other indices is that there is a paucity of negative mean returns. For example, in Kim (1988) each of the 5 indices examined had at least one day when the index mean return was negative. Traders and investors will of course wish to avoid negative mean returns and gain positive mean returns. In the case of the indices that demonstrated daily seasonality across the parametric and non-parametric methods only the ISE Financial index has a negative mean return, on a Monday. Moreover, this is not statistically significant from zero!

However, as the return that is being avoided is smaller than the cumulative costs which would be incurred then there is little economic rationale to so do. Thus, as a trading strategy this daily seasonal in the ISE Financial index will not yield superior economic performance. However, for trades which were in any case going to be made then there is a timing performance which can be achieved.

9.8. Conclusion And International Comparisons

The evidence above may be summarised simply – there is some evidence that indices of Irish quoted equities exhibit daily seasonality. This seasonality is however at once more complex than the typical pattern, with more than one day appearing to be significant, and unusual, in that Wednesday seems to be an important day.

Evidence from such as Jaffe and Westerfield (1985),Board and Sutcliffe (1988), Coutts and Hayes (1999) and Agrawal and Tandon (1994) on the UK equity market, with which the Irish market is closely allied and linked as we have seen, is that a negative Monday effect, with Monday risk showing as high, is commonly found. This UK evidence mirrors that found consistently in the USA, by authors from French (1980), through Lakonishok and Levi (1982), Lakonishok and Smidt (1988) and Agrawal and Tandon (1994). No UK research of which I am aware finds a significant Wednesday effect. It would seem highly unlikely, prime facia, that the negative Monday in the UK is translated as a positive in the Irish market. There is no guide in the literature as to a mecha nism by which this may occur.

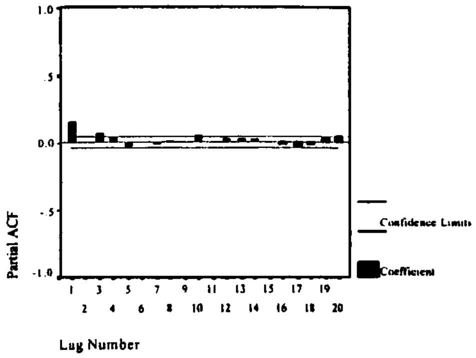
Looking at smaller markets that may be classifiable, like the Dublin market, as satellites of larger, we find that there is no pattern quite like the one noted above. In Brussels for example, Corhay (1991) finds a negative Tuesday; Lee, Pettit and Swankoski (1990) show a negative Tuesday for Singapore; Alexakis and Xanthakis (1995) for Greece and Pena (1995) for Spain show a negative Tuesday return. Nowhere is there a positive significant Wednesday return as the dominant feature.

In another point of dis-congruence with the literature, the majority of the coefficients are positive in the parametric analysis. In broad, this is the pattern found in Taiwan by Ho (1990), Lee (1992) and Wong, Hui and Chan (1992), However, while these researchers all found all positive coefficients, they also found no evidence , under parametric analysis, of daily seasonality. While there are a number of negative mean returns evident in the analysis above, none are significant.

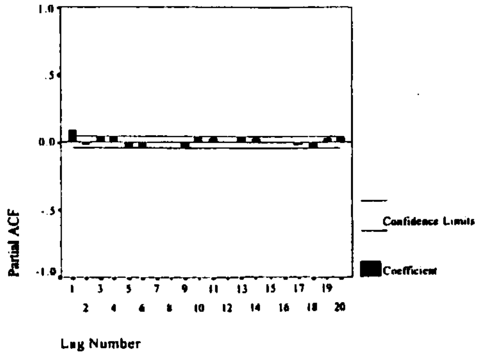
The evidence regarding the daily seasonal in higher moments also diverges from the international practice. As noted, the extent of such evidence, as opposed to reportage of differential variances, is not high internationally. We have already seen that the pattern of these moments does not neatly mirror that of the lower moments. In the case of variance, our proxy for risk, there is limited evidence that a day of the week effect exists for some indices. For the four indices in which at least on daily variance estimate is different to that of others a GARCH specification finds evidence only in two cases. Finally, the evidence for higher moments is similar to that of Tang (1997) , who finds evidence for individual pairs of days to have differences in their higher moments.

We have also seen that these daily seasonal are probably not economically significant in that a trading strategy based on them may not profitable. A timing strategy will however yield useful performance increases

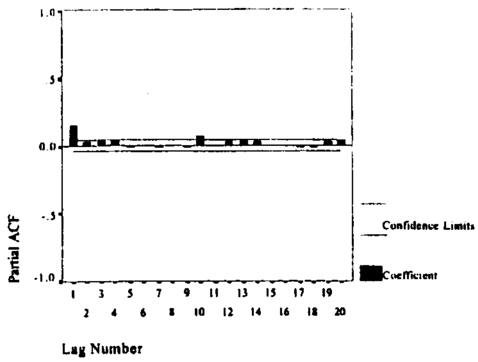
ISEQ



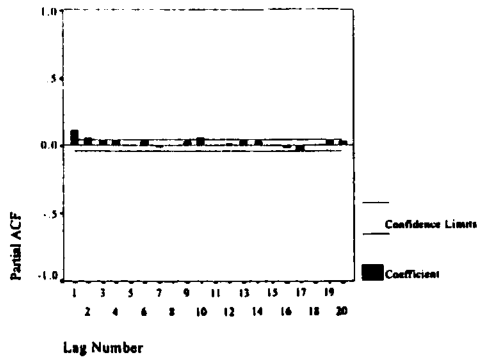
ISEFINS



ISEQR



ISEGNRL



10. Are Pre-Holiday Effects Evident In The Irish Data[#]?

Table 29 shows means and standard deviations for days preceding and following two different types of holidays. Initially, holidays are defined as those days when the Irish stock exchange was closed. Over the periods of analysis all such days represented official state holidays. No special closings were affected. However, as we have seen a number of major equities have in fact a dual or triple listing on the Irish, UK and US markets. Accordingly, Unique Irish holidays are defined as those days on which the Irish market is closed but the US and UK markets are open. If any pre-holiday effects were in fact driven by the known pre-holiday effects of these markets, we would expect to see the days preceding unique Irish holidays as not being statistically different from days which were not such. Kim and Park (1994) & Cadsby and Ratner (1992) have demonstrated that the anomalous positive pre-holiday returns of their data sets are local, rather than reflections of international, phenomena. An analysis of the data here reveals a number of facts.

First, the majority of the indices show a positive pre-holiday return, however holidays are defined. The mean return on days preceding unique Irish holidays are less likely to be positive, with the major indices, the ISEQ, and its dividend inclusive version showing small negative returns. Excess Pre-holiday is defined as Pre-Holiday Mean Return + Post-Holiday Return. If this is positive it indicates that the pre-holiday returns, typically positive, are not fully eroded by the post-holiday return, typically negative. Excess Pre Unique Irish Holiday is defined analogously

[#] The results of this chapter also appears in abridged form *in Lucey, B.M. (2002) "Are Local Or International Influences Responsible For The Pre-Holiday Behaviour Of Irish Equities"* ***Applied Financial Economics*** *(forthcoming)*, and in *Lucey, B.M. (2001) "Pre-Holiday Calendar Regularities In Ireland"* ***Atlantic Economic Review****, 29(4)* for uniquely Irish holidays. While some indices show negative Excess pre-holiday / excess pre-unique Irish holiday, indicating that the holiday period overall results in a decline in the market, this disappears almost totally in the trimmed data series.

Second, a number of indices do in fact show negative pre-holiday returns. For holidays in general, the equally weighted quartile 4 and overall indices, and the value weighted quartile 1 and 2 indices, both in trimmed and untrimmed forms, show negative pre-holiday returns. For unique Irish holidays, there are a greater number of negative pre-holiday returns. Interestingly, these are concentrated outside the quartile indices. The ISEQ index shows a negative return prior to unique Irish holidays. In general, the negative returns are not carried through to the trimmed series. International evidence is overwhelmingly in favour of a positive pre-holiday effect, with only Agrawal and Tandon (1994) finding a negative return in Brazil, and then only for days preceding the Christmas / New Year period.

Third, there would seem to be unusual relationships between pre-holiday returns and regular daily returns. It is highly unusual in the literature to find pre-holiday returns as lower than regular returns. All the value weighted quartile indices show this for unique Irish holidays, as do the official market indices.

Finally, the standard deviations, acting as a proxy for risk, of the pre-holiday returns, both for general holidays and unique Irish holidays, are almost always lower than those of regular days. The differential between these daily returns and the pre-holiday returns is, as might be expected, much reduced in the trimmed series.

Testing formally for such differences Table 30 and Table 31 show that neither for the general nor for the uniquely Irish holidays can we accept, for any index bar one, the total equal weighted index, the equality of mean returns as between days preceding holidays in general or uniquely Irish holidays as against days that are not preceding holidays. There is a pre-holiday effect in the Irish market. In addition, the statistical significance of uniquely Irish pre-holidays seems to indicate that the holiday effects are of a local rather than an international origin. However, the variances of a number of indices, both for general and uniquely Irish holidays, as between pre-holiday and regular days, seem to be statistically similar in many cases. This further strengthens the anomaly – if the risk profiles were similar one might expect the returns to be so also. The evidence indicates that, like what has been found previously, local effects dominate international effects in pre-holiday returns.

The evidence on the pre-holiday effect is that firstly the typical index shows a positive pre-holiday return, this return not being eroded by an equal or greater post holiday decline, and that these returns are locally derived rather than internationally derived. The evidence presented here is that while the Irish market conforms to the second prescription, the first cannot be as easily accepted. A number of major indices, including among them the official stock market indices show negative pre-holiday returns, this effect however disappearing in the trimmed indices. Coupled with the results of Lucey (2000), this indicates that the data generating process for stocks in the Irish market results in a pattern of returns that is significantly different to that found in other markets.

TABLE 29: MOMENTS OF THE DISTRIBUTION: DAYS PRECEDING AND POST HOLIDAYS

		ISEQ	ISEQR	ISEFIN	ISEGEN	TISEQ	TISEQR	TISEFIN	TISEGEN
Pre Holiday	Mean	0.035	0.048	0.082	0.054	0.058	0.079	0.094	0.066
	N	115	80	73	73	112	77	69	68
	Std. Deviation	0.268	0.278	0.407	0.276	0.232	0.234	0.294	0.221
	Kurtosis	1.838	1.404	4.213	0.575	0.645	(0.007)	0.415	(0.434)
	Skewness	(0.440)	(0.547)	(0.770)	(0.224)	0.342	0.263	0.162	0.087
Post Holiday	Mean	(0.003)	0.043	0.061	0.041	0.043	0.037	0.068	0.013
	N	114	79	72	72	92	56	59	56
	Std. Deviation	0.606	0.666	0.792	0.609	0.222	0.225	0.331	0.217
	Kurtosis	9.453	7.657	8.112	11.892	1.909	0.799	0.201	1.119
	Skewness	(1.696)	(1.437)	(0.864)	(0.990)	0.728	0.388	0.427	0.388
Pre Unique Irish Holiday	Mean	(0.005)	(0.003)	0.002	0.010	0.017	0.041	0.059	0.053
	N	78	53	48	48	76	50	46	45
	Std. Deviation	0.249	0.284	0.410	0.274	0.213	0.223	0.304	0.224
	Kurtosis	2.272	1.266	4.584	0.356	0.861	(0.300)	0.562	(0.579)
	Skewness	(0.782)	(0.791)	(1.380)	(0.527)	(0.033)	0.077	0.159	0.103
Post Unique Irish Holiday	Mean	(0.030)	0.035	0.043	0.019	0.051	0.051	0.052	(0.005)
	N	64	44	40	40	50	30	31	31
	Std. Deviation	0.735	0.800	0.952	0.745	0.244	0.273	0.362	0.262
	Kurtosis	7.079	6.349	6.695	9.471	1.398	(0.142)	(0.151)	(0.028)
	Skewness	(1.662)	(1.562)	(0.880)	(1.001)	0.613	0.060	0.139	0.272
Total	Mean	0.030	0.030	0.031	0.016	0.028	0.029	0.032	0.015
	N	4041	2778	2516	2516	3637	2500	2264	2264

	Std. Deviation	0.457	0.393	0.546	0.372	0.232	0.246	0.343	0.230		
	Kurtosis	17.214	8.028	5.779	13.364	0.448	(0.342)	(0.316)	(0.366)		
	Skewness	(0.550)	(0.247)	(0.186)	(0.450)	0.238	0.099	0.163	0.054		
Excess Pre-holiday	Mean	0.033	0.091	0.143	0.095	0.101	0.116	0.162	0.079		
Excess Pre Unique Irish Holiday	Mean	(0.035)	0.031	0.045	0.029	0.068	0.092	0.111	0.048		
		EWP1	EWP2	EWP3	EWP4	EWP	VWP1	VWP2	VWP3	VWP4	VWP
Pre Holiday	Mean	0.059	0.058	0.018	(0.030)	0.004	(0.100)	0.007	0.056	0.077	0.070
	N	47	47	47	47	47	47	47	47	47	47
	Std. Deviation	0.177	0.369	0.199	0.606	0.228	0.309	0.130	0.174	0.455	0.372
	Kurtosis	4.758	37.560	2.905	21.936	16.151	8.287	0.956	9.318	11.214	10.896
	Skewness	2.117	5.807	0.014	3.571	2.725	(2.530)	0.110	1.837	(0.346)	0.080
Post Holiday	Mean	(0.039)	(0.231)	0.518	(0.093)	0.083	(0.223)	0.140	0.548	0.116	0.160
	N	46	46	46	46	46	46	46	46	46	46
	Std. Deviation	3.942	3.074	3.027	1.039	0.213	14.647	2.147	1.586	0.652	0.346
	Kurtosis	14.974	26.382	27.180	10.835	2.592	21.341	11.939	15.363	10.200	2.843
	Skewness	(0.080)	(4.123)	4.628	(3.046)	0.760	(0.582)	0.478	3.892	0.165	1.037
Pre Unique Irish Holiday	Mean	0.042	0.087	(0.014)	0.048	0.030	(0.028)	0.011	0.038	0.001	0.011
	N	30	30	30	30	30	30	30	30	30	30
	Std. Deviation	0.176	0.451	0.176	0.727	0.270	0.220	0.122	0.119	0.502	0.412
	Kurtosis	8.215	26.222	2.550	15.765	12.395	10.859	2.139	2.274	12.245	12.199
	Skewness	2.634	4.982	(1.328)	3.098	2.491	(2.434)	0.046	(0.310)	(0.312)	0.199
Post Unique Irish Holiday	Mean	0.008	(0.016)	0.024	0.187	0.089	0.107	(0.020)	0.126	0.155	0.139
	N	24	24	24	24	24	24	24	24	24	24
	Std. Deviation	0.153	0.158	0.169	0.434	0.225	0.639	0.138	0.207	0.377	0.302
	Kurtosis	1.625	1.157	4.231	2.933	3.724	7.295	3.164	0.795	0.077	(0.100)
	Skewness	0.996	(0.391)	1.449	(0.255)	0.503	1.418	(1.108)	1.177	0.507	0.349
Total	Mean	0.022	0.020	0.026	0.043	0.033	0.041	0.038	0.047	0.046	0.046
	N	1511	1511	1511	1511	1511	1511	1511	1511	1511	1511

	Std. Deviation	0.874	0.618	0.675	0.533	0.274	2.596	0.497	0.705	0.396	0.344
	Kurtosis	200.091	500.479	422.509	63.731	94.707	650.223	150.460	377.960	12.615	13.149
	Skewness	(0.062)	(15.428)	9.036	2.014	(3.320)	(3.235)	1.070	9.123	(0.044)	0.157
Excess Pre-holiday	Mean	0.020	(0.173)	0.536	(0.122)	0.087	(0.323)	0.147	0.603	0.192	0.230
Excess Pre Unique Irish Holiday	Mean	0.050	0.072	0.010	0.235	0.119	0.080	(0.008)	0.164	0.156	0.150
		TEW1	TEW2	TEW3	TEW4	TEW	TVW1	TVW2	TVW3	TVW4	TVW
Pre Holiday	Mean	0.045	0.015	0.027	(0.001)	(0.003)	(0.033)	0.007	0.038	0.031	0.042
	N	46	45	42	40	44	44	47	46	42	43
	Std. Deviation	0.149	0.105	0.114	0.187	0.113	0.160	0.130	0.128	0.153	0.149
	Kurtosis	4.005	1.869	0.954	0.664	0.202	1.299	0.956	1.404	0.770	2.036
	Skewness	1.916	0.514	0.080	0.541	0.010	(0.336)	0.110	(0.521)	0.915	1.419
Post Holiday	Mean	0.006	(0.002)	0.004	0.124	0.055	0.020	0.034	0.053	0.105	0.104
	N	38	39	40	36	40	37	40	38	38	39
	Std. Deviation	0.171	0.118	0.125	0.200	0.103	0.220	0.132	0.156	0.260	0.219
	Kurtosis	1.574	1.127	1.657	0.176	(0.220)	1.093	(0.017)	0.929	(0.539)	(0.458)
	Skewness	0.619	0.251	(0.077)	0.355	0.483	0.497	0.388	0.496	(0.027)	(0.134)
Pre Unique Irish Holiday	Mean	0.018	0.007	0.020	0.033	0.010	0.004	0.011	0.038	0.005	0.010
	N	29	29	28	26	28	29	30	30	28	28
	Std. Deviation	0.123	0.111	0.122	0.208	0.119	0.136	0.122	0.119	0.135	0.111
	Kurtosis	7.819	2.447	0.574	(0.284)	(0.209)	2.410	2.139	2.274	2.696	2.469
	Skewness	2.192	0.923	(0.215)	0.431	0.197	0.585	0.046	(0.310)	1.007	1.235
Post Unique Irish Holiday	Mean	0.008	0.002	0.001	0.131	0.065	0.033	(0.001)	0.082	0.085	0.086
	N	24	23	23	20	21	21	23	22	20	20
	Std. Deviation	0.153	0.137	0.127	0.198	0.097	0.229	0.104	0.151	0.242	0.200
	Kurtosis	1.625	0.809	2.625	0.590	0.247	1.936	(0.738)	0.511	(0.483)	(0.659)
	Skewness	0.996	0.157	0.378	0.161	0.274	0.445	0.317	0.895	0.332	0.228
Total	Mean	0.025	0.027	0.023	0.038	0.033	0.023	0.036	0.030	0.043	0.044
	N	1359	1359	1359	1359	1359	1359	1359	1359	1359	1359
	Std. Deviation	0.195	0.121	0.135	0.209	0.121	0.263	0.143	0.163	0.226	0.195

	Kurtosis	1.206	0.408	0.275	(0.192)	(0.253)	0.732	0.066	(0.163)	(0.413)	(0.414)
	Skewness	0.442	0.347	0.313	0.252	0.075	0.398	0.360	0.185	0.166	0.178
Excess Pre-holiday	Mean	0.051	0.013	0.031	0.123	0.053	(0.012)	0.041	0.091	0.136	0.145
Excess Pre Unique Irish Holiday	Mean	0.027	0.009	0.021	0.164	0.075	0.038	0.010	0.120	0.090	0.096

TABLE 30: TESTING FOR EQUALITY OF VARIANCE AND EQUALITY OF MEANS, DAYS PRECEEDING HOLIDAY VS. OTHER DAYS.

	Levene's Test for equality of variance	Sig	t-test for equality of means	Sig (2-tailed)
EWP	0.444	0.505	0.875	0.386
EWP1	2.032	0.154	-1.098	0.274
EWP2	0.108	0.742	-0.705	0.484
EWP3	0.386	0.535	0.245	0.807
EWP4	0.043	0.835	0.84	0.405
ISEFIN	4.263	0.039	-0.809	0.419
ISEGEN	1.887	0.17	-1.191	0.237
ISEQ	5.805	0.016	-0.135	0.893
ISEQR	4.343	0.037	-0.413	0.68
TEW	1.434	0.231	2.152	0.037
TEW1	3.655	0.056	-0.932	0.356
TEW2	2.85	0.092	0.763	0.449
TEW3	2.126	0.145	-0.204	0.839
TEW4	4.214	0.04	1.179	0.239
TISEFIN	3.419	0.065	-1.769	0.081
TISEGEN	0.21	0.647	-1.926	0.058
TISEQ	0	0.99	-1.405	0.163
TISEQR	0.696	0.404	-1.888	0.063
TVW	7.592	0.006	0.065	0.948
TVW1	9.325	0.002	1.429	0.153
TVW2	3.664	0.056	1.54	0.13
TVW3	5.863	0.016	-0.357	0.721
TVW4	12.177	0	0.351	0.726
VWP	0.271	0.603	-0.451	0.654
VWP1	0.377	0.539	1.758	0.079
VWP2	2.362	0.125	1.393	0.167
VWP3	1.239	0.266	-0.289	0.773
VWP4	0.121	0.728	-0.469	0.641

TABLE 31: TESTING FOR EQUALITY OF VARIANCE AND EQUALITY OF MEANS, DAYS PRECEEDING UNIQUE IRISH HOLIDAYS VERSUS OTHER DAYS

	Levene Statistic	Sig	2-tailed t-test	Sig
EWP	0.444	0.505	0.875	0.386
EWP1	2.032	0.154	-1.098	0.274
EWP2	0.108	0.742	-0.705	0.484
EWP3	0.386	0.535	0.245	0.807
EWP4	0.043	0.835	0.84	0.405
ISEFIN	4.263	0.039	-0.809	0.419
ISEGEN	1.887	0.17	-1.191	0.237
ISEQ	5.805	0.016	-0.135	0.893
ISEQR	4.343	0.037	-0.413	0.68
TEW	1.434	0.231	2.152	0.037
TEW1	3.655	0.056	-0.932	0.356
TEW2	2.85	0.092	0.763	0.449
TEW3	2.126	0.145	-0.204	0.839
TEW4	4.214	0.04	1.179	0.239
TISEFIN	3.419	0.065	-1.769	0.081
TISEGEN	0.21	0.647	-1.926	0.058
TISEQ	0	0.99	-1.405	0.163
TISEQR	0.696	0.404	-1.888	0.063
TVW	7.592	0.006	0.065	0.948
TVW1	9.325	0.002	1.429	0.153
TVW2	3.664	0.056	1.54	0.13
TVW3	5.863	0.016	-0.357	0.721
TVW4	12.177	0	0.351	0.726
VWP	0.271	0.603	-0.451	0.654
VWP1	0.377	0.539	1.758	0.079
VWP2	2.362	0.125	1.393	0.167
VWP3	1.239	0.266	-0.289	0.773
VWP4	0.121	0.728	-0.469	0.641

TABLE 32: NON PARAMETRIC TESTING FOR EQUALITY OF MEANS, DAYS PRECEDING IRISH HOLIDAYS VS. OTHER DAYS.

	Mann-Whitney U	Wilcoxon W	Asymp. Sig. (2-tailed)
EWP1	32032.5	1104413	0.418235
EWP2	32757	33885	0.575579
EWP3	34278	1106658	0.965863
EWP4	27537	28665	0.019689
EWP	28501	29629	0.044985
VWP1	28821	29949	0.057412
VWP2	31301	32429	0.291731
VWP3	31494	1103874	0.322991
VWP4	33484.5	1105865	0.754825

VWP	33933.5	1106314	0.873045
ISEQ	216866	7925567	0.469472
ISEQR	101237	3742188	0.344525
ISEFIN	79528	3064874	0.114929
ISEGEN	80821	3066167	0.17225
TEW1	28522.5	891163.5	0.518762
TEW2	27872	28907	0.5126
TEW3	26832	894735	0.741733
TEW4	23068	23888	0.175585
TEW	23725	24715	0.042091
TVW1	25505	26495	0.17978
TVW2	27729	28857	0.240185
TVW3	28024	890665	0.405772
TVW4	26449.5	27352.5	0.629612
TVW	27333.5	28279.5	0.704481
TISEQ	182767	6397342	0.178283
TISEQR	82666	3019342	0.088567
TISEFIN	66003	2476113	0.068942
TISEGEN	65138	2477444	0.072763

TABLE 33: NON PARAMETRIC TESTING FOR EQUALITY OF MEANS, DAYS PRECEDING UNIQUE IRISH HOLIDAYS VS. OTHER DAYS.

	Mann-Whitney U	Wilcoxon W	Asymp. Sig. (2-tailed)
EWP1	22018.5	1119440	0.933478
EWP2	20480	20945	0.462984
EWP3	20953.5	21418.5	0.59387
EWP4	20299	20764	0.418052
EWP	19931	20396	0.334381
VWP1	20771	21236	0.540799
VWP2	20644	21109	0.50651
VWP3	20857	1118278	0.565987
VWP4	20059.5	20524.5	0.362287
VWP	19912.5	20377.5	0.330482
ISEQ	150360	153441	0.679446
ISEQR	70124.5	71555.5	0.718069
ISEFIN	58369	3105115	0.86255
ISEGEN	58218	3104964	0.838806
TEW1	18786.5	19221.5	0.810258
TEW2	16799	17234	0.233851
TEW3	18457.5	904903.5	0.931549
TEW4	16830	17181	0.801207
TEW	16336	16742	0.263497
TVW1	18556	18991	0.726561
TVW2	18364	18829	0.459592
TVW3	18577	902362	0.522904
TVW4	16478.5	16884.5	0.294259
TVW	16329.5	16735.5	0.26215

TISEQ	134964	137890	0.968627
TISEQR	59401.5	3061877	0.714488
TISEFIN	47717	2508588	0.452467
TISEGEN	45399	2508489	0.296899

11. Is Monthly Seasonality Present In Irish Equity Indices[#]?

11.1. Parametric Investigation Of The First Moment

From the moments show in Table 13 we can see a number of stylised facts. First, there appears to be some evidence of a January effect in the Irish data. Second, that this is not obviously risk related, and third, that in general there does not appear to be the predicted or expected risk-return relationship across months of the year. Table 34 shows the results of an OLS analysis of the first moment.

TABLE 34: INITIAL ESTIMATES OF MONTHLY SEASONALITY IN THE IRISH MARKET

	Variable	Coeff	T-Stat	Signif
ISEQ	JAN	0.108	4.209	0.000
	FEB	0.064	2.422	0.015
	MARCH	0.042	1.626	0.104
	APRIL	0.029	1.128	0.259
	MAY	0.015	0.591	0.554
	JUNE	0.005	0.195	0.845
	JULY	0.042	1.667	0.096
	AUG	(0.056)	(2.196)	0.028
	SEP	(0.019)	(0.736)	0.462
	OCT	0.015	0.594	0.553
	NOV	(0.006)	(0.221)	0.825
	DEC	0.066	2.508	0.012
	N	2,778		
	F(11,N-11)	2.845		
	Sig F	0.001		
ISEQR	JAN	0.112	4.357	0.000
	FEB	0.068	2.582	0.010
	MARCH	0.049	1.912	0.056
	APRIL	0.035	1.351	0.177
	MAY	0.027	1.080	0.280
	JUNE	0.011	0.416	0.677

[#] The results of this chapter also appears in abridged form in *Lucey, B and Shane Whelan (2002) "A Promising timing strategy in Equity Markets: Ireland 1933-2000"* *Journal of the Statistical and Social Inquiry Society of Ireland (forthcoming)*

	Variable	Coeff	T-Stat	Signif
	JULY	0.040	1.578	0.115
	AUG	(0.048)	(1.884)	0.060
	SEP	(0.013)	(0.518)	0.605
	OCT	0.017	0.653	0.514
	NOV	0.005	0.198	0.843
	DEC	0.067	2.533	0.011
	N	2,778		
	F(11,N-11)	2.628		
	Sig F	0.002		
ISEFIN	JAN	0.083	2.180	0.029
	FEB	0.091	2.366	0.018
	MARCH	0.030	0.797	0.426
	APRIL	0.045	1.196	0.232
	MAY	(0.017)	(0.450)	0.653
	JUNE	0.004	0.107	0.915
	JULY	0.059	1.620	0.105
	AUG	(0.097)	(2.581)	0.010
	SEP	(0.004)	(0.108)	0.914
	OCT	0.061	1.644	0.100
	NOV	0.032	0.861	0.389
	DEC	0.095	2.468	0.014
	N	2,516		
	F(11,N-11)	2.103		
	Sig F	0.017		
ISEGEN	JAN	0.101	3.864	0.000
	FEB	0.056	2.148	0.032
	MARCH	0.038	1.491	0.136
	APRIL	0.022	0.857	0.392
	MAY	(0.001)	(0.033)	0.974
	JUNE	(0.019)	(0.740)	0.459
	JULY	0.027	1.088	0.277
	AUG	(0.023)	(0.886)	0.376
	SEP	(0.045)	(1.768)	0.077
	OCT	(0.011)	(0.445)	0.657
	NOV	0.000	0.018	0.985
	DEC	0.048	1.842	0.066
	N	2,516		
	F(11,N-11)	2.482		
	Sig F	0.004		
EWP1	JAN	0.096	1.227	0.220
	FEB	(0.045)	(0.562)	0.574
	MARCH	0.069	0.881	0.378
	APRIL	(0.020)	(0.257)	0.798
	MAY	0.024	0.304	0.761
	JUNE	0.039	0.492	0.622
	JULY	0.032	0.424	0.672
	AUG	(0.051)	(0.658)	0.511
	SEP	(0.018)	(0.231)	0.817
	OCT	(0.026)	(0.332)	0.740

	Variable	Coeff	T-Stat	Signif
	NOV	0.091	1.170	0.242
	DEC	0.076	0.963	0.336
	N	1,512		
	F(11,N-11)	0.463		
	Sig F	0.926		
EWP2	JAN	(0.003)	(0.055)	0.956
	FEB	0.063	1.125	0.261
	MARCH	(0.000)	(0.009)	0.993
	APRIL	0.059	1.065	0.287
	MAY	0.073	1.332	0.183
	JUNE	0.015	0.272	0.785
	JULY	0.039	0.719	0.473
	AUG	(0.036)	(0.648)	0.517
	SEP	(0.012)	(0.215)	0.830
	OCT	(0.021)	(0.378)	0.705
	NOV	0.024	0.444	0.657
	DEC	0.035	0.619	0.536
	N	1,512		
	F(11,N-11)	0.404		
	Sig F	0.955		
EWP3	JAN	0.317	5.304	0.000
	FEB	(0.000)	(0.007)	0.995
	MARCH	(0.059)	(0.981)	0.327
	APRIL	0.060	0.992	0.322
	MAY	0.031	0.520	0.603
	JUNE	0.018	0.290	0.772
	JULY	(0.008)	(0.133)	0.894
	AUG	(0.036)	(0.603)	0.547
	SEP	(0.047)	(0.806)	0.420
	OCT	(0.002)	(0.035)	0.972
	NOV	0.034	0.570	0.569
	DEC	0.009	0.155	0.877
	N	1,512		
	F(11,N-11)	2.684		
	Sig F	0.002		
EWP4	JAN	0.042	0.884	0.377
	FEB	0.046	0.955	0.340
	MARCH	0.057	1.208	0.227
	APRIL	0.064	1.327	0.185
	MAY	0.020	0.431	0.667
	JUNE	0.076	1.569	0.117
	JULY	0.029	0.630	0.529
	AUG	(0.045)	(0.938)	0.348
	SEP	(0.001)	(0.013)	0.990
	OCT	0.101	2.123	0.034
	NOV	0.062	1.321	0.187
	DEC	0.069	1.428	0.153
	N	1,512		
	F(11,N-11)	0.660		

	Variable	Coeff	T-Stat	Signif
	Sig F	0.777		
EWP	JAN	0.121	4.973	0.000
	FEB	0.034	1.357	0.175
	MARCH	0.008	0.327	0.744
	APRIL	0.053	2.157	0.031
	MAY	0.035	1.442	0.150
	JUNE	0.045	1.826	0.068
	JULY	0.020	0.859	0.391
	AUG	(0.041)	(1.670)	0.095
	SEP	(0.017)	(0.711)	0.477
	OCT	0.038	1.562	0.119
	NOV	0.051	2.136	0.033
	DEC	0.047	1.906	0.057
	N	1,512		
	F(11,N-11)	2.710		
	Sig F	0.002		
VWP1	JAN	0.050	0.215	0.830
	FEB	0.019	0.081	0.935
	MARCH	0.051	0.221	0.825
	APRIL	0.007	0.030	0.976
	MAY	0.002	0.009	0.993
	JUNE	0.068	0.291	0.771
	JULY	(0.005)	(0.023)	0.981
	AUG	(0.067)	(0.289)	0.773
	SEP	0.074	0.323	0.746
	OCT	(0.030)	(0.128)	0.898
	NOV	0.171	0.741	0.459
	DEC	0.151	0.641	0.522
	N	1,512		
	F(11,N-11)	0.089		
	Sig F	1.000		
VWP2	JAN	0.114	2.568	0.010
	FEB	0.014	0.318	0.750
	MARCH	0.062	1.408	0.159
	APRIL	0.065	1.460	0.144
	MAY	0.063	1.436	0.151
	JUNE	0.027	0.612	0.541
	JULY	0.034	0.796	0.426
	AUG	(0.032)	(0.730)	0.466
	SEP	(0.022)	(0.505)	0.614
	OCT	(0.019)	(0.437)	0.662
	NOV	0.104	2.362	0.018
	DEC	0.049	1.093	0.274
	N	1,512		
	F(11,N-11)	1.151		
	Sig F	0.317		
VWP3	JAN	0.296	4.733	0.000
	FEB	0.006	0.089	0.929
	MARCH	0.032	0.515	0.606

	Variable	Coeff	T-Stat	Signif
	APRIL	0.068	1.074	0.283
	MAY	0.041	0.661	0.508
	JUNE	(0.001)	(0.018)	0.986
	JULY	0.012	0.194	0.846
	AUG	0.149	2.381	0.017
	SEP	(0.042)	(0.677)	0.498
	OCT	(0.072)	(1.153)	0.249
	NOV	0.041	0.669	0.504
	DEC	0.033	0.514	0.608
	N	1,512		
	F(11,N-11)	2.343		
	Sig F	0.007		
VWP4	JAN	0.104	2.950	0.003
	FEB	0.037	1.042	0.298
	MARCH	0.019	0.553	0.580
	APRIL	0.072	2.031	0.042
	MAY	0.024	0.677	0.498
	JUNE	0.050	1.404	0.161
	JULY	0.035	1.027	0.305
	AUG	(0.071)	(2.008)	0.045
	SEP	0.040	1.152	0.250
	OCT	0.083	2.362	0.018
	NOV	0.064	1.822	0.069
	DEC	0.100	2.789	0.005
	N	1,512		
	F(11,N-11)	1.729		
	Sig F	0.062		
VWP	JAN	0.125	4.102	0.000
	FEB	0.032	1.043	0.297
	MARCH	0.023	0.752	0.452
	APRIL	0.070	2.289	0.022
	MAY	0.027	0.886	0.376
	JUNE	0.043	1.403	0.161
	JULY	0.031	1.040	0.298
	AUG	(0.041)	(1.355)	0.176
	SEP	0.029	0.960	0.337
	OCT	0.059	1.938	0.053
	NOV	0.064	2.103	0.036
	DEC	0.092	2.974	0.003
	N	1,512		
	F(11,N-11)	1.822		
	Sig F	0.046		

We seem to have significant evidence of overall monthly seasonality as indicated by the F statistics. For the ISE indices the F statistic is highly significant, as it is for the larger value and equal weighted portfolio indices. Only for E(V)WP1, E(V)WP2 and

E(V)WP4 can we reject the concept of monthly seasonality as measured by the equality of monthly dummy variable coefficients.

Picking up on what we have found earlier, we also find that January effects are prominent. The coefficient on the January dummy is significant in all save EWP1, EWP2, EWP4 and VWP1. Only for EWP1, EWP2 and VWP1 do we find no monthly coefficient with statistical significance. Other months that appear significant with some regularity are February (all the ISE indices); August (ISEQ, ISEFIN, VWP, VWP4, but with a negative coefficient save for VWP4); October (EWP4, VWP4) and December (ISEQ, ISEQR, ISEFIN, VWP4, VWP)

Despite previous evidence of an April seasonal in the Irish market (Mckillop and Hutchinson (1989), Donnelly (1991) & Gahan (1993)) this stylised fact does not seem to carry through to this analysis. Only for EWP4, EWP, VWP4 and VWP do we find an April dummy coefficient with statistical significance.

However, the equation is not well specified, as shown by the results of a number of regression diagnostic procedures detailed in Table 35.

11.1.1. Re-estimation Of The First Moment

Regression residual diagnostics for the initial regression of the month of the year model of Table 34, are show in Table 35. A number of problems emerge which cast some doubt on the appropriateness of the OLS procedure.

TABLE 35: REGRESSION RESIDUAL DIAGNOSTICS FOR MONTH OF THE YEAR OLS MODEL

	Autocorrelation Tests		Heteroskedasticity Tests					Normality
	Q(36) b	ARCH1c	ARCH2	ARCH3	ARCH4	ARCH5	White's Test	Jarque-Bera Statistic
ISEQ	26,206.50	2,614.69	2,369.68	2,185.50	2,003.08	1,853.67	64.72	7,585.84
	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.00
ISEQR	3,513.17	2,361.81	2,049.08	1,845.10	1,687.51	1,402.83	64.50	7,309.04
	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.00
ISEFIN	18,730.34	976.73	806.06	1,009.86	985.16	712.30	59.21	3,513.17
	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
ISEGEN	2,561,662.86	849.59	590.79	976.06	736.48	720.26	53.75	18,730.34
	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
EWP1	3.66	0.01	0.04	0.01	7.21	0.00	30.10	2,561,662.86
	0.96	1.00	1.00	1.00	0.21	1.00	1.00	0.00
EWP2	0.90	0.01	0.01	0.01	0.01	0.00	18.39	15,891,815.17
	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00
EWP3	0.54	0.00	0.01	0.00	0.01	0.00	15.80	10,847,964.39
	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00
EWP4	12.00	0.01	0.36	0.37	0.01	0.01	18.20	260,486.36
	0.29	1.00	1.00	1.00	1.00	1.00	1.00	0.00
EWP	25.67	0.00	0.09	1.48	0.01	0.05	9.92	570,953.35
	0.00	1.00	1.00	0.92	1.00	1.00	1.00	0.00
VWP1	0.21	0.00	0.02	0.00	0.00	0.00	23.01	26,745,944.66
	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00
VWP2	3.18	0.03	0.01	0.04	0.02	0.05	32.74	1,446,940.99
	0.97	1.00	1.00	1.00	1.00	1.00	1.00	0.00
VWP3	0.59	0.01	0.00	0.02	0.01	0.02	11.56	9,105,286.17
	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00
VWP4	4.37	0.17	0.99	0.08	0.01	3.63	39.34	9,805.57
	0.92	1.00	0.96	1.00	1.00	0.60	1.00	0.00
VWP	6.39	0.03	0.12	0.12	0.23	3.04	37.06	11,281.52
	0.78	1.00	1.00	1.00	1.00	0.69	1.00	0.00

Heteroskedasticity: Whites test indicates that in no case is there generalized heteroskedasticity. Investigation of ARCH effects reveals however that the null of no ARCH effects is rejected for ISE indices Thus what hetroskedastic disturbances exist are ARCH form and are thus amenable to direct modelling.

Serial Correlation: There is however substantial evidence of serial correlation in the residuals of the ISE indices. Again, following the lead of Chang, Pinegar and Ravichandran (1993), Easton and Faff (1994), Mills and Coutts (1995) Peiro (1994), the data are adjusted where appropriate for autocorrelation. Whites correction for disturbances in the error terms was used.Despite the absence of measured serial correlation in the equal and value weighted portfolios, the knowledge that these contain significant numbers of thinly traded stocks indicates that modelling these indices without any adjustment for this would make little sense. Accordingly, for these indices a single lag adjustment was used. For the ISE indices the choice of lag structure is as already discussed in 9.1.1

Normality of Residuals: Finally, based on the Jarque-Bera test there is clear evidence of non-normality in the residuals.

While White's procedure allows correction of the covariance matrix for heteroskedasticity of an unknown form, we do have evidence as to the particular form of ARCH in the error terms. Therefore, Table 37 shows results of an ARCH modelling, while the regression diagnostics for these models are contained in Table 38. The ARCH modelling here do not fit the data as well as the ARCH modelling of the day of the week effects. The evidence is that the ARCH model does not account for the non-normality of the data, and there is some evidence that the specification here does not account for the serial correlation which remains a problem. In addition, the values and signs of the monthly coefficients are changes substantially from that of the initial OLS estimate. Accordingly, Table 36 shows robust regression based estimates of the month of the year effect.

TABLE 36: ROBUST ESTIMATES OF MONTHLY SEASONALITY IN THE IRISH MARKET

			OLS			AR			LAD				TLS		
	Variable	Bayesian T/F	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Bayesian T/F	Coeff	T-Stat	Signif
ISEQ	JAN	2.812	0.108	4.209	0.000	0.108	2.809	0.005	0.075	2.793	0.005	2.789	0.051	2.770	0.006
	FEB	2.812	0.064	2.422	0.015	0.064	2.119	0.034	0.052	2.475	0.013	2.789	0.045	2.436	0.015
	MARCH	2.812	0.042	1.626	0.104	0.042	1.459	0.144	0.039	1.709	0.087	2.789	0.055	3.042	0.002
	APRIL	2.812	0.029	1.128	0.259	0.029	1.188	0.235	0.033	1.778	0.075	2.789	0.058	3.144	0.002
	MAY	2.812	0.015	0.591	0.554	0.015	0.706	0.480	0.010	0.575	0.565	2.789	0.019	1.081	0.280
	JUNE	2.812	0.005	0.195	0.845	0.005	0.243	0.808	(0.003)	(0.162)	0.871	2.789	(0.007)	(0.414)	0.679
	JULY	2.812	0.042	1.667	0.096	0.042	1.825	0.068	0.056	3.120	0.002	2.789	0.065	3.793	0.000
	AUG	2.812	(0.056)	(2.196)	0.028	(0.056)	(1.377)	0.168	(0.032)	(1.446)	0.148	2.789	(0.011)	(0.586)	0.558
	SEP	2.812	(0.019)	(0.736)	0.462	(0.019)	(0.578)	0.563	(0.022)	(0.999)	0.318	2.789	(0.008)	(0.443)	0.658
	OCT	2.812	0.015	0.594	0.553	0.015	0.292	0.770	0.024	1.012	0.312	2.789	0.028	1.510	0.131
	NOV	2.812	(0.006)	(0.221)	0.825	(0.006)	(0.217)	0.828	(0.007)	(0.344)	0.731	2.789	0.006	0.349	0.727
	DEC	2.812	0.066	2.508	0.012	0.066	2.520	0.012	0.060	2.859	0.004	2.789	0.055	2.929	0.003
	N		2,778			2,778			2,778				2,454		
	F(11,N-11)	8.052	2.845			28.178			'42.501			7.940	2.553		
	Sig F		0.001			0.005			0.000				0.003		
ISEQR	JAN	2.812	0.112	4.357	0.000	0.112	2.998	0.003	0.080	2.980	0.003	2.787	0.033	1.848	0.065
	FEB	2.812	0.068	2.582	0.010	0.068	2.262	0.024	0.055	2.667	0.008	2.787	0.039	2.186	0.029
	MARCH	2.812	0.049	1.912	0.056	0.049	1.733	0.083	0.046	2.053	0.040	2.787	0.058	3.290	0.001
	APRIL	2.812	0.035	1.351	0.177	0.035	1.428	0.153	0.035	1.854	0.064	2.787	0.046	2.594	0.010
	MAY	2.812	0.027	1.080	0.280	0.027	1.307	0.191	0.024	1.486	0.137	2.787	0.032	1.913	0.056
	JUNE	2.812	0.011	0.416	0.677	0.011	0.514	0.607	0.004	0.230	0.818	2.787	0.001	0.050	0.960
	JULY	2.812	0.040	1.578	0.115	0.040	1.705	0.088	0.052	2.801	0.005	2.787	0.058	3.449	0.001

			OLS			AR			LAD				TLS		
	Variable	Bayesian T/F	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Bayesian T/F	Coeff	T-Stat	Signif
	AUG	2.812	(0.048)	(1.884)	0.060	(0.048)	(1.270)	0.204	(0.027)	(1.204)	0.228	2.787	(0.006)	(0.338)	0.735
	SEP	2.812	(0.013)	(0.518)	0.605	(0.013)	(0.404)	0.686	(0.017)	(0.761)	0.446	2.787	0.009	0.487	0.626
	OCT	2.812	0.017	0.653	0.514	0.017	0.321	0.748	0.019	0.783	0.434	2.787	0.020	1.112	0.266
	NOV	2.812	0.005	0.198	0.843	0.005	0.194	0.846	0.004	0.214	0.830	2.787	0.014	0.812	0.417
	DEC	2.812	0.067	2.533	0.011	0.067	2.559	0.010	0.061	2.942	0.003	2.787	0.058	3.225	0.001
	N		2,778			2,778			2,778				2,430		
	F(11,N-11)	8.052	2.628			25.315			45.098			7.932	1.681		
	Sig F		0.002			0.013			0.000				0.072		
ISEFIN	JAN	2.794	0.083	2.180	0.029	0.083	1.677	0.094	0.056	1.524	0.128	2.768	0.043	1.617	0.106
	FEB	2.794	0.091	2.366	0.018	0.091	2.131	0.033	0.067	2.075	0.038	2.768	0.035	1.373	0.170
	MARCH	2.794	0.030	0.797	0.426	0.030	0.820	0.412	0.031	1.062	0.288	2.768	0.056	2.183	0.029
	APRIL	2.794	0.045	1.196	0.232	0.045	1.313	0.189	0.034	1.259	0.208	2.768	0.028	1.090	0.276
	MAY	2.794	(0.017)	(0.450)	0.653	(0.017)	(0.546)	0.585	(0.017)	(0.692)	0.489	2.768	(0.010)	(0.385)	0.701
	JUNE	2.794	0.004	0.107	0.915	0.004	0.146	0.884	(0.012)	(0.541)	0.588	2.768	(0.016)	(0.635)	0.525
	JULY	2.794	0.059	1.620	0.105	0.059	1.601	0.109	0.072	2.465	0.014	2.768	0.089	3.616	0.000
	AUG	2.794	(0.097)	(2.581)	0.010	(0.097)	(1.793)	0.073	(0.074)	(2.494)	0.013	2.768	(0.024)	(0.919)	0.358
	SEP	2.794	(0.004)	(0.108)	0.914	(0.004)	(0.087)	0.930	(0.004)	(0.126)	0.900	2.768	0.011	0.429	0.668
	OCT	2.794	0.061	1.644	0.100	0.061	0.891	0.373	0.085	2.250	0.024	2.768	0.093	3.567	0.000
	NOV	2.794	0.032	0.861	0.389	0.032	0.822	0.411	0.032	1.084	0.278	2.768	0.038	1.507	0.132
	DEC	2.794	0.095	2.468	0.014	0.095	2.163	0.031	0.073	2.369	0.018	2.768	0.056	2.028	0.043
	N		2,516			2,516			2,516				2,192		
	F(11,N-11)	7.963	2.103			25.315			34.280			7.839	2.214		
	Sig F		0.017			0.013			0.001				0.012		
ISEGEN	JAN	2.794	0.101	3.864	0.000	0.101	2.780	0.005	0.078	2.982	0.003	2.767	0.047	2.612	0.009
	FEB	2.794	0.056	2.148	0.032	0.056	2.072	0.038	0.048	2.485	0.013	2.767	0.042	2.393	0.017
	MARCH	2.794	0.038	1.491	0.136	0.038	1.309	0.191	0.031	1.360	0.174	2.767	0.028	1.563	0.118
	APRIL	2.794	0.022	0.857	0.392	0.022	0.940	0.347	0.024	1.289	0.198	2.767	0.026	1.500	0.134
	MAY	2.794	(0.001)	(0.033)	0.974	(0.001)	(0.046)	0.964	0.005	0.343	0.732	2.767	0.013	0.753	0.452

	Variable	Bayesian T/F	OLS Coeff	OLS T-Stat	OLS Signif	AR Coeff	AR T-Stat	AR Signif	LAD Coeff	LAD T-Stat	LAD Signif	Bayesian T/F	TLS Coeff	TLS T-Stat	TLS Signif
	JUNE	2.794	(0.019)	(0.740)	0.459	(0.019)	(0.894)	0.371	(0.018)	(1.014)	0.310	2.767	(0.011)	(0.659)	0.510
	JULY	2.794	0.027	1.088	0.277	0.027	1.236	0.216	0.037	2.037	0.042	2.767	0.048	2.971	0.003
	AUG	2.794	(0.023)	(0.886)	0.376	(0.023)	(0.595)	0.552	(0.007)	(0.305)	0.760	2.767	0.018	1.016	0.310
	SEP	2.794	(0.045)	(1.768)	0.077	(0.045)	(1.497)	0.134	(0.044)	(2.172)	0.030	2.767	(0.039)	(2.274)	0.023
	OCT	2.794	(0.011)	(0.445)	0.657	(0.011)	(0.218)	0.827	(0.009)	(0.376)	0.707	2.767	(0.004)	(0.221)	0.825
	NOV	2.794	0.000	0.018	0.985	0.000	0.019	0.984	(0.007)	(0.390)	0.697	2.767	(0.006)	(0.359)	0.720
	DEC	2.794	0.048	1.842	0.066	0.048	1.939	0.053	0.044	2.051	0.040	2.767	0.032	1.741	0.082
	N		2,516			2,516			2,516				2,172		
	F(11,N-11)	7.963	2.482			24.617			33.183			7.831	2.417		
	Sig F		0.004			0.017			0.001				0.006		
EWP1	JAN	2.698	0.096	1.227	0.220	0.096	0.449	0.654	0.119	3.048	0.002	2.623	0.098	4.024	0.000
	FEB	2.698	(0.045)	(0.562)	0.574	(0.045)	(0.850)	0.395	(0.023)	(0.747)	0.455	2.623	0.010	0.400	0.689
	MARCH	2.698	0.069	0.881	0.378	0.069	1.454	0.146	0.033	1.297	0.195	2.623	0.019	0.859	0.390
	APRIL	2.698	(0.020)	(0.257)	0.798	(0.020)	(0.782)	0.434	(0.009)	(0.438)	0.661	2.623	0.027	1.099	0.272
	MAY	2.698	0.024	0.304	0.761	0.024	1.172	0.241	0.023	1.332	0.183	2.623	0.044	1.781	0.075
	JUNE	2.698	0.039	0.492	0.622	0.039	0.484	0.628	0.030	1.066	0.286	2.623	0.048	2.024	0.043
	JULY	2.698	0.032	0.424	0.672	0.032	0.528	0.598	0.007	0.294	0.768	2.623	0.004	0.176	0.861
	AUG	2.698	(0.051)	(0.658)	0.511	(0.051)	(1.005)	0.315	(0.017)	(0.522)	0.602	2.623	0.008	0.314	0.753
	SEP	2.698	(0.018)	(0.231)	0.817	(0.018)	(0.461)	0.645	0.002	0.064	0.949	2.623	0.034	1.451	0.147
	OCT	2.698	(0.026)	(0.332)	0.740	(0.026)	(0.570)	0.569	(0.010)	(0.358)	0.720	2.623	(0.005)	(0.210)	0.834
	NOV	2.698	0.091	1.170	0.242	0.091	1.720	0.086	0.061	2.290	0.022	2.623	0.050	2.097	0.036
	DEC	2.698	0.076	0.963	0.336	0.076	2.127	0.033	0.058	2.208	0.027	2.623	0.058	2.309	0.021
	N		1,512			1,512			1,512				1,033		
	F(11,N-11)	7.515	0.463			14.534			25.241			7.196	1.433		
	Sig F		0.926			0.268			0.014				0.152		
EWP2	JAN	2.698	(0.003)	(0.055)	0.956	0.317	1.939	0.053	0.075	3.189	0.001	2.649	0.060	4.340	0.000
	FEB	2.698	0.063	1.125	0.261	(0.000)	(0.018)	0.986	0.026	1.818	0.069	2.649	0.015	1.136	0.256
	MARCH	2.698	(0.000)	(0.009)	0.993	(0.059)	(0.626)	0.531	0.033	2.084	0.037	2.649	0.024	1.836	0.067

		OLS				AR			LAD				TLS		
	Variable	Bayesian T/F	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Bayesian T/F	Coeff	T-Stat	Signif
	APRIL	2.698	0.059	1.065	0.287	0.060	3.389	0.001	0.064	3.458	0.001	2.649	0.052	3.889	0.000
	MAY	2.698	0.073	1.332	0.183	0.031	1.939	0.052	0.064	4.843	0.000	2.649	0.056	4.354	0.000
	JUNE	2.698	0.015	0.272	0.785	0.018	0.986	0.324	0.016	1.037	0.300	2.649	0.029	2.230	0.026
	JULY	2.698	0.039	0.719	0.473	(0.008)	(0.420)	0.675	0.031	1.858	0.063	2.649	0.042	3.430	0.001
	AUG	2.698	(0.036)	(0.648)	0.517	(0.036)	(1.571)	0.116	(0.025)	(1.476)	0.140	2.649	0.000	0.039	0.969
	SEP	2.698	(0.012)	(0.215)	0.830	(0.047)	(2.331)	0.020	(0.009)	(0.521)	0.602	2.649	0.018	1.411	0.159
	OCT	2.698	(0.021)	(0.378)	0.705	(0.002)	(0.107)	0.915	(0.006)	(0.377)	0.706	2.649	0.008	0.648	0.517
	NOV	2.698	0.024	0.444	0.657	0.034	0.577	0.564	0.023	1.582	0.114	2.649	0.039	2.861	0.004
	DEC	2.698	0.035	0.619	0.536	0.009	0.491	0.623	0.032	1.977	0.048	2.649	0.036	2.648	0.008
	N		1,512			1,512			1,512				1,173		
	F(11,N-11)	7.515	0.404			41.467			66.758			7.301	2.141		
	Sig F		0.955			0.000			0.000				0.016		
EWP3	JAN	2.698	0.317	5.304	0.000	0.042	0.462	0.644	0.138	5.056	0.000	2.660	0.065	4.365	0.000
	FEB	2.698	(0.000)	(0.007)	0.995	0.046	1.005	0.315	0.001	0.049	0.961	2.660	0.006	0.404	0.686
	MARCH	2.698	(0.059)	(0.981)	0.327	0.057	1.482	0.138	0.029	2.032	0.042	2.660	0.040	3.006	0.003
	APRIL	2.698	0.060	0.992	0.322	0.064	2.048	0.041	0.056	3.471	0.001	2.660	0.041	2.966	0.003
	MAY	2.698	0.031	0.520	0.603	0.020	0.742	0.458	0.033	2.193	0.028	2.660	0.058	4.235	0.000
	JUNE	2.698	0.018	0.290	0.772	0.076	2.119	0.034	0.018	1.076	0.282	2.660	0.033	2.463	0.014
	JULY	2.698	(0.008)	(0.133)	0.894	0.029	0.941	0.347	(0.008)	(0.481)	0.631	2.660	0.008	0.628	0.530
	AUG	2.698	(0.036)	(0.603)	0.547	(0.045)	(1.438)	0.150	(0.027)	(1.482)	0.138	2.660	(0.006)	(0.453)	0.651
	SEP	2.698	(0.047)	(0.806)	0.420	(0.001)	(0.012)	0.990	(0.038)	(2.147)	0.032	2.660	(0.011)	(0.850)	0.395
	OCT	2.698	(0.002)	(0.035)	0.972	0.101	1.581	0.114	0.004	0.211	0.833	2.660	0.017	1.310	0.190
	NOV	2.698	0.034	0.570	0.569	0.062	1.114	0.265	0.069	3.282	0.001	2.660	0.039	2.839	0.005
	DEC	2.698	0.009	0.155	0.877	0.069	2.549	0.011	0.010	0.576	0.564	2.660	0.017	1.169	0.243
	N		1,512			1,512			1,512				1,244		
	F(11,N-11)	7.515	2.684			30.573			65.895			7.349	3.033		
	Sig F		0.002			0.002			0.000				0.001		
EWP4	JAN	2.698	0.042	0.884	0.377	0.121	3.521	0.000	0.047	1.707	0.088	2.669	0.055	2.663	0.008

			OLS			AR			LAD				TLS		
	Variable	Bayesian T/F	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Bayesian T/F	Coeff	T-Stat	Signif
	FEB	2.698	0.046	0.955	0.340	0.034	1.693	0.090	0.046	1.890	0.059	2.669	0.040	1.974	0.049
	MARCH	2.698	0.057	1.208	0.227	0.008	0.184	0.854	0.024	1.026	0.305	2.669	0.022	1.104	0.270
	APRIL	2.698	0.064	1.327	0.185	0.053	3.370	0.001	0.050	1.993	0.046	2.669	0.045	2.123	0.034
	MAY	2.698	0.020	0.431	0.667	0.035	2.324	0.020	0.026	1.105	0.269	2.669	0.050	2.453	0.014
	JUNE	2.698	0.076	1.569	0.117	0.045	2.533	0.011	0.051	2.185	0.029	2.669	0.046	2.232	0.026
	JULY	2.698	0.029	0.630	0.529	0.020	1.409	0.159	0.030	1.126	0.260	2.669	0.046	2.238	0.025
	AUG	2.698	(0.045)	(0.938)	0.348	(0.041)	(2.007)	0.045	(0.025)	(1.041)	0.298	2.669	0.005	0.247	0.805
	SEP	2.698	(0.001)	(0.013)	0.990	(0.017)	(0.650)	0.515	0.016	0.612	0.540	2.669	0.019	0.967	0.334
	OCT	2.698	0.101	2.123	0.034	0.038	1.213	0.225	0.054	1.686	0.092	2.669	0.031	1.444	0.149
	NOV	2.698	0.062	1.321	0.187	0.051	2.382	0.017	0.051	2.351	0.019	2.669	0.053	2.724	0.007
	DEC	2.698	0.069	1.428	0.153	0.047	2.980	0.003	0.064	2.645	0.008	2.669	0.056	2.729	0.006
	N		1,512			1,512			1,512				1,303		
	F(11,N-11)	7.515	0.660			25.343			35.593			7.388	0.628		
	Sig F		0.777			0.013			0.000				0.806		
EWP	JAN	2.698	0.121	4.973	0.000	0.050	0.064	0.949	0.088	5.086	0.000	2.667	0.063	5.341	0.000
	FEB	2.698	0.034	1.357	0.175	0.019	0.380	0.704	0.024	1.661	0.097	2.667	0.021	1.749	0.081
	MARCH	2.698	0.008	0.327	0.744	0.051	0.942	0.346	0.033	2.612	0.009	2.667	0.037	3.113	0.002
	APRIL	2.698	0.053	2.157	0.031	0.007	0.203	0.839	0.050	3.623	0.000	2.667	0.049	3.933	0.000
	MAY	2.698	0.035	1.442	0.150	0.002	0.074	0.941	0.041	3.217	0.001	2.667	0.047	4.065	0.000
	JUNE	2.698	0.045	1.826	0.068	0.068	1.931	0.053	0.037	2.865	0.004	2.667	0.037	3.084	0.002
	JULY	2.698	0.020	0.859	0.391	(0.005)	(0.145)	0.885	0.021	1.561	0.119	2.667	0.029	2.492	0.013
	AUG	2.698	(0.041)	(1.670)	0.095	(0.067)	(1.735)	0.083	(0.020)	(1.375)	0.169	2.667	0.008	0.675	0.500
	SEP	2.698	(0.017)	(0.711)	0.477	0.074	0.971	0.332	0.000	0.025	0.980	2.667	0.015	1.294	0.196
	OCT	2.698	0.038	1.562	0.119	(0.030)	(0.581)	0.561	0.028	1.691	0.091	2.667	0.030	2.479	0.013
	NOV	2.698	0.051	2.136	0.033	0.171	2.358	0.018	0.053	4.110	0.000	2.667	0.039	3.267	0.001
	DEC	2.698	0.047	1.906	0.057	0.151	2.211	0.027	0.048	3.480	0.001	2.667	0.049	4.089	0.000
	N		1,512			1,512			1,512				1,284		
	F(11,N-11)	7.515	2.710			59.928			103.315			7.376	10.388		

			OLS			AR			LAD				TLS		
	Variable	Bayesian T/F	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Bayesian T/F	Coeff	T-Stat	Signif
	Sig F		0.002			0.000			0.000				0.000		
VWP1	JAN	2.698	0.050	0.215	0.830	0.050	0.064	0.949	0.146	2.195	0.028	2.637	0.072	2.384	0.017
	FEB	2.698	0.019	0.081	0.935	0.019	0.380	0.704	0.017	0.351	0.726	2.637	0.028	0.904	0.366
	MARCH	2.698	0.051	0.221	0.825	0.051	0.942	0.346	0.043	1.023	0.306	2.637	0.054	1.828	0.068
	APRIL	2.698	0.007	0.030	0.976	0.007	0.203	0.839	0.009	0.278	0.781	2.637	0.031	0.990	0.322
	MAY	2.698	0.002	0.009	0.993	0.002	0.074	0.941	0.004	0.137	0.891	2.637	0.038	1.243	0.214
	JUNE	2.698	0.068	0.291	0.771	0.068	1.931	0.053	0.062	1.810	0.070	2.637	0.031	1.042	0.297
	JULY	2.698	(0.005)	(0.023)	0.981	(0.005)	(0.145)	0.885	(0.008)	(0.216)	0.829	2.637	0.013	0.448	0.655
	AUG	2.698	(0.067)	(0.289)	0.773	(0.067)	(1.735)	0.083	(0.064)	(1.768)	0.077	2.637	(0.038)	(1.231)	0.219
	SEP	2.698	0.074	0.323	0.746	0.074	0.971	0.332	0.023	0.461	0.645	2.637	(0.017)	(0.558)	0.577
	OCT	2.698	(0.030)	(0.128)	0.898	(0.030)	(0.581)	0.561	(0.019)	(0.445)	0.656	2.637	0.003	0.083	0.934
	NOV	2.698	0.171	0.741	0.459	0.171	2.358	0.018	0.119	2.336	0.019	2.637	0.068	2.201	0.028
	DEC	2.698	0.151	0.641	0.522	0.151	2.211	0.027	0.109	2.234	0.025	2.637	0.062	1.915	0.056
	N		1,512			1,512			1,512				1,103		
	F(11,N-11)	7.515	0.089			20.289			23.395			7.250	1.226		
	Sig F		1.000			0.062			0.025				0.264		
VWP2	JAN	2.698	0.114	2.568	0.010	0.114	0.980	0.327	0.070	3.339	0.001	2.650	0.067	4.416	0.000
	FEB	2.698	0.014	0.318	0.750	0.014	0.313	0.754	0.039	1.976	0.048	2.650	0.056	3.576	0.000
	MARCH	2.698	0.062	1.408	0.159	0.062	3.500	0.000	0.054	3.296	0.001	2.650	0.050	3.257	0.001
	APRIL	2.698	0.065	1.460	0.144	0.065	3.208	0.001	0.059	3.257	0.001	2.650	0.064	4.011	0.000
	MAY	2.698	0.063	1.436	0.151	0.063	3.414	0.001	0.059	3.594	0.000	2.650	0.059	3.798	0.000
	JUNE	2.698	0.027	0.612	0.541	0.027	1.356	0.175	0.024	1.415	0.157	2.650	0.033	2.127	0.034
	JULY	2.698	0.034	0.796	0.426	0.034	1.774	0.076	0.031	1.734	0.083	2.650	0.031	2.107	0.035
	AUG	2.698	(0.032)	(0.730)	0.466	(0.032)	(1.434)	0.152	(0.022)	(1.381)	0.167	2.650	(0.010)	(0.657)	0.511
	SEP	2.698	(0.022)	(0.505)	0.614	(0.022)	(0.590)	0.555	0.007	0.383	0.702	2.650	0.028	1.859	0.063
	OCT	2.698	(0.019)	(0.437)	0.662	(0.019)	(0.452)	0.651	0.011	0.586	0.558	2.650	0.026	1.696	0.090
	NOV	2.698	0.104	2.362	0.018	0.104	2.305	0.021	0.051	2.740	0.006	2.650	0.060	3.824	0.000
	DEC	2.698	0.049	1.093	0.274	0.049	2.600	0.009	0.044	2.683	0.007	2.650	0.040	2.550	0.011

			OLS			AR			LAD				TLS		
	Variable	Bayesian T/F	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Bayesian T/F	Coeff	T-Stat	Signif
	N		1,512			1,512			1,512				1,180		
	F(11,N-11)	7.515	1.151			55.674			71.546			7.305	2.079		
	Sig F		0.317			0.000			0.000				0.019		
VWP3	JAN	2.698	0.296	4.733	0.000	0.296	3.271	0.001	0.157	5.040	0.000	2.665	0.077	4.456	0.000
	FEB	2.698	0.006	0.089	0.929	0.006	0.157	0.875	0.008	0.304	0.761	2.665	0.010	0.586	0.558
	MARCH	2.698	0.032	0.515	0.606	0.032	2.014	0.044	0.034	2.077	0.038	2.665	0.047	3.056	0.002
	APRIL	2.698	0.068	1.074	0.283	0.068	3.459	0.001	0.063	3.475	0.001	2.665	0.064	3.979	0.000
	MAY	2.698	0.041	0.661	0.508	0.041	2.136	0.033	0.039	2.214	0.027	2.665	0.040	2.435	0.015
	JUNE	2.698	(0.001)	(0.018)	0.986	(0.001)	(0.062)	0.951	0.001	0.057	0.954	2.665	0.027	1.657	0.098
	JULY	2.698	0.012	0.194	0.846	0.012	0.547	0.585	0.011	0.570	0.569	2.665	0.010	0.667	0.505
	AUG	2.698	0.149	2.381	0.017	0.149	0.985	0.325	0.001	0.047	0.963	2.665	0.018	1.071	0.284
	SEP	2.698	(0.042)	(0.677)	0.498	(0.042)	(1.941)	0.052	(0.036)	(1.997)	0.046	2.665	(0.008)	(0.537)	0.591
	OCT	2.698	(0.072)	(1.153)	0.249	(0.072)	(0.693)	0.488	0.028	1.329	0.184	2.665	0.038	2.379	0.018
	NOV	2.698	0.041	0.669	0.504	0.041	1.403	0.161	0.048	2.190	0.028	2.665	0.032	2.023	0.043
	DEC	2.698	0.033	0.514	0.608	0.033	1.656	0.098	0.030	1.598	0.110	2.665	0.031	1.884	0.060
	N		1,512			1,512			1,512				1,272		
	F(11,N-11)	7.515	2.343			40.796			60.224			7.368	2.106		
	Sig F		0.007			0.000			0.000				0.017		
VWP4	JAN	2.698	0.104	2.950	0.003	0.104	2.104	0.035	0.066	2.214	0.027	2.670	0.064	2.879	0.004
	FEB	2.698	0.037	1.042	0.298	0.037	1.264	0.206	0.027	1.009	0.313	2.670	0.042	1.937	0.053
	MARCH	2.698	0.019	0.553	0.580	0.019	0.726	0.468	0.018	0.764	0.445	2.670	0.033	1.543	0.123
	APRIL	2.698	0.072	2.031	0.042	0.072	2.805	0.005	0.063	2.617	0.009	2.670	0.059	2.618	0.009
	MAY	2.698	0.024	0.677	0.498	0.024	0.867	0.386	0.030	1.236	0.216	2.670	0.050	2.273	0.023
	JUNE	2.698	0.050	1.404	0.161	0.050	1.901	0.057	0.037	1.586	0.113	2.670	0.026	1.185	0.236
	JULY	2.698	0.035	1.027	0.305	0.035	0.958	0.338	0.041	1.565	0.118	2.670	0.062	2.830	0.005
	AUG	2.698	(0.071)	(2.008)	0.045	(0.071)	(1.834)	0.067	(0.043)	(1.467)	0.142	2.670	0.009	0.390	0.697
	SEP	2.698	0.040	1.152	0.250	0.040	1.160	0.246	0.030	1.168	0.243	2.670	0.027	1.231	0.218
	OCT	2.698	0.083	2.362	0.018	0.083	1.434	0.151	0.075	2.510	0.012	2.670	0.061	2.614	0.009

			OLS			AR			LAD				TLS		
	Variable	Bayesian T/F	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Bayesian T/F	Coeff	T-Stat	Signif
	NOV	2.698	0.064	1.822	0.069	0.064	2.289	0.022	0.069	2.470	0.014	2.670	0.062	2.928	0.003
	DEC	2.698	0.100	2.789	0.005	0.100	3.839	0.000	0.077	3.387	0.001	2.670	0.044	1.994	0.046
	N		1,512			1,512			1,512				1,306		
	F(11,N-11)	7.515	1.729			47.253			47.239			7.390	0.645		
	Sig F		0.062			0.000			0.000				0.798		
VWP	JAN	2.698	0.125	4.102	0.000	0.125	3.506	0.000	0.086	3.344	0.001	2.669	0.058	3.030	0.002
	FEB	2.698	0.032	1.043	0.297	0.032	1.240	0.215	0.027	1.183	0.237	2.669	0.042	2.182	0.029
	MARCH	2.698	0.023	0.752	0.452	0.023	1.005	0.315	0.022	1.074	0.283	2.669	0.036	1.898	0.058
	APRIL	2.698	0.070	2.289	0.022	0.070	3.159	0.002	0.062	2.969	0.003	2.669	0.063	3.225	0.001
	MAY	2.698	0.027	0.886	0.376	0.027	1.142	0.253	0.033	1.595	0.111	2.669	0.048	2.495	0.013
	JUNE	2.698	0.043	1.403	0.161	0.043	1.943	0.052	0.034	1.701	0.089	2.669	0.025	1.297	0.195
	JULY	2.698	0.031	1.040	0.298	0.031	1.012	0.311	0.037	1.629	0.103	2.669	0.051	2.738	0.006
	AUG	2.698	(0.041)	(1.355)	0.176	(0.041)	(0.966)	0.334	(0.032)	(1.220)	0.223	2.669	0.016	0.805	0.421
	SEP	2.698	0.029	0.960	0.337	0.029	0.973	0.330	0.024	1.081	0.280	2.669	0.036	1.897	0.058
	OCT	2.698	0.059	1.938	0.053	0.059	1.182	0.237	0.062	2.382	0.017	2.669	0.056	2.776	0.006
	NOV	2.698	0.064	2.103	0.036	0.064	2.595	0.009	0.067	2.800	0.005	2.669	0.066	3.582	0.000
	DEC	2.698	0.092	2.974	0.003	0.092	4.051	0.000	0.072	3.646	0.000	2.669	0.049	2.560	0.011
	N		1,512			1,512			1,512				1,301		
	F(11,N-11)	7.515	1.822			57.839			60.111			7.387	0.622		
	Sig F		0.046			0.000			0.000				0.812		

TABLE 37: ARCH MODELLING OF THE MONTH OF THE YEAR EFFECT

	ISEQ			ISEQR			ISEFIN			ISEGEN		
Variable	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif	Coeff	T-Stat	Signif
AR1	1.00	44.24	0.00	0.68	72.78	0.00	0.57	25.38	0.00	0.54	20.08	0.00
AR2	0.10	3.62	0.00	0.13	12.19	0.00	0.10	3.29	0.00	0.09	2.96	0.00
AR3	-0.11	-7.70	0.00	0.07	10.67	0.00	0.26	14.51	0.00	0.29	10.05	0.00
AR4				0.06	16.46	0.00						
January	0.00	3.86	0.00	-0.00	-4.66	0.00	0.02	4.73	0.00	0.02	6.65	0.00
February	0.00	4.14	0.00	-0.00	-10.24	0.00	0.02	5.26	0.00	0.01	2.66	0.01
March	0.00	4.87	0.00	0.00	7.72	0.00	-0.00	-1.58	0.11	0.00	0.85	0.39
April	0.00	2.46	0.01	-0.00	-3.97	0.00	0.01	4.09	0.00	-0.01	-1.20	0.23
May	0.00	1.05	0.30	0.02	87.50	0.00	0.01	4.06	0.00	0.01	2.05	0.04
June	0.00	2.11	0.03	-0.01	-62.05	0.00	-0.00	-0.46	0.65	0.02	7.27	0.00
July	0.00	4.55	0.00	0.00	0.67	0.50	0.02	5.02	0.00	-0.00	-0.19	0.85
August	0.00	3.61	0.00	0.02	207.28	0.00	0.04	21.74	0.00	-0.01	-1.90	0.06
September	0.00	3.41	0.00	0.00	21.32	0.00	0.01	4.21	0.00	-0.01	-1.66	0.10
October	0.00	5.18	0.00	-0.00	-7.29	0.00	0.03	10.68	0.00	-0.00	-1.24	0.22
November	0.00	0.66	0.51	0.00	1.72	0.09	0.02	6.16	0.00	-0.01	-2.63	0.01
December	0.00	1.70	0.09	0.00	1.30	0.19	0.02	10.47	0.00	-0.01	-1.58	0.11
Variance(Constant)	0.00	16.08	0.00	0.00	13.77	0.00	0.00	4.93	0.00	0.00	12.19	0.00
ARCH1	0.09	11.53	0.00	7.11	66.88	0.00	1.70	20.16	0.00	1.45	18.64	0.00
ARCH2	0.09	8.12	0.00	0.11	5.22	0.00	1.65	19.95	0.00	0.36	8.23	0.00
ARCH3	0.04	6.75	0.00	-0.00	1.00		0.14	4.92	0.00	0.38	8.09	0.00
ARCH4	0.47	14.00	0.00	-0.00	-0.08	0.94	0.27	10.04	0.00	0.22	4.99	0.00

TABLE 38: REGRESSION DIAGNOSTICS FOR ARCH MODELLING OF MONTH OF THE YEAR

	ISEQ		ISEQR		ISEFIN		ISEGEN	
	Test	Signif	Test	Signif	Test	Signif	Test	Signif
The Ljung-Box Q-Test for Serial Correlation in NRESIDS								
LB(4)	14.55	0.00			11.81	0.00	11.18	0.00
LB(8)	90.61	0.00	67.21	0.00	13.82	0.02	17.48	0.00
LB(12)	157.27	0.00			17.59	0.04	20.07	0.02
LB(16)	249.88	0.00	149.71	0.00	21.00	0.07	21.20	0.07
LB(20)	355.03	0.00			29.09	0.03	25.59	0.08
LB(24)	443.02	0.00	216.82	0.00	32.63	0.05	28.00	0.14
The Jarque-Bera Normality Test, ChiSqr(2), for NRESIDS								
	28,730.05	0.00	262,563.47	0.00	7,181.74	0.00	12,484.34	0.00
F-Test of no ARCH vs. ARCH in NRESIDS								
ARCH(4)	2.71	0.03	0.26	0.90	0.91	0.46	0.99	0.41
ARCH(8)	2.80	0.00	0.23	0.98	0.94	0.48	0.64	0.74
ARCH(12)	2.60	0.00	1.85	0.04	0.85	0.60	0.61	0.84
ARCH(16)	3.01	0.00	1.41	0.13	0.68	0.81	0.60	0.89
ARCH(20)	5.34	0.00	1.16	0.28	1.04	0.42	0.47	0.98
ARCH(24)	5.26	0.00	1.14	0.29	0.70	0.85	0.30	1.00
The Ljung-Box Q-Test for Serial Correlation in SQNRESIDS								
LB(4)	10.19	0.00			6.25	0.01	4.73	0.03
LB(8)	22.12	0.00	1.78	0.78	9.49	0.09	5.98	0.31
LB(12)	27.11	0.00			11.02	0.27	6.30	0.71
LB(16)	43.02	0.00	23.04	0.03	13.53	0.41	21.87	0.06
LB(20)	103.87	0.00			35.41	0.01	21.93	0.19
LB(24)	116.82	0.00	27.76	0.12	36.25	0.02	22.29	0.38

11.1.2. Overall Significance As A Test Of Monthly Seasonality

In the case of the ISE indices it seems reasonable to state that there exists monthly seasonality. For ISEQ, ISEFIN, and ISEGEN the F statistic is statistically significant under all forms of adjustment. For ISEQR it is so under all save TLS. This is not entirely convincing however, as this finding is weakened when we consider the number of observations under consideration. Correcting for this we find that all indices show a statistically significant F statistic under adjustment for autocorrelation and under LAD estimation, but none do so under OLS or TLS. Thus the choice of estimation method and the choice of priors' dictates the result obtained. Only under the AR and LAD estimators do we find that the F statistic is statistically significant regardless of adjusting for number of data points. Similar patterns are obtained when one analyses the portfolio indices. In all cases save E (V) WP1 the pattern above holds: the AR and LAD estimators agree regardless of the statistical criteria, while other estimators give differing results according to the criteria used.

11.1.3. Statistically Significant Months

The F test is a joint test that all the coefficients are jointly and severally equal to each other and zero. We have some evidence that, allowing for the non normality of the data and the amount of data under analysis, there exist some coefficients that are not so. Thus an investigation of which months if any are different is warranted.

Looking first at the values and significance of the various coefficients on the monthly dummies in Table 36, we note a number of points. We have already noted the significance of January in the OLS analysis. For the ISE indices this significance is not determined by the method of analysis; in the ISEQ and ISEGEN indices January is significant across all methods of analysis, while for ISEQR and ISEFIN only for TLS analysis is January not significant. In the portfolio indices, we note that when January is not significant under OLS it is so under TLS. January is almost never (save for VWP2 under LAD) significant under AR or LAD estimation.

There is an important role here for the number of data points, as was the case in the investigation of overall significance. January is never significant under adjustment for the data points for the ISEFIN. It is significant regardless of this for the ISEQR under all save TLS and for the ISEQ under OLS (which is however a poor modelling approach), and under OLS and LAD for ISEGEN. Accepting that the MAD and TLS methods are more efficient in the presence of deviations from normality, we find that in no case do both of these methods, with and without adjustment for data points, indicate that January is statistically significant. Again, a similar result, that the significance of the January coefficients is highly dependent on the method of analysis and the degree of adjustment pervades the portfolio indices. In no case do we find in any index that any month is statistically significant across the range of estimation methods and the choice of priors. This indicates that while monthly seasonality may be present it is not statistically robust.

Another approach is to examine the pairs of months that appear different one from the other. As noted earlier this can be achieved by using either Tamhanes T^2 test or Tukey's HSD test, depending on whether the variance is or is not homogeneous. We can see from the evidence in Table 39 that in almost all cases, the exception being the equal weighted total index, EWP, we can reject the null of homogeneity of variance. For the trimmed indices the evidence is that for the ISE indices and for the trimmed

TVW3 and TVW4 indices there is some evidence of a monthly variation in volatility. Table 39 informs us that in many cases we can assume that there is monthly variation in the variance.

TABLE 39: TEST OF HOMOGENEITY OF VARIANCE BY MONTH OF THE YEAR

	Levene Statistic	df1	df2	Sig.		Levene Statistic	df1	df2	Sig.
ISEQ	6.962	11	2767	.000	TISEQ	3.036	11	2528	.000
ISEQR	6.931	11	2766	.000	TISEQR	2.002	11	2488	.025
ISEFIN	6.173	11	2504	.000	TISEFIN	3.289	11	2252	.000
ISEGEN	6.386	11	2504	.000	TISEGEN	2.011	11	2252	.024
EWP1	3.725	11	1499	.000	TEW1	.853	11	1347	.586
EWP2	3.183	11	1499	.000	TEW2	1.448	11	1347	.145
EWP3	4.411	11	1499	.000	TEW3	1.510	11	1347	.122
EWP4	2.088	11	1499	.018	TEW4	.434	11	1347	.941
EWP	1.528	11	1499	.115	TEW	1.196	11	1347	.285
VWP1	2.883	11	1499	.001	TVW1	1.432	11	1347	.152
VWP2	3.043	11	1499	.000	TVW2	.607	11	1347	.824
VWP3	3.426	11	1499	.000	TVW3	2.213	11	1347	.012
VWP4	3.355	11	1499	.000	TVW4	1.883	11	1347	.038
VWP	3.531	11	1499	.000	TVW	1.416	11	1347	.159

Shown in Table 40are the results of the appropriate test as indicated by the Levene test. Very few monthly pairs are show to be significantly different. Those that are so shown are January-August for ISEQ and ISEQR, May-August for EWP2, March-August for VWP2, January-September and April-September for VWP3 under Tamhane's T^2 test. EWP under Tukey's HSD Statistic shows more pairs, January-March/August/September. Again, this generalised rejection of statistically significant monthly differences mirrors that found in the analysis of daily seasonality.

TABLE 40: DIFFERENCES IN MEANS BY MONTH OF THE YEAR

Tamhane's T² Test		Feb		Mar		Apr		May		June		July		Aug		Sep		Oct		Nov		Dec	
		Diff.	Sig.	Diff.	Sig.	Diff.	Sig.	Diff.	Sig.	Diff.	Sig.	Diff.	Sig.	Diff.	Sig.	Diff.	Sig.	Diff.	Sig.	Diff.	Sig.	Diff.	Sig.
ISEQ	Jan	-0.04	1.00	-0.07	1.00	-0.08	0.84	-0.09	0.42	-0.10	0.15	-0.07	0.98	-0.16	0.01	-0.13	0.09	-0.09	0.98	-0.11	0.13	-0.04	1.00
	Feb			-0.02	1.00	-0.03	1.00	-0.05	1.00	-0.06	0.99	-0.02	1.00	-0.12	0.23	-0.08	0.87	-0.05	1.00	-0.07	0.96	0.00	1.00
	Mar					-0.01	1.00	-0.03	1.00	-0.04	1.00	0.00	1.00	-0.10	0.61	-0.06	1.00	-0.03	1.00	-0.05	1.00	0.02	1.00
	Apr							-0.01	1.00	-0.02	1.00	0.01	1.00	-0.09	0.82	-0.05	1.00	-0.01	1.00	-0.03	1.00	0.04	1.00
	May									-0.01	1.00	0.03	1.00	-0.07	0.98	-0.03	1.00	0.00	1.00	-0.02	1.00	0.05	1.00
	June											0.04	1.00	-0.06	1.00	-0.02	1.00	0.01	1.00	-0.01	1.00	0.06	0.92
	July													-0.10	0.46	-0.06	0.99	-0.03	1.00	-0.05	1.00	0.02	1.00
	Aug															0.04	1.00	0.07	1.00	0.05	1.00	0.12	0.12
	Sep																	0.03	1.00	0.01	1.00	0.09	0.70
	Oct																			-0.02	1.00	0.05	1.00
	Nov																					0.07	0.85
ISEQR	Jan	-0.04	1.00	-0.06	1.00	-0.08	0.87	-0.08	0.64	-0.10	0.18	-0.07	0.94	-0.16	0.01	-0.13	0.11	-0.10	0.97	-0.11	0.22	-0.05	1.00
	Feb			-0.02	1.00	-0.03	1.00	-0.04	1.00	-0.06	0.99	-0.03	1.00	-0.12	0.26	-0.08	0.90	-0.05	1.00	-0.06	0.99	-0.00	1.00
	Mar					-0.01	1.00	-0.02	1.00	-0.04	1.00	-0.01	1.00	-0.10	0.59	-0.06	1.00	-0.03	1.00	-0.04	1.00	0.02	1.00
	Apr							-0.01	1.00	-0.02	1.00	0.00	1.00	-0.08	0.83	-0.05	1.00	-0.02	1.00	-0.03	1.00	0.03	1.00
	May									-0.02	1.00	0.01	1.00	-0.08	0.93	-0.04	1.00	-0.01	1.00	-0.02	1.00	0.04	1.00
	June											0.03	1.00	-0.06	1.00	-0.02	1.00	0.01	1.00	-0.01	1.00	0.06	0.98
	July													-0.09	0.72	-0.05	1.00	-0.02	1.00	-0.03	1.00	0.03	1.00
	Aug															0.04	1.00	0.07	1.00	0.05	1.00	0.11	0.18
	Sep																	0.03	1.00	0.02	1.00	0.08	0.82
	Oct																			-0.01	1.00	0.05	1.00
	Nov																					0.06	0.98
ISEFIN	Jan	0.01	1.00	-0.05	1.00	-0.04	1.00	-0.10	0.97	-0.08	1.00	-0.02	1.00	-0.18	0.20	-0.09	1.00	-0.02	1.00	-0.05	1.00	0.01	1.00
	Feb			-0.06	1.00	-0.05	1.00	-0.11	0.80	-0.09	0.98	-0.03	1.00	-0.19	0.08	-0.09	1.00	-0.03	1.00	-0.06	1.00	0.00	1.00
	Mar					0.02	1.00	-0.05	1.00	-0.03	1.00	0.03	1.00	-0.13	0.75	-0.03	1.00	0.03	1.00	0.00	1.00	0.06	1.00
	Apr							-0.06	1.00	-0.04	1.00	0.01	1.00	-0.14	0.43	-0.05	1.00	0.02	1.00	-0.01	1.00	0.05	1.00
	May									0.02	1.00	0.08	1.00	-0.08	1.00	0.01	1.00	0.08	1.00	0.05	1.00	0.11	0.81
	June											0.05	1.00	-0.10	0.95	-0.01	1.00	0.06	1.00	0.03	1.00	0.09	0.98
	July													-0.16	0.27	-0.06	1.00	0.00	1.00	-0.03	1.00	0.04	1.00
	Aug															0.09	1.00	0.16	0.79	0.13	0.76	0.19	0.09
	Sep																	0.07	1.00	0.04	1.00	0.10	1.00
	Oct																			-0.03	1.00	0.03	1.00
	Nov																					0.06	1.00
ISEGEN	Jan	-0.04	1.00	-0.06	1.00	-0.08	0.89	-0.10	0.21	-0.12	0.06	-0.07	0.94	-0.12	0.30	-0.15	0.02	-0.11	0.84	-0.10	0.37	-0.05	1.00
	Feb			-0.02	1.00	-0.03	1.00	-0.06	0.98	-0.07	0.65	-0.03	1.00	-0.08	0.97	-0.10	0.25	-0.07	1.00	-0.06	1.00	-0.01	1.00

	Mar					-0.02	1.00	-0.04	1.00	-0.06	0.99	-0.01	1.00	-0.06	1.00	-0.08	0.73	-0.05	1.00	-0.04	1.00	0.01	1.00
	Apr							-0.02	1.00	-0.04	1.00	0.01	1.00	-0.04	1.00	-0.07	0.94	-0.03	1.00	-0.02	1.00	0.03	1.00
	May									-0.02	1.00	0.03	1.00	-0.02	1.00	-0.04	1.00	-0.01	1.00	0.00	1.00	0.05	0.99
	June											0.05	1.00	-0.00	1.00	-0.03	1.00	0.01	1.00	0.02	1.00	0.07	0.75
	July													-0.05	1.00	-0.07	0.79	-0.04	1.00	-0.03	1.00	0.02	1.00
	Aug															-0.02	1.00	0.01	1.00	0.02	1.00	0.07	0.99
	Sep																	0.03	1.00	0.05	1.00	0.09	0.31
	Oct																			0.01	1.00	0.06	1.00
	Nov																					0.05	1.00
EWP1	Jan	-0.14	1.00	-0.03	1.00	-0.12	1.00	-0.07	1.00	-0.06	1.00	-0.06	1.00	-0.15	1.00	-0.11	1.00	-0.12	1.00	-0.01	1.00	-0.02	1.00
	Feb			0.11	1.00	0.02	1.00	0.07	1.00	0.08	1.00	0.08	1.00	-0.01	1.00	0.03	1.00	0.02	1.00	0.13	0.99	0.12	0.98
	Mar					-0.09	1.00	-0.04	1.00	-0.03	1.00	-0.04	1.00	-0.12	1.00	-0.09	1.00	-0.09	1.00	0.02	1.00	0.01	1.00
	Apr							0.04	1.00	0.06	1.00	0.05	1.00	-0.03	1.00	0.00	1.00	-0.01	1.00	0.11	0.99	0.10	0.87
	May									0.02	1.00	0.01	1.00	-0.07	1.00	-0.04	1.00	-0.05	1.00	0.07	1.00	0.05	1.00
	June											-0.01	1.00	-0.09	1.00	-0.06	1.00	-0.06	1.00	0.05	1.00	0.04	1.00
	July													-0.08	1.00	-0.05	1.00	-0.06	1.00	0.06	1.00	0.04	1.00
	Aug															0.03	1.00	0.03	1.00	0.14	0.98	0.13	0.95
	Sep																	-0.01	1.00	0.11	1.00	0.09	1.00
	Oct																			0.12	1.00	0.10	1.00
	Nov																					-0.01	1.00
EWP2	Jan	0.07	1.00	0.00	1.00	0.06	1.00	0.08	1.00	0.02	1.00	0.04	1.00	-0.03	1.00	-0.01	1.00	-0.02	1.00	0.03	1.00	0.04	1.00
	Feb			-0.06	1.00	-0.00	1.00	0.01	1.00	-0.05	1.00	-0.02	1.00	-0.10	0.84	-0.07	1.00	-0.08	1.00	-0.04	1.00	-0.03	1.00
	Mar					0.06	1.00	0.07	1.00	0.02	1.00	0.04	1.00	-0.04	1.00	-0.01	1.00	-0.02	1.00	0.02	1.00	0.04	1.00
	Apr							0.01	1.00	-0.04	1.00	-0.02	1.00	-0.09	0.27	-0.07	1.00	-0.08	1.00	-0.04	1.00	-0.02	1.00
	May									-0.06	0.75	-0.03	1.00	-0.11	0.01	-0.08	0.91	-0.09	0.88	-0.05	0.90	-0.04	1.00
	June											0.02	1.00	-0.05	1.00	-0.03	1.00	-0.04	1.00	0.01	1.00	0.02	1.00
	July													-0.07	0.66	-0.05	1.00	-0.06	1.00	-0.01	1.00	-0.00	1.00
	Aug															0.02	1.00	0.02	1.00	0.06	0.86	0.07	0.58
	Sep																	-0.01	1.00	0.04	1.00	0.05	1.00
	Oct																			0.04	1.00	0.06	1.00
	Nov																					0.01	1.00
EWP3	Jan	-0.32	0.98	-0.38	0.96	-0.26	1.00	-0.29	1.00	-0.30	0.99	-0.33	0.97	-0.36	0.91	-0.37	0.86	-0.32	0.98	-0.29	1.00	-0.31	0.99
	Feb			-0.06	1.00	0.06	0.92	0.03	1.00	0.02	1.00	-0.01	1.00	-0.04	1.00	-0.05	1.00	-0.00	1.00	0.03	1.00	0.01	1.00
	Mar					0.12	1.00	0.09	1.00	0.08	1.00	0.05	1.00	0.02	1.00	0.01	1.00	0.06	1.00	0.09	1.00	0.07	1.00
	Apr							-0.03	1.00	-0.04	1.00	-0.07	0.47	-0.10	0.07	-0.11	0.01	-0.06	0.79	-0.03	1.00	-0.05	0.98
	May									-0.01	1.00	-0.04	1.00	-0.07	0.67	-0.08	0.20	-0.03	1.00	0.00	1.00	-0.02	1.00
	June											-0.03	1.00	-0.05	0.99	-0.06	0.74	-0.02	1.00	0.02	1.00	-0.01	1.00
	July													-0.03	1.00	-0.04	1.00	0.01	1.00	0.04	1.00	0.02	1.00
	Aug															-0.01	1.00	0.03	1.00	0.07	1.00	0.05	1.00
	Sep																	0.05	1.00	0.08	1.00	0.06	0.97
	Oct																			0.04	1.00	0.01	1.00
	Nov																					-0.02	1.00
EWP4	Jan	0.00	1.00	0.02	1.00	0.02	1.00	-0.02	1.00	0.03	1.00	-0.01	1.00	-0.09	1.00	-0.04	1.00	0.06	1.00	0.02	1.00	0.03	1.00
	Feb			0.01	1.00	0.02	1.00	-0.03	1.00	0.03	1.00	-0.02	1.00	-0.09	1.00	-0.05	1.00	0.05	1.00	0.02	1.00	0.02	1.00

	Mar					0.01	1.00	-0.04	1.00	0.02	1.00	-0.03	1.00	-0.10	0.93	-0.06	1.00	0.04	1.00	0.01	1.00	0.01	1.00
	Apr							-0.04	1.00	0.01	1.00	-0.03	1.00	-0.11	0.63	-0.06	1.00	0.04	1.00	-0.00	1.00	0.01	1.00
	May									0.06	1.00	0.01	1.00	-0.06	1.00	-0.02	1.00	0.08	1.00	0.04	1.00	0.05	1.00
	June											-0.05	1.00	-0.12	0.48	-0.08	1.00	0.02	1.00	-0.01	1.00	-0.01	1.00
	July													-0.07	1.00	-0.03	1.00	0.07	1.00	0.03	1.00	0.04	1.00
	Aug															0.04	1.00	0.15	0.94	0.11	1.00	0.11	0.31
	Sep																	0.10	1.00	0.06	1.00	0.07	1.00
	Oct																			-0.04	1.00	-0.03	1.00
	Nov																					0.01	1.00
VWP1	Jan	-0.03	1.00	0.00	1.00	-0.04	1.00	-0.05	1.00	0.02	1.00	-0.06	1.00	-0.12	1.00	0.02	1.00	-0.08	1.00	0.12	1.00	0.10	1.00
	Feb			0.03	1.00	-0.01	1.00	-0.02	1.00	0.05	1.00	-0.02	1.00	-0.09	1.00	0.05	1.00	-0.05	1.00	0.15	1.00	0.13	1.00
	Mar					-0.04	1.00	-0.05	1.00	0.02	1.00	-0.06	1.00	-0.12	0.99	0.02	1.00	-0.08	1.00	0.12	1.00	0.10	1.00
	Apr							-0.00	1.00	0.06	1.00	-0.01	1.00	-0.07	1.00	0.07	1.00	-0.04	1.00	0.16	0.95	0.14	0.98
	May									0.07	1.00	-0.01	1.00	-0.07	1.00	0.07	1.00	-0.03	1.00	0.17	0.90	0.15	0.95
	June											-0.07	1.00	-0.14	0.52	0.01	1.00	-0.10	1.00	0.10	1.00	0.08	1.00
	July													-0.06	1.00	0.08	1.00	-0.02	1.00	0.18	0.90	0.16	0.95
	Aug															0.14	1.00	0.04	1.00	0.24	0.27	0.22	0.32
	Sep																	-0.10	1.00	0.10	1.00	0.08	1.00
	Oct																			0.20	0.83	0.18	0.91
	Nov																					-0.02	1.00
VWP2	Jan	-0.10	1.00	-0.05	1.00	-0.05	1.00	-0.05	1.00	-0.09	1.00	-0.08	1.00	-0.15	1.00	-0.14	1.00	-0.13	1.00	-0.01	1.00	-0.07	1.00
	Feb			0.05	1.00	0.05	1.00	0.05	1.00	0.01	1.00	0.02	1.00	-0.05	1.00	-0.04	1.00	-0.03	1.00	0.09	1.00	0.03	1.00
	Mar					0.00	1.00	0.00	1.00	-0.04	1.00	-0.03	1.00	-0.09	0.05	-0.08	0.94	-0.08	0.99	0.04	1.00	-0.01	1.00
	Apr							-0.00	1.00	-0.04	1.00	-0.03	1.00	-0.10	0.08	-0.09	0.94	-0.08	0.99	0.04	1.00	-0.02	1.00
	May									-0.04	1.00	-0.03	1.00	-0.10	0.06	-0.09	0.93	-0.08	0.99	0.04	1.00	-0.01	1.00
	June											0.01	1.00	-0.06	0.95	-0.05	1.00	-0.05	1.00	0.08	1.00	0.02	1.00
	July													-0.07	0.80	-0.06	1.00	-0.05	1.00	0.07	1.00	0.01	1.00
	Aug															0.01	1.00	0.01	1.00	0.14	0.40	0.08	0.27
	Sep																	0.00	1.00	0.13	0.90	0.07	1.00
	Oct																			0.12	0.96	0.07	1.00
	Nov																					-0.05	1.00
VWP3	Jan	-0.29	0.19	-0.27	0.26	-0.23	0.61	-0.26	0.34	-0.30	0.09	-0.29	0.15	-0.15	1.00	-0.34	0.02	-0.37	0.40	-0.26	0.41	-0.27	0.27
	Feb			0.03	1.00	0.06	1.00	0.04	1.00	-0.01	1.00	0.01	1.00	0.14	1.00	-0.05	1.00	-0.08	1.00	0.04	1.00	0.03	1.00
	Mar					0.04	1.00	0.01	1.00	-0.03	1.00	-0.02	1.00	0.12	1.00	-0.07	0.37	-0.10	1.00	0.01	1.00	0.00	1.00
	Apr							-0.03	1.00	-0.07	0.51	-0.06	0.98	0.08	1.00	-0.11	0.01	-0.14	1.00	-0.03	1.00	-0.04	1.00
	May									-0.04	1.00	-0.03	1.00	0.11	1.00	-0.08	0.25	-0.11	1.00	0.00	1.00	-0.01	1.00
	June											0.01	1.00	0.15	1.00	-0.04	1.00	-0.07	1.00	0.04	1.00	0.03	1.00
	July													0.14	1.00	-0.05	1.00	-0.08	1.00	0.03	1.00	0.02	1.00
	Aug															-0.19	1.00	-0.22	1.00	-0.11	1.00	-0.12	1.00
	Sep																	-0.03	1.00	0.08	0.83	0.07	0.55
	Oct																			0.11	1.00	0.10	1.00
	Nov																					-0.01	1.00
VWP4	Jan	-0.07	1.00	-0.08	1.00	-0.03	1.00	-0.08	1.00	-0.05	1.00	-0.07	1.00	-0.17	0.34	-0.06	1.00	-0.02	1.00	-0.04	1.00	-0.00	1.00
	Feb			-0.02	1.00	0.03	1.00	-0.01	1.00	0.01	1.00	-0.00	1.00	-0.11	0.86	0.00	1.00	0.05	1.00	0.03	1.00	0.06	1.00

	Mar					0.05	1.00	0.00	1.00	0.03	1.00	0.02	1.00	-0.09	0.98	0.02	1.00	0.06	1.00	0.04	1.00	0.08	0.90
	Apr							-0.05	1.00	-0.02	1.00	-0.04	1.00	-0.14	0.17	-0.03	1.00	0.01	1.00	-0.01	1.00	0.03	1.00
	May									0.03	1.00	0.01	1.00	-0.09	0.97	0.02	1.00	0.06	1.00	0.04	1.00	0.08	0.95
	June											-0.01	1.00	-0.12	0.52	-0.01	1.00	0.03	1.00	0.01	1.00	0.05	1.00
	July													-0.11	0.97	0.00	1.00	0.05	1.00	0.03	1.00	0.06	1.00
	Aug															0.11	0.92	0.15	0.81	0.13	0.32	0.17	0.03
	Sep																	0.04	1.00	0.02	1.00	0.06	1.00
	Oct																			-0.02	1.00	0.02	1.00
	Nov																					0.04	1.00
VWP	Jan	-0.09	0.91	-0.10	0.65	-0.06	1.00	-0.10	0.73	-0.08	0.96	-0.10	0.95	-0.17	0.18	-0.10	0.92	-0.07	1.00	-0.06	1.00	-0.03	1.00
	Feb					0.04	1.00	-0.01	1.00	0.01	1.00	-0.00	1.00	-0.07	1.00	-0.00	1.00	0.03	1.00	0.03	1.00	0.06	1.00
	Mar					0.05	1.00	0.00	1.00	0.02	1.00	0.01	1.00	-0.06	1.00	0.01	1.00	0.04	1.00	0.04	1.00	0.07	0.92
	Apr							-0.04	1.00	-0.03	1.00	-0.04	1.00	-0.11	0.79	-0.04	1.00	-0.01	1.00	-0.01	1.00	0.02	1.00
	May									0.02	1.00	0.00	1.00	-0.07	1.00	0.00	1.00	0.03	1.00	0.04	1.00	0.07	0.96
	June											-0.01	1.00	-0.08	1.00	-0.01	1.00	0.02	1.00	0.02	1.00	0.05	1.00
	July													-0.07	1.00	-0.00	1.00	0.03	1.00	0.03	1.00	0.06	1.00
	Aug															0.07	1.00	0.10	1.00	0.11	0.90	0.13	0.39
	Sep																	0.03	1.00	0.04	1.00	0.06	1.00
	Oct																			0.00	1.00	0.03	1.00
	Nov																					0.03	1.00
Tukey's HSD Test																							
EWP	January	0.09	0.31	0.11	0.04	0.07	0.68	0.09	0.31	0.08	0.53	0.10	0.11	0.16	0.00	0.14	0.00	0.08	0.38	0.07	0.64	0.08	0.57
	February			0.03	1.00	-0.02	1.00	-0.00	1.00	-0.01	1.00	0.01	1.00	0.07	0.60	0.05	0.95	-0.01	1.00	-0.02	1.00	-0.01	1.00
	March					-0.04	0.98	-0.03	1.00	-0.04	1.00	-0.01	1.00	0.05	0.96	0.03	1.00	-0.03	1.00	-0.04	0.98	-0.04	0.99
	April							0.02	1.00	0.01	1.00	0.03	1.00	0.09	0.23	0.07	0.67	0.01	1.00	0.00	1.00	0.01	1.00
	May									-0.01	1.00	0.01	1.00	0.08	0.55	0.05	0.93	-0.00	1.00	-0.02	1.00	-0.01	1.00
	June											0.02	1.00	0.09	0.35	0.06	0.80	0.01	1.00	-0.01	1.00	-0.00	1.00
	July													0.06	0.82	0.04	0.99	-0.02	1.00	-0.03	1.00	-0.03	1.00
	August															-0.02	1.00	-0.08	0.48	-0.09	0.24	-0.09	0.32
	September																	-0.06	0.89	-0.07	0.68	-0.06	0.77
	October																			-0.01	1.00	-0.01	1.00
	November																					0.00	1.00

11.2. Non-Parametric Analysis Of Monthly Seasonality

As is the case in regard to the investigation of daily seasonality, the use of non-parametric approaches has been little used in the investigation of monthly seasonality. The results in Table 41 show a non-parametric analysis of monthly seasonality. As with the daily seasonality issue here again the Kruskal-Wallis H statistic is employed.

In this case, the null therefore is that the data, the indices, do not differ as to the month of the year. A finding of a low significance therefore would indicate a rejection of the null, and an indication that a month of the year effect is present, the distributions of the index differing by month. The Kruskal-Wallis test therefore allows the parametric F tests to be augmented. Testing for a day of the week effect using both the regression F and Kruskal-Wallis test, Elyasiani, Perera and Puri (1996) in their examination of Sri Lankan data found that the two tests were in agreement, indicating no day of the week effect. This agreement between the two forms of tests was also found in Arsad and Coutts (1997) and Steeley (1999). No paper seems to have used these non-parametric tests in conjunction with parametric tests when investigating monthly seasonality.

TABLE 41: NON-PARAMETRIC TEST FOR MONTH OF THE YEAR EFFECT

	Chi-Square	df	Significance.		Chi-Square	df	Significance.
ISEQ	28.771	11	.002	TISEQ	27.536	11	.004
ISEQR	24.944	11	.009	TISEQR	19.282	11	.056
ISEFIN	26.415	11	.006	TISEFIN	24.243	11	.012
ISEGEN	28.892	11	.002	TISEGEN	26.729	11	.005
EWP1	21.335	11	.030	TEW1	15.495	11	.161
EWP2	33.144	11	.000	TEW2	19.108	11	.059
EWP3	59.656	11	.000	TEW3	34.208	11	.000
EWP4	8.720	11	.648	TEW4	5.248	11	.919
EWP	36.308	11	.000	TEW	19.891	11	.047
VWP1	17.954	11	.083	TVW1	11.765	11	.382
VWP2	25.531	11	.008	TVW2	22.287	11	.022
VWP3	40.731	11	.000	TVW3	22.248	11	.023
VWP4	16.556	11	.122	TVW4	7.545	11	.753
VWP	19.011	11	.061	TVW	7.737	11	.737

What we note from this is that there is considerable evidence of a monthly seasonal. Only for EWP4, VWP1, VWP4 and VWP can we conclude that there is no non-parametric evidence of monthly seasonality. These findings are also, at the 10% level, generally robust to trimming, with only EWP1 showing a difference in conclusions as between the trimmed and original data. These findings are therefore at variance with the findings for non-parametric results in daily seasonality.

11.3. STOCHASTIC DOMINANCE ANALYSIS OF MONTHLY SEASONALITY

In no case was first order stochastic dominance found in monthly analysis. Considerable evidence was found however of second order stochastic dominance. January achieves second order stochastic dominance over all other months for ISEQ, ISEQR, ISEGEN, EWP1, EWP3, EWP, VWP2-4 and VWP all. Again, as was found in the case of daily seasonality this pattern is not robust under trimming. Only for EWP, VWP2 and VWP3 does January achieve second order stochastic dominance for both trimmed and untrimmed data.

11.4. Resampling Analyses

Show in Table 42 is the result of a series of resampling analyses. In each case 1000 random draws were made from the data (the daily returns to the index in question), each of N, where N equalled the number of days returns in each month in question. For each month therefore for which the mean daily returns was identified as being highest or lowest, for both the first and second moment, the table shows the percentage of drawings where the moment of the random draw exceeded or was lower than the moment of the empirical distribution.

TABLE 42: RESAMPLING ANALYSIS OF MONTHLY SEASONALITY

	ISEQ	ISEQR	ISEFIN	ISEGEN	
Maximum Mean	January	January	December	January	
% Above Mean	0.1%	0%	2.8%	0%	
Maximum St Dev	October	October	October	October	
% Above St Dev	0.1%	0%	0%	0%	
Minimum Mean	August	August	August	September	
% Below Mean	0.1%	0%	0%	0.3%	
Minimum St Dev	June	June	June	May	
% Below St Dev	0%	0%	0%	0.2%	
	EWP1	EWP2	EWP3	EWP4	EWP
Maximum Mean	January	May	January	October	January
% Above Mean	7.0%	4.5%	0.0%	3.5%	0.0%
Maximum St Dev	January	January	January	January	March
% Above St Dev	0%	0%	0.0%	0.0%	0.3%
Minimum Mean	August	August	March	August	August
% Below Mean	5.8%	8.6%	1.9%	0.2%	0.0%
Minimum St Dev	May	November	May	December	December
% Below St Dev	0%	0.1%	0.0%	0.2%	0.7%
	VWP1	VWP2	VWP3	VWP4	VWP
Maximum Mean	November	January	January	January	January
% Above Mean	15.7%	0.7%	0.0%	0.6%	0.0%
Maximum St Dev	January	January	August	October	October
% Above St Dev	0.0%	0.0%	0.0%	0.0%	0.0%
Minimum Mean	August	August	October	August	August
% Below Mean	16.5%	0.7%	0.1%	0.0%	0.0%
Minimum St Dev	May	March	March	June	June
% Below St Dev	0.0%	0.3%	0.0%	0.1%	0.0%

A number of points are evident. First, there appears to be significant support here for the mean daily return in January not to be a statistical artefact. In all cases except that of EWP1 and VSP1 the actual January return was not exceeded in 1000 drawings in more than 5% of the drawings. In general, the first two moments are remarkably robust to this non-parametric technique.

11.5. ANALYSIS OF THE SECOND MOMENT OF RETURNS BY MONTH

We have already seen in Table 39 that there exists in almost all cases, the exception being the equal weighted total index, EWP, evidence that we can reject the null of homogeneity of variance.

In analysing the monthly variation in volatility, there is little if any guidance from the literature. As noted earlier, the models that use an ARCH type process either include all potential explanatory (calendar, here monthly) variables or else use those that have been hypothesised to be important in determining volatility or have been see as important determinants of mean returns.

In the absence of a theoretical guide, the best approach is to appeal to previous research, in particular that of Beller and Nofsinger (1998). They advocate the use of (n-1) dummy variables directly in the variance equation, an approach that is used here. There is no justification for employing ARCH type models, including EGARCH, where there is no evidence of such effects. We have seen from Table 35 that in the ISE indices there is evidence of such effects, allowing the use of ARCH models. Thus investigation of those months of the year that drive monthly seasonal variation in the volatility is limited to those indices which both show ARCH effects and also show a difference between months by the Levene test. In this case this is ISEQ, ISEQR, ISEFIN and ISEGEN.

The results of this approach, using an EGARCH (3,1,4)-M with 11 dummies representing January through November specification are contained in Table 43, and the diagnostics are contained in Table 44, where we see that the estimated equations are well specified in general, with the only potential problem being possible serial correlation in the normalised residuals in the ISEGEN equation.

TABLE 43: EGARCH ESTIMATION OF MONTH OF THE YEAR EFFECTS IN VARIANCE OF SELECTED INDICES

	ISEQ			ISEQR			ISEGEN			ISEFIN		
	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig
AR (1)	0.22	10.56	0.00	0.22	10.59	0.00	0.19	8.28	0.00	0.14	6.12	0.00
AR (2)	0.00	0.05	0.96	0.03	1.30	0.19	0.04	1.97	0.05	0.01	0.50	0.62
AR (3)	0.04	1.90	0.06	0.03	1.40	0.16	0.03	1.48	0.14	0.01	0.71	0.48
Constant Variance	0.02	2.35	0.02	0.03	3.17	0.00	-0.66	-6.59	0.00	0.03	3.28	0.00
ARCH1	0.20	8.18	0.00	0.22	8.30	0.00	0.31	8.85	0.00	0.24	8.53	0.00
ARCH2	-0.11	-2.79	0.01	-0.10	-2.91	0.00	-0.06	-1.53	0.13	-0.06	-1.74	0.08
ARCH3	0.03	0.74	0.46	-0.05	-1.36	0.17	0.10	2.86	0.00	-0.12	-3.41	0.00
ARCH4	-0.04	-1.46	0.15	0.01	0.38	0.70	0.02	0.68	0.50	0.02	0.81	0.42
ARV	0.98	302.82	0.00	0.99	359.26	0.00	0.73	20.08	0.00	0.99	441.06	0.00
Leverage Term	0.26	4.32	0.00	0.33	4.92	0.00	0.04	0.70	0.48	0.45	6.69	0.00
January	-0.04	-3.80	0.00	-0.04	-4.15	0.00	0.24	4.16	0.00	-0.03	-2.64	0.01
February	-0.09	-7.85	0.00	-0.09	-8.00	0.00	-0.01	-0.25	0.80	-0.07	-6.15	0.00
March	-0.03	-2.86	0.00	-0.03	-2.54	0.00	0.10	1.89	0.06	-0.03	-2.41	0.02
April	-0.08	-7.90	0.00	-0.09	-8.56	0.00	0.02	0.45	0.65	-0.06	-5.60	0.00
May	-0.06	-5.99	0.00	-0.04	-4.95	0.00	-0.10	-1.91	0.06	-0.06	-5.49	0.00
June	-0.08	-6.60	0.00	-0.08	-6.85	0.00	-0.05	-1.10	0.27	-0.04	-2.89	0.00
July	-0.06	-4.45	0.00	-0.07	-4.80	0.00	0.30	5.67	0.00	-0.06	-4.43	0.00
August	-0.06	-6.17	0.00	-0.05	-5.79	0.00	-0.02	-0.37	0.71	-0.02	-2.35	0.02
September	0.02	1.54	0.12	0.01	0.59	0.55	0.48	6.81	0.00	-0.03	-2.65	0.01
October	-0.11	-11.31	0.00	-0.11	-11.83	0.00	0.00	0.10	0.92	-0.05	-4.49	0.00
November	-0.02	-1.67	0.10	-0.02	-1.69	0.09	0.11	2.09	0.04	-0.02	-1.40	0.16
ARCH-in-Mean	0.15	2.18	0.03	0.12	1.79	0.07	0.16	2.03	0.04	0.12	1.65	0.10

TABLE 44: REGRESSION DIAGNOSTICS FOR EGARCH ESTIMATION OF MONTH OF THE YEAR EFFECT

	ISEQ		ISEQR		ISEGEN		ISEFIN	
	Stat	Sig	Stat	Sig	Stat	Sig	Stat	Sig
The Ljung-Box Q-Test for Serial Correlation in Normalised Residuals [a]								
LB (4)	1.49	0.22	1.67	0.20	4.79	0.03	1.61	0.20
LB (8)	4.53	0.48	4.83	0.44	7.27	0.20	6.19	0.29
LB (12)	11.96	0.22	12.99	0.16	13.98	0.12	10.99	0.28
LB (16)	16.05	0.25	15.66	0.27	21.82	0.06	13.83	0.39
LB (20)	20.49	0.25	19.70	0.29	30.79	0.02	15.77	0.54
LB (24)	26.82	0.18	26.98	0.17	38.13	0.01	21.96	0.40
The Ljung-Box Q-Test for Serial Correlation in Squared Normalised Residuals [a]								
LB (4)	2.09	0.15	2.23	0.13	0.89	0.34	2.03	0.15
LB (8)	2.70	0.75	2.73	0.74	1.58	0.90	4.82	0.44
LB (12)	4.16	0.90	3.26	0.95	3.62	0.93	6.34	0.71
LB (16)	6.60	0.92	6.44	0.93	4.52	0.98	10.08	0.69
LB (20)	7.26	0.98	7.10	0.98	6.77	0.99	12.36	0.78
LB (24)	8.49	0.99	8.23	0.99	9.25	0.99	15.88	0.78
Jarque-Bera Test for Normality of residuals [b]								
	1741.12	0.00	1345.46	0.00	2064.39	0.00	1289.10	0.00
F-Test of no ARCH vs. ARCH in Normalised Residuals [c]								
ARCH (4)	0.56	0.69	0.57	0.68	0.23	0.92	0.49	0.74
ARCH (8)	0.36	0.94	0.36	0.94	0.20	0.99	0.59	0.78
ARCH (12)	0.37	0.97	0.29	0.99	0.29	0.99	0.52	0.91
ARCH (16)	0.41	0.98	0.39	0.99	0.27	1.00	0.61	0.88
ARCH (20)	0.39	0.99	0.37	1.00	0.33	1.00	0.61	0.91
ARCH (24)	0.37	1.00	0.35	1.00	0.38	1.00	0.64	0.91

a: Ho: No Serial Correlation; b: Ho: Normality ; c: Ho: No ARCH

The ARCH-in-Mean term in Table 43 is, unlike that in the examination of daily seasonality (Table 26), significant or nearly so in all cases. Interpreting the coefficients on the monthly dummies as the difference in risk profiles of each month vis-à-vis that of December (whose contribution is subsumed in the constant of the variance equation, in each case being significant) we that we can begin to assert the importance of individual months. For the ISEQ and ISEQR, the months that are important are all save September and November; for ISEFIN all bar November, and for ISEGEN only

January, July, September and November. Note again the absence of April as an important month in a number of the indices.

12. Investigation Of Hypotheses

Refreshing our memory from the discussion in 2 & 4, we can find the following hypotheses discussed in the literature to explain the daily seasonal.

Market Settlement Hypotheses

These are divisible into two main categories:

- Settlement Interest Effects
  - Daily seasonality disappears if we account for the cost of carry using the risk free rate of interest
  - Daily seasonality disappears if we account for liquidity effects
- Settlement Delays
  - Daily seasonality will disappear if we account for effect of the settlement system

News Specific to the Market

- Daily seasonality is caused by unspecified market specific information arrival: (The daily seasonality pattern in the % of firms whose price rises/falls/unchanged mirrors the pattern of daily seasonality of returns and risk)
- Daily seasonality is caused by the arrival of macroeconomic information, and will disappear when we account for the daily pattern of market sensitive macroeconomic information releases.
- Firm Specific News

- An index of firms reporting on any given day displays different seasonal patterns from the index of firms reporting on all other days (Daily seasonality is caused by firm specific information arrival
- Firms that release 'bad news' over the weekend display different daily seasonal patterns to those that do not so release.

❖ Daily seasonality disappears if adjust the data for dividend payments

❖ Daily seasonality disappears if we adjust the data to account for ex-dividend dates

It is clear that these hypotheses, while not in opposition to each other, rely on fundamentally different causal mechanisms to induce seasonality. It is also clear that a number of these hypotheses assume that what is to be explained is a negative Monday / positive Friday pattern. This is not the case here, except in the case of the ISE Financial indices. For example, the work of Lakonishok and Levi (1982)and those who have followed their route, such as Bell and Levin (1998) assumes two main beliefs. First, it is assumed that the calendar time hypothesis is in fact correct, and second, that there is a negative Monday return occurring from the operation of rolling settlement systems. This is not to be confused with the potential for a negative Monday return occurring from account week settlement.

Likewise, although not explicitly stated anywhere in the literature, it seems reasonable to assume that either there is an effect which moves the market as a whole, whether this be macroeconomic news releases or other news releases, or this news is in fact an aggregation of individual firms reporting better or worse news, a firm specific news announcement. If both of these factors are operating simultaneously, there is no guide in the literature as to a test that may allow the researcher to distinguish between them.

Appealing to Occam's Razor, the philosophical principle that states that where there are two equally appealing causal mechanisms to a particular phenomenon the simplest should be accepted as the probable cause, it seems reasonable to investigate first of all whether or not any one of these sets of hypotheses seems reasonable. If for example we find the change in the settlement system has no effect on the seasonality, in that seasonality remains and in a manner for which the literature has not suggested an explanation, then it would appear profitless to pursue sub hypotheses relating to settlement systems and settlement liquidity. If the Pettengill and Buster (1994) test procedure indicates that it is unlikely that the seasonality is as a result of news arriving in, as opposed to being generated within, the market then in a similar manner it would seem reasonable not to examine the Steeley (2001) hypothesis that it is macroeconomic news releases that drive the daily seasonal. It should also be borne in mind that nowhere in the literature surveyed does any researcher suggest a mechanism that will induce positive Wednesday returns, which seems to be the prevailing feature of the main indices that demonstrate significant and persistent seasonality.

12.1. Settlement Hypotheses In General

A number of the hypotheses adduced in the literature to explain daily seasonality revolve around the existence of a settlement system, which has the potential to induce particular daily seasonals. Clearly, if the settlement system has an effect on the observed pattern of daily seasonality, as hypothesised by Donnelly (1991), Bell and Levin (1998) etc, then one immediate consequence will be that as the settlement system changes so too will the pattern of seasonality. A simple test therefore for the hypothesis that the settlement system is a proximate cause of the daily seasonal is to examine such pattern under different settlement regimens. If it is found that the move from one settlement system to another results in a change in the observed daily pattern of stock returns then investigation can be focused on the particular time period within which the seasonal pattern of interest manifests itself. In Ireland, over the period under examination, there have been three separate settlement systems[69]. This provides a natural experiment that would allow investigation of the hypothesis. As noted in section 6.3, the settlement week system was in use up to July 1994, after which a rolling settlement system operated. Although the settlement system was initially on a 10-day basis, subsequently this reduced to 5 days. In both rolling systems the expectation is that rolling settlement results in less observed daily seasonality than the fixed settlement system. In fact, Jaffe and Westerfield (1985) show, analysing the Canadian settlement system, that such a rolling settlement should have no effect on the expected returns for any weekday. The settlement system hypotheses however are predicated on the assumption that there is a negative Monday. This is not the case here.

12.2. SETTLEMENT SYSTEM CHANGES AND DAILY SEASONALITY

A settlement week system, as we have seen in 4.1.1, 4.1.2 and 6.3.5 can induce settlement effects. Generally, researchers have found the expected effect, which the first Monday of an account period should exhibit a higher return than Mondays that are not at the start of such a period. However, in the light of the results obtained in Chapter 9, concerning the two indices for which there is agreement as between parametric and non-parametric methods as to the existence of a daily seasonal, the ISEQ and the ISE-Financial indices, this would seem prime facia to rule out a settlement effect. Recall

[69] One – the fixed settlement system; two –the 10 day rolling settlement; three- the five day (as at present) rolling settlement system. As the 10 day system was in existence for less than a year, and as the system was a simple multiple of the five day system, the analysis of the effect of such settlement systems has been conditioned on two regimes : fixed (to July 1994) and rolling thereafter.

from Table 15 & Table 17 that in these indices there is no hard evidence either for a Monday seasonal or for a negative Monday return. However for the ISEQ and ISEQ dividend inclusive index, Monday coefficients are statistically insignificant in a regression which exhibits overall statistical significance. Table 15 & Table 17 reinforce this uncertainty. It is therefore not clear what is the pattern of Monday returns. Were we able to assert that Monday returns were negative this would be in line with international market analyses. Were it to be possible to assert Monday returns as positive this might indicate that the settlement-system-induced high return on those Mondays on which the account period opened dominated the general tendency for Mondays to be negative[70]. Neither possibility is credible here, although the evidence may point slightly towards the former, even though almost without exception the return on Monday is positive. However, a formal test of how, if, seasonality and settlement regimes are related is warranted.

TABLE 45: DAILY RETURN AND STANDARD DEVIATION BY SETTLEMENT REGIME 1988-1998

		Total		Fixed Settlement (to July 1994)		Rolling Settlement (from July 1994)		Change from fixed to rolling	
		Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
ISEQ	Monday	0.00	0.45	-0.006	0.48	0.016	0.395	0.02	-0.08
	Tuesday	0.03	0.41	0.020	0.38	0.049	0.463	0.03	0.09
	Wednesday	0.05	0.39	0.026	0.39	0.097	0.365	0.07	-0.03
	Thursday	0.03	0.37	0.041	0.34	0.015	0.412	-0.03	0.07
	Friday	0.01	0.35	-0.006	0.34	0.033	0.368	0.04	0.02
ISEFINS	Monday	-0.01	0.57	-0.021	0.61	0.005	0.512	0.03	-0.10
	Tuesday	0.05	0.55	0.024	0.49	0.100	0.631	0.08	0.14
	Wednesday	0.06	0.54	0.010	0.55	0.133	0.506	0.13	-0.05
	Thursday	0.04	0.57	0.040	0.51	0.050	0.644	0.01	0.13
	Friday	0.01	0.49	0.000	0.49	0.020	0.500	0.02	0.01

[70] This finding of a settlement induced Monday seasonal is the result found in Donnelly (1991).

Table 45 shows the daily returns and standard deviations broken down by settlement system. For the most part, daily returns are greater, but not markedly so, under the rolling settlement system. A move from fixed to rolling settlement is expected to have the effect on Monday returns of reducing them if the settlement interest hypotheses of Lakonishok & Levi and Bell & Levin were correct, but this has not in fact occurred. It is interesting to note that the ISEQ index over account week settlement demonstrates a pattern similar to that found by Donnelly (1991) in his analysis of non account week returns.

For risk, as proxied by standard deviation, the pattern is clearer. Risk has reduced on Monday and Wednesday as we move from fixed to rolling settlement, but overall risk levels are increased. Table 46shows the variance across days of the week differs across settlement regimes. Under account period settlement, we cannot reject this hypothesis for any but the trimmed dividend inclusive index, at a 10% level of significance. However, under the rolling settlement system we cannot accept that the variances are equal across the days of the week. Thus, the introduction of rolling settlement appears to be associated with an increase in daily seasonal effects in the risk profile of the indices. This is not predicted in the literature.

TABLE 46: TESTING FOR EQUALITY OF VARIANCE BY DAY OF THE WEEK UNDER DIFFERENT SETTLEMENT SYSTEMS.

	Account Period Settlement		Rolling Settlement	
	Levene's Test	Sig.	Levene's Test	Sig.
ISEQ	76.441	0.00	0.199	0.939
ISEFIN	2.095	0.079	0.685	0.603

TABLE 47: KRUSKAL WALLIS H TEST OF DAILY SEASONALITY BY SETTLEMENT REGIME

	Rolling Settlement		Fixed Settlement	
	Chi-Square	Sig.	Chi-Square	Sig
ISEQ	11.32	0.02	6.49	0.17
ISEFINS	15.84	0.00	5.65	0.23

TABLE 48: PAIR WISE ANALYSIS OF DIFFERENCES IN MEAN RETURN BY DAY OF THE WEEK UNDER DIFFERENT SETTLEMENT REGIMES

		Tuesday		Wednesday		Thursday		Friday	
Fixed Settlement:		Diff.	Sig	Diff.	Sig	Diff.	Sig	Diff.	Sig
Tukey's HSD Test									
ISEQ	Monday	0.02	0.98	-0.09	0.01	-0.02	0.97	0.00	1.00
	Tuesday			-0.11	0.00	-0.03	0.75	-0.01	0.99
	Wednesday					0.08	0.04	0.10	0.00
	Thursday							0.02	0.94
ISEFIN	Monday	0.01	0.99	0.01	1.00	-0.01	1.00	0.04	0.68
	Tuesday			-0.01	1.00	-0.02	0.97	0.03	0.90
	Wednesday					-0.01	1.00	0.03	0.77
	Thursday							0.04	0.89
Floating Settlement:									
Tamhanes Test									
ISEQ	Monday	-0.03	1.00	-0.08	0.32	0.00	1.00	-0.02	1.00
	Tuesday			-0.05	0.94	0.03	1.00	0.02	1.00
	Wednesday					0.08	0.29	0.06	0.55
	Thursday							-0.02	1.00
ISEFIN	Monday	-0.02	1.00	-0.06	0.76	0.02	1.00	0.01	1.00
	Tuesday			-0.04	0.99	0.04	0.99	0.03	1.00
	Wednesday					0.07	0.44	0.06	0.56
	Thursday							-0.01	1.00

TABLE 49: ROBUST ANALYSIS OF DAY OF THE WEEK EFFECT BY SETTLEMENT REGIMEN

	Bayes t/f Stat	Variable	OLS Coeff	T-Stat	Sig	AR Coeff	T-Stat	Sig	LAD Coeff	T-Stat	Sig	Bayes t/f Stat	TLS Coeff	T-Stat	Sig
Fixed Settlement															
ISEQ	2.75	MON	0.02	0.59	0.55	0.02	0.73	0.46	0.02	1.65	0.10	2.73	0.02	0.01	0.13
N=1980	2.75	TUE	- 0.04	- 1.36	0.17	-0.04	-1.57	0.12	-0.01	-0.84	0.40	2.73	0.01	0.01	0.42
Trimmed N = 1789	2.75	WED	0.14	5.57	0.00	0.14	3.40	0.00	0.11	3.43	0.00	2.73	0.06	0.01	0.00
	2.75	THU	0.01	0.51	0.61	0.01	0.70	0.49	0.02	1.71	0.09	2.73	0.03	0.01	0.01
	2.75	FRI	0.01	0.38	0.70	0.01	0.69	0.49	0.01	0.88	0.38	2.73	0.01	0.01	0.27
F Statistic	7.65			6.77	0.00		17.45	0.00		6.45	0.00	7.53		18.91	0.00
ISEFINS	2.47	MON	- 0.01	- 0.19	0.85	-0.01	-0.19	0.85	0.02	1.64	0.10	2.44	-0.01	- 0.33	0.74
N=455	2.47	TUE	- 0.08	- 1.29	0.20	-0.08	-1.43	0.15	-0.01	-0.87	0.38	2.44	0.03	0.83	0.41
Trimmed N=401	2.47	WED	- 0.05	- 0.83	0.41	-0.05	-0.73	0.46	0.11	3.48	0.00	2.44	0.01	0.19	0.85
	2.47	THU	0.06	1.04	0.30	0.06	1.03	0.30	0.02	1.68	0.09	2.44	0.07	1.77	0.08
	2.47	FRI	0.00	0.02	0.98	0.00	0.02	0.98	0.01	0.85	0.39	2.44	0.02	0.62	0.53
F Statistic	6.27			0.79	0.53		5.37	0.37		19.08	0.00	6.16		0.87	10.50
Rolling Settlement															
ISEQ															
N=1003	2.63	MON	0.02	0.55	0.58	0.02	0.57	0.57	-0.00	-0.15	0.88	2.60	0.01	0.42	0.67
Trimmed N = 891	2.63	TUE	0.05	1.76	0.08	0.05	1.53	0.13	0.06	3.13	0.00	2.60	0.07	3.74	0.00

	Bayes t/f Stat	Variable	OLS Coeff	T-Stat	Sig	AR Coeff	T-Stat	Sig	LAD Coeff	T-Stat	Sig	Bayes t/f Stat	TLS Coeff	T-Stat	Sig
	2.63	WED	0.10	3.46	0.00	0.10	3.84	0.00	0.09	4.40	0.00	2.60	0.09	5.11	0.00
	2.63	THU	0.02	0.56	0.58	0.02	0.54	0.59	0.04	1.86	0.06	2.60	0.05	2.95	0.00
	2.63	FRI	0.03	1.17	0.24	0.03	1.29	0.20	0.05	2.57	0.01	6.89	0.07	3.68	0.00
F Statistic	7.00			1.41	0.23		23.71	0.00		39.29	0.00			12.52	0.00
ISEFINS	2.63	MON	0.00	0.12	0.91	0.00	0.13	0.90	-0.03	-1.03	0.30	2.60	-0.02	- 0.68	0.50
N= 1003	2.63	TUE	0.10	2.55	0.01	0.10	2.28	0.02	0.11	3.70	0.00	2.60	0.10	3.91	0.00
Trimmed N=875	2.63	WED	0.13	3.39	0.00	0.13	3.78	0.00	0.12	3.92	0.00	2.60	0.10	3.97	0.00
	2.63	THU	0.05	1.28	0.20	0.05	1.12	0.26	0.07	2.14	0.03	2.60	0.06	2.46	0.01
	7.00	FRI	0.02	0.52	0.60	0.02	0.59	0.56	0.04	1.35	0.18	6.87	0.04	1.55	0.12
				1.82	0.12		24.11	0.00		36.51	0.00			7.99	0.00

Shown in Table 47 is a non-parametric analysis of the extent of daily seasonality under the differing settlement regimes. The evidence here is that from a non-parametric perspective, we can only accept the existence of daily seasonality under rolling settlement.

Table 48 shows pair-wise differences in daily mean returns across settlement regimens, using either Tukey's or Tamhane's tests. The test chosen depends on the results from Table 46. From this we see that under account week (fixed) settlement statistically significant differences appear as between Wednesday and all other days for the ISEQ. No other statistically significant daily differences appear in this analysis. All analyses of account week settlement systems, from Jaffe and Westerfield (1985), through Condoyanni, O'Hanlon and Ward (1987) to Donnelly (1991) indicate that if account week settlement does induces a daily seasonal then this should manifest itself on a Monday. The result here is a strong indication that whatever the causal mechanism is of daily seasonality in the Irish market it is unlikely to be the account week settlement system that operated up to 1994.

Despite the evidence that the daily seasonal in risk is stronger under rolling settlement, as seen in Table 46, the pair-wise differences in mean return are all statistically insignificant. Rolling settlement system introduction appears therefore to have resulted in the major indices displaying a set of mean return characteristics more in keeping with the predictions of the standard financial economics model (no seasonal) than was the case under account week settlement. Table 49 shows a robust parametric analysis of the daily coefficients conducted along similar lines to Table 46. What is noticeable is that while the ISEQ shows seasonality, by means of the regression F statistic, under all forms of adjustment under fixed settlement, under rolling settlement it is only after adjusting for known characteristics of the index that such seasonality becomes evident. The ISEFIN demonstrates seasonality only under LAD estimation for fixed settlement, while under rolling settlement it too exhibits seasonality under all bar OLS estimation. Wednesday appears significant under all forms of estimation for the ISEQ under both fixed and rolling settlement, while for the ISEFIN index it is only under rolling settlement that we find Wednesday significant other than under LAD estimation. Tuesday becomes significant only under adjusted estimation procedures under rolling settlement.

There is therefore some conflict as between the parametric and non-parametric statistical evidence as to the effect of introducing rolling settlement. The parametric evidence indicates that the extent of daily seasonality has increased, while the non-parametric evidence is that if anything it has decreased. It is clear however, that two facts arise from this analysis. First, the conditions necessary for further investigation of settlement hypotheses, namely that there be persistent and consistently negative returns on Mondays with persistent and consistently positive returns on Friday, and that changes in the settlement system are associated with changes in the seasonality pattern, are not met unambiguously. Second, the change in the settlement system has had an effect on the seasonality, but analysis of change is not statistically robust. Therefore, I conclude that the settlement system is unlikely to be the cause for the daily seasonal in the Irish equity market.

12.3. News In The Market Or News To The Market?

Pettengill and Buster (1994) attempt to distinguish between an effect caused by firm specific news to one caused by news that affects the entire market, as has been noted earlier. One issue that immediately arises in the Irish context is that with the exception of the Datastream indices there are no published rise/fall/unchanged statistics for the indices under investigation. To overcome this I undertook an analysis of the constituents of the ISEQ, ISE Financial and Datastream indices. At all periods the constituents of the Datastream market index and financial index consisted exclusively of a subset of the ISEQ and ISE Financial constituents. Thus, using these Datastream indices of rises/falls/unchanged as a basis I calculated indices of ISEQ and ISE Financial rises/falls/unchanged. Table 50 shows the daily variation in proportions of firms showing rises, falls or remaining unchanged in price for the ISEQ and ISE financial Indices.

Table 50: Comparison Of Mean Index Return And Proportion Of Securities Direction 1988-1998

	Monday	Tuesday	Wednesday	Thursday	Friday	Total
ISEQ	0.002	0.031	0.052	0.032	0.008	0.025
ISEQ-Rises	23.664	24.913	24.251	24.122	24.739	24.351
ISEQ-Falls	22.916	22.391	22.303	22.760	22.103	22.486
ISEQ-Unchanged	53.420	52.696	53.446	53.118	53.159	53.163
ISEFINS	-0.011	0.054	0.057	0.044	0.008	0.031
ISEFIN-Rises	20.259	22.303	21.920	21.604	23.253	21.901
ISEFIN-Fall	19.803	19.573	18.026	19.657	17.318	18.855
ISEFIN-Unchanged	59.937	58.124	59.853	58.537	59.428	59.161

TABLE 51: ANALYSIS OF DIFFERENCES IN MEAN PROPORTIONS OF RETURN DIRECTION BY DAY OF WEEK.

	Kruskal-Wallis H Test		ANOVA F Test	
	Chi-Square	Sig	F	Sig
ISEQ Index				
Rises	1.642	0.801	0.64	0.63
Falls	1.316	0.859	0.40	0.81
Unchanged	1.772	0.778	0.20	0.94
ISE Financial Index				
Rises	6.431	0.169	1.75	0.14
Falls	12.002	0.017	2.51	0.04
Unchanged	6.168	0.187	1.02	0.39

For the ISEQ index the highest mean return is on a Wednesday with the highest proportion of rises on a Tuesday. The lowest mean return is on Monday, with it and Thursday showing essentially the same, highest, proportion of falling stocks. For the ISE Financial Index the highest mean return occurs on Wednesday with the highest proportion of rising stocks occurring on Tuesday with the second highest occurring on Wednesday. The lowest mean return occurs on Monday, which is the day with the highest proportion of falling stocks.

The work of Pettengill and Buster (1994) assumes implicitly that the market reacts in certain ways. It assumes that there is no lag in the market as between a high proportion of falling or rising stocks and mean return, and it assumes that the market reacts symmetrically to rising and fallings stocks. While these may be reasonable assumptions, especially in the liquid US market it may be that some lags and asymmetric responses occur in less liquid and less sophisticated markets. Regardless of this, for both indices the low mean return – high proportion of falling stocks relationship posited by Pettengill and Buster is evident. The High mean return – high proportion of rising stocks is present only with a one-day lag in the ISEQ and ISE

Financial indices. Thus, there exists at least some evidence that a market wide phenomenon may be at work.

This can be formally tested by means of an analysis of variance, parametric or non-parametric (Kruskal-Wallis H). Table 51 shows the results of these analyses of variance to investigate the hypothesis that there exist differences in these proportions. Both indicate that, with the exception of the ISE financial index proportion of falls we cannot accept at a 5% level of significance that there is a significant variation across days of the week in terms of the proportion of shares showing a particular sign. This evidence is robust to parametric and non-parametric methods of investigation. Thus, while the statistical evidence indicates that a market wide effect is not in operation this conflicts with the observed evidence; the relationship between the low mean return and high proportion of falling stocks along the lines posited by Pettengill & Buster being observable in the ISE Financial index.

It would seem reasonable therefore, to assume that there is some evidence that for financial stocks in the Irish market a market wide news arrival causes the observed daily seasonality. However, despite the high weight of financial stocks in the ISEQ index as a whole this market wide news arrival does not appear to carry through to the overall market.

12.4. Firm Specific News And Its Effect On The ISEQ

The results of work by such as Patell and Wolfson (1982),Penman (1987),Aboudi and Thon (1994) and Aggarwal and Schatzberg (1997) indicates that there is no clear link between firm specific news releases and daily seasonality. Indeed, when placed alongside the results of the study by Berry and Howe (1994) of news releases by

Reuters, showing an inverted U shape with most news releases on Tuesday-Wednesday-Thursday , and similar results for dividends by Schatzberg and Datta (1992), there seems little doubt that , for the US , the release of firm specific news may not be a significant cause of the weekend/Monday effects. Given however that the daily seasonal in the ISEQ index is a mid-week seasonal it seems plausible that results, earnings and other firm specific announcements may, if they cluster in the early part of the week, provide an explanation. However almost without exception (only 5 instances over 10 years for 30 stocks) Irish stocks go ex dividend on days other than Monday. Going ex-dividend leads to a reduction in the price that an individual will pay for a stock, reducing the Monday return. As the seasonal here is a positive Wednesday seasonal, the dividend status of the stock seems not to offer a solution. Accordingly, for the 10 non-financial equities with the largest contribution (in terms of market value) to the ISEQ over the period 1993-1998[71] details of the days on which they release dividend/earnings information was sought from the Financial Times FT-McCarthy Database. This covers the Financial times, other leading UK newspapers, as well as the Investors Chronicle, and the major Irish daily and Sunday newspaper Table 52 provides details of the reportage seasonality. Over the course of the period the market value of the top 10 companies fluctuated between 75 and 80% of the total ISEQ value. Thus an analysis of the information releases of these companies can be expected to act as a good proxy for those of the ISEQ as a whole.

[71] See **Table 4**

TABLE 52: INFORMATION SEASONALITY OF LARGE NON-FINANCIAL FIRMS 1993-1998

Day	#	%
Monday	19	20.88%
Tuesday	28	30.77%
Wednesday	30	32.97%
Thursday	12	13.19%
Friday	2	2.20%

12.4.1. MICROECONOMIC NEWS SEASONALITY & THE ISEQ INDEX

The tendency, it is evident from Table 52, is for information to be released most frequently on Tuesday and Wednesday. This invested U shape of reporting seasonality follows a similar pattern to that noted in the US, as commented on earlier. However, the majority of the news releases occur prior to the Wednesday peak in the ISEQ. To test whether the company data releases have any significant effect on the daily seasonal pattern I estimated the equation $ISEQ_t = \sum_{t=1}^{n} \alpha_t D_t + \beta CODAT + \varepsilon_t$, over the 1993-1998 period, where CODAT takes the value 1 on a day when company results are announced and 0 otherwise. The α coefficients are now conditional mean returns. If company announcements provide an adequate explanation of the daily seasonal we should see that (1) there is a substantial change in the daily return means, and (2) the β coefficient should be statistically significant. The estimated equation parameters are show in Table 53

TABLE 53: ROBUST EXAMINATION OF THE EFFECT OF COMPANY ANNOUNCEMENTS ON DAILY SEASONALITY IN THE ISEQ

	OLS			AR			LAD			TLS		
Variable	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig
MON	0.03	1.29	0.20	0.03	1.22	0.22	-0.01	-0.51	0.61	0.02	1.00	0.32
TUE	0.06	2.63	0.01	0.06	2.41	0.02	0.03	2.29	0.02	0.06	3.67	0.00
WED	0.08	3.41	0.00	0.08	3.47	0.00	0.04	2.87	0.00	0.08	5.08	0.00
THU	0.03	1.45	0.15	0.03	1.55	0.12	0.04	3.12	0.00	0.05	3.20	0.00
FRI	0.01	0.57	0.57	0.01	0.64	0.53	0.01	0.76	0.44	0.03	2.20	0.03
CODATA	-0.04	-0.99	0.32	-0.04	-0.86	0.39	-0.00	-0.03	0.97	-0.02	-0.73	0.47
F (5,1506)		1.13	0.34		18.45	0.01		24.27	0.00		1.86	0.10

The results from Table 53 provide mixed evidence as to the importance of microeconomic seasonality. The CODATA dummy variable is not in itself significant, under either classical or Bayesian assumptions and under various adjustments to the residuals of the series, and in fact seems to indicate that on average the market perceives the average company announcement to be negative. However, the coefficients on the daily dummies, which are the mean return on these days to the ISEQ when the effect of any company announcement are factored in, have almost all increased from the unconditional means, with the exception of that for Friday returns. In all cases, these differences in mean returns and mean returns conditional on microeconomic information seasonality are statistically significant, although Wednesday returns remain the largest of the week. Tuesday conditional mean returns, while significant under classical assumptions are not so under Bayesian assumptions [72]. Thus, while there is some evidence that the microeconomic seasonality of company accounts releases has an effect on the daily seasonality it would not seem to provide a full explanation.

[72] The equation above assumes instantaneous transmission of information and reaction to the company releases. However, it is also reasonable to assume that there is some delay in the process of incorporation of information. Replacing the CODATA variable with its lagged value, CODATA-1 allows for examination of this hypothesis. Little change occurs in the conditional mean returns and CODATA-1 is insignificant under classical and Bayesian assumptions, regardless of any adjustment made to the residuals.

12.5. Macroeconomic News Arrivals And The ISE Financial Index

12.5.1. Macroeconomic News Arrivals Revisited

Based on the analysis of rises/falls and their relationship with the pattern of mean returns, section 10.3 indicated that for the ISE financial index a hypothesis of market wide news arrivals affecting the mean daily returns was a reasonable starting point. This raises the issue immediately of what type of news.

Research has concentrated on the perspective of macroeconomic news, as distinguished from micro, firm specific, news, as being a potential cause of daily seasonality. Some papers, such as Chang, Pinegar and Ravichandran (1993) have used the innovations in the returns of large company stocks as a proxy for macroeconomic news. Another approach, characterised by the papers of Liano and Gup (1989)and Kohers and Kohers (1995) have investigated shifts in daily seasonal patterns when the economy is in an expansionary as opposed to a contractionary phase, concluding that day of the week effects are generally stronger in contractionary environments.

It is only in Steeley (1999) that we see an examination directly of the daily patterns of news releases and how, if, these relate to the pattern of daily seasonality in the UK. Steeley partitions the data according to whether or not there is a macroeconomic announcement of potential interest, or not. The set of macroeconomic variables whose announcement or release believed potentially important is inflation, labour market conditions, government borrowing, official interest rate changes and money supply. He finds that although there are no statistically discernable day of the week effects overall that partitioning the data into positive and negative returns series both leads to significant day of the week (here Monday and Friday returns) effects in the negative, bear market, conditions and that this pattern is strengthened when the negative returns series is conditioned on announcements. Thus, he concludes, there is support for the contention that macroeconomic announcements are a potential cause of the day of the week effect. Steeley also finds that the impact of the information release differs as to the kind of information released.

12.5.2. MACROECONOMIC INFLUENCES ON THE ISE FINANCIAL INDEX

While there is no dearth of published research on the Irish financial system there has been no study that has focused on the empirics of the relevant stock market index, the ISE Financial Index. Clearly therefore there is no body of research to draw on to ascertain the macroeconomic influences on the index. Accordingly, the researcher is forced to infer such inferences from the known concentration of financial stocks (see for example Bacon Associates (1999)) and the literature on the macro dynamics of the market as a whole. The most prominent research in the literature is Gallagher (1995),Gallagher and Twomey (1998), Devine (1996) and Kearney (1998). However, with the exception of Devine none of these papers has focused directly on the issue of the macroeconomic influences on the Irish market. None of these examined the ISE financial sector index. Gallagher examines, in both papers, the influences of other national markets on the changes in the Irish market.

Kearney examines the causes of volatility over the 1975-1994 period, using monthly data. He finds that, after changes in the ISEQ and the FTSE indices that the macroeconomic determinants of changes in the ISEQ are changes in interest rates and industrial production. Devine proceeds by means of data selection from two sources;

applications of the Arbitrage Pricing Theory and interviews with market participants. With the variables thus identified a Vector Auto-regression analysis identified that the macroeconomic variables, which most influenced monthly stock returns on the ISEQ index, were the 10-year bond yield, the dollar exchange rate, and the three-month interbank rate. Industrial and retail economic output indicators had little impact on the market.

From the work of the authors above, we see that a number of macroeconomic data series are associated with movements in the main indices under examination. Of those variables that are determined exogenously to the markets, the official interest rate appears to be the only major influence. However, for completeness sake, as well as to allow comparison with Steeley, it was determined that collection of the release dates of the major industrial as well as financial series would be useful. Accordingly, release dates of the following data for the 1988-1998 period were sourced from the Central Statistics Office and the Central Bank of Ireland ; From the CSO, National Income and Expenditure, Balance of International Payments, Industrial Production & Industrial Employment, Consumer , Wholesale and Agriculture Price Indices, numbers of persons on the Liver Register (unemployment claims) and Output, Input and Income in Agriculture: From the Central Bank of Ireland the relevant monetary and financial statistics, Official External Reserves, Official Lending Rate (the central bank lending rate charged to the interbank market), domestic credit growth and Broad Money (money and other liquid assets). From January 1988 onwards, coinciding with the start of the series under investigation, the central bank adopted a policy of releasing the Monthly Statistical Bulletin on the first Thursday of the month.[73] Notification of changes in

[73] The author of this work was, at the time of this decision, the relevant officer in the statistical division of the Central Bank of Ireland, and thus the person responsible for this harmonisation of release dates.

official interest rates, defined here as the Short Term Facility, or STF, can occur of course on any date. Table 54 provides details of these releases.

TABLE 54: MACROECONOMIC INFORMATION SEASONALITY 1988-1998

	Monday	Tuesday	Wednesday	Thursday	Friday
Numbers					
All Releases	96	67	69	251	142
Industrial, BOP & GNP	14	28	26	53	26
Central Banking Data				119	
Agriculture	24	16	31	32	30
CPI	2	7		29	16
Unemployment	34	13	6		67
STF Rate Change	22	3	6	18	3
Percentage					
All Releases	15.36%	10.72%	11.04%	40.16%	22.72%
Industrial, BOP & GNP	9.52%	19.05%	17.69%	36.05%	17.69%
Central Banking Data				100.00%	
Agriculture	18.05%	12.03%	23.31%	24.06%	22.56%
CPI	3.70%	12.96%		53.70%	29.63%
Unemployment	28.33%	10.83%	5.00%		55.83%
STF Rate Change	42.31%	5.77%	11.54%	34.62%	5.77%

Steeley (2001) examines UK macroeconomic information releases, and indicates that the majority of these releases are concentrated at midweek. This is not the case here.

12.5.3. MACROECONOMIC NEWS SEASONALITY & THE ISE FINANCIAL INDEX

Table 55 shows the results of a series of robust regressions with the dependent variable being the ISE Financial Index, with separate results for those days on which there is and is not a macroeconomic announcement. We note that in no case is the macroeconomic announcement dummy statistically significant. Table 56 shows the results of a test of pairwise mean daily differences. The test used is Tamhane's T^2 test, as Levene's test of homogeneity of variance indicated that both the sub samples, days with and without macroeconomic announcements, displayed significant differences in variance of mean daily returns[74]. The results of this test, in both sub-samples, indicate no evidence of daily differences.

[74] The test statistics were 1.354 and 2.256, with marginal significance levels of .249 and .096, for daily mean returns on days with and without macroeconomic releases, respectively.

TABLE 55: ROBUST ANALYSIS OF MACROECONOMIC SEASONALITY AND DAILY SEASONALITY, ISE FINANCIAL INDEX 1988-1998

	Unconditional Mean	OLS			AR			LAD			TLS		
		Coeff	T	Sig	Coeff	T	Sig	Coeff	T	Sig	Coeff	T	Sig
MON	-0.011	-0.006	-0.239	0.811	-0.006	-0.235	0.814	-0.031	-1.536	0.125	-0.017	-0.998	0.319
TUE	0.054	0.057	2.349	0.019	0.057	2.257	0.024	0.056	2.871	0.004	0.058	3.577	0.000
WED	0.057	0.060	2.461	0.014	0.060	2.476	0.013	0.052	2.478	0.013	0.052	3.243	0.001
THU	0.044	0.054	2.018	0.044	0.054	2.049	0.040	0.059	3.005	0.003	0.057	3.232	0.001
FRI	0.008	0.014	0.569	0.569	0.014	0.650	0.516	0.014	0.762	0.446	0.021	1.287	0.198
Macro		-0.023	-0.865	0.387	-0.023	-0.815	0.415	-0.019	-0.918	0.359	-0.014	-0.773	0.440
F			1.340	0.244		13.278	0.039		24.422	0.000		5.965	0.000

TABLE 56: PAIRWISE ANALYSIS OF DAILY SEASONALITY AND MACROECONOMIC ANNOUNCEMENTS

Panel A: Days with Macroeconomic Announcements								
	Tuesday		Wednesday		Thursday		Friday	
	Diff	Sig	Diff	Sig	Diff	Sig	Diff	Sig
Monday	-0.13	0.762	-0.14	0.747	-0.1	0.955	-0.04	1.000
Tuesday			-0.01	1.000	0.038	1.000	0.099	0.795
Wednesday					0.046	0.999	0.107	0.792
Thursday							0.061	0.984

Panel B: Days without Macroeconomic Announcements								
	Tuesday		Wednesday		Thursday		Friday	
	Diff	Sig	Diff	Sig	Diff	Sig	Diff	Sig
Monday	-0.13	0.089	-0.14	0.857	-0.100	0.908	-0.04	1.000
Tuesday			-0.01	1.000	0.038	1.000	0.099	0.993
Wednesday					0.046	1.000	0.107	0.988
Thursday							0.061	0.995

The evidence from Table 56 shows no evidence of any days being different in their returns from any other day, using Tamhane's T2 test. Clearly however, from Table 55 the macroeconomic announcements are causing some alteration in the pattern of daily seasonality even though the evidence from there is that there is no statistically significant effect on the pattern of daily seasonality.

Steeley (2001) suggests a test to ascertain which, if any, of the macroeconomic variables are causing such changes. This takes the form of a regression of the index return on its own lagged value, to account for autocorrelation, and on a series of dummy variables, each corresponding to a particular macroeconomic announcement. His results indicate that base rate changes are the most important in terms of daily seasonality. Steeley also includes a dummy variable for Monday. Although to that stage in the paper no clear and unambiguous Monday effect was evident, the evidence in the UK is that there is at least an intermittent Monday seasonal, which, although not explicitly stated, presumably motivates the inclusion of the Monday dummy. In the case of the ISEFIN, conditioned on macroeconomic announcements, there is no clear candidate for a daily seasonal. However, Table 48 & Table 49 provide some evidence that, especially under rolling settlement (post 1994) that Tuesday and Wednesday are important. Therefore Table 57shows the results of series of robust regressions of the form below:

$$R_t = \alpha_T T + \alpha_w W +$$
$$\beta_I Indata_t + \beta_{CB} CBdata_t + \beta_{AG} AGdata_t + \beta_{CPI} CPI_t + \beta_{UE} UE_t + \beta_{STF} CBrate_t + \varepsilon_t$$

where T and W refer to dummies taking the value 1 on Tuesday and Wednesday respectively, Indata, CBdata , AGdata, CPI, UE and CBrate are dummies that take the value 1 on days when Industrial, Central Bank, Agriculture, Consumer Prices, Unemployment and Short-term Facility Rate Change data are announced and 0 otherwise. This is estimated only over the post 1994, rolling settlement period.

TABLE 57: MACROECONOMIC ANNOUNCEMENT EFFECTS ON DAILY SEASONALITY: ROLLING SETTLEMENT ONLY

	OLS			AR			LAD			TLS		
Variable	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig	Coeff	T-Stat	Sig
TUE	0.102	2.590	0.010	0.102	2.240	0.025	0.052	2.688	0.007	0.087	3.519	0.000
WED	0.125	3.161	0.002	0.125	3.461	0.001	0.048	2.276	0.023	0.096	3.859	0.000
INDATA	0.085	1.164	0.245	0.085	1.318	0.187	0.056	1.723	0.085	0.026	0.576	0.565
CBDATA	0.045	0.544	0.586	0.045	0.447	0.655	0.041	1.015	0.310	0.067	1.314	0.189
AGDATA	0.039	0.511	0.609	0.039	0.439	0.661	-0.012	-0.307	0.759	0.001	0.020	0.984
CPI	-0.151	-1.514	0.130	-0.151	-0.910	0.363	0.019	0.247	0.805	0.154	2.312	0.021
UE	-0.098	-1.200	0.230	-0.098	-1.132	0.258	-0.088	-2.271	0.023	0.034	0.665	0.506
CBRATE	0.390	2.069	0.039	0.390	1.228	0.219	0.063	0.822	0.411	-0.031	-0.243	0.808
		3.526	0.000		25.041	0.002		23.009	0.003		4.930	0.000

It is again not immediately clear what is the effect of various announcements on the financial system. The daily dummies remain significant throughout the various estimation procedures and the overall significance remain via the F test. Adjusting for Bayesian data however we note that the significance of the daily dummies declines, with neither Wednesday nor Tuesday retaining significance over all estimation approaches. Also, the sign of the dummies for the various macroeconomic announcements is unstable over the various estimation procedures, with no dummy retaining its sign over more than 2 approaches. Thus the effect of the individual announcements seems to vary with the estimation process and is not significant in any case. We may therefore conclude that there is little evidence of macroeconomic announcements being a determining factor in the pattern of daily seasonality in the ISEFIN index

13. Conclusion And Discussion

This work had three main objectives.

By way of setting the scene, a preliminary task was undertaken of reviewing, very briefly, the standard model of asset pricing, showing that little room exists within this for long-term persistence of calendar regularities. The importance of any such regularity for the standard model research programme, or paradigm, was emphasised by a brief survey of the philosophy of science literature, financial economics being at heart and in its origins a social science.

The first objective was to provide a comprehensive review of the extensive literature on calendar regularities in financial asset returns, concentrating on equity returns and on daily regularities. The literature on non-daily seasonal regularities illustrates how research programmes working within the standard model can incorporate such regularities, albeit with difficulty. In completion of the task of reviewing daily seasonality the material was seen to suggest a number of regularities commonly seen in across national markets and over time, particularly that markets open low during the week and close high. This typically manifests itself in abnormally high returns on Fridays and abnormally low returns on Monday, with this Monday effect spilling over into abnormally low returns on Tuesday for what can be classed as satellite markets. The literature has tended to bifurcate. The first branch consists of those papers that concentrate on empirical verification of these regularities, using different statistical and econometric techniques, or using different datasets or subdividing the time period under investigation according to various presupposed regimes. The second branch consists of those works that, while providing reassurance that the phenomenon exists in the frame of interest, attempt to provide and test explanatory hypotheses. A sub literature on returns around public holidays shows that returns prior to these holidays is also significantly higher, and that this effect appears to be driven by local, as opposed to international, causes.

The second objective this work has achieved is provision of an outline of the Irish equity market, placing it in context geographically, in terms of organization and regulation, and in terms of its relationships with the large, liquid, London market. The importance of this task is twofold. First, from the literature reviewed in pursuance of the first task, it is clear that significant potential explanatory power for any daily regularity exists in the microstructure of the market under investigation. Second, the period selected for analysis in the third task is not arbitrary, but emerges from the political economy of the Irish market.

The third objective involved testing the behaviour of equity returns in the Irish market via three sequential elements; methodology, investigation, and hypothesis testing. First, methodological issues are discussed extensively and intensively. This emerges from an analysis of the methods used as noted in the first task, partially from statistical considerations which I believe have not been heretofore given sufficient prominence in the search for daily and other regularities, and partially from considerations of the philosophy of science. Using robust and appropriate methodology, and adapting it as circumstances warrant, I investigate the existence and extent of daily, monthly and holiday seasonality in the Irish equity market. The final element in the sequence that completes task three is the testing of these hypotheses.

The major findings of the work naturally therefore emerge from the third objective. These results are novel in the Irish context, and are internationally novel in both their manifestation and I believe in terms of the variety and complexity of statistics deployed in seeking them. In summary, these are

1) Daily seasonality in the Irish equity market appears to exist across a wide range of indices and index construction methods.

   a) This seasonality is more readily detected using parametric methods, even when these methods have been adjusted to account for the number of data points (what I have called a Bayesian approach), than under non-parametric methods. However, with adjustment to account for the distributional characteristics of the indices the evidence for such seasonality is much weakened.

   b) There is some evidence that a number of indices, in particular the ISEQ and ISE Financial index demonstrate daily seasonality.

   c) The form of this seasonality is unusual as compared to its manifestation in other equity markets. In Ireland, there is almost never a negative Monday/Tuesday. Instead, the predominant form of seasonality appears to be a persistent and positive Wednesday effect.

   d) The daily seasonal appears not to be a risk effect, as there is no evidence that the pattern of varying volatility found reflects the pattern of varying returns.

   e) The daily seasonal appears not to be a reflection of the microstructure, the settlement system, of the Irish equity market. A natural experiment, the changing of the settlement system from a fixed period to a rolling settlement system, in 1994 allows experimentation along these lines

f) There is some evidence that differential news impacts drive the general market index (microeconomic, or firm specific news) and the financial market (macroeconomic news announcements). However, further examination indicates that these news impacts provide at best only a partial explanation for the daily seasonal.

2) The Irish equity market demonstrates a pre-holiday anomaly, with the local effect dominating

3) There is a persistent and important January seasonal in the Irish market, but the April seasonal found in previous literature seems not to be in evidence. This finding is, unlike that for the daily seasonal, robust as to the estimation procedure and the method of interpretation.

Therefore, the daily seasonal, in particular, in the Irish equity market remains a mystery. The main hypotheses found in the literature either provide for explanations that are predicated on a pattern not found here or do not appear to provide a full explanation. One therefore has to ask whether this matters, and if so on what grounds.

There are three main reasons for this finding on daily seasonality being at the least intriguing.

First, while the magnitude of the differences in relative returns across days of the week are low, perhaps indicating that a trading strategy based on them would, after commission and trading costs, be uneconomical, these differential returns, although not statistically robust, do perhaps provide guidance as to trade timing. This approach is well summarised by the title of Yale Hirsch's 1986 volume – *"Don't Sell Stocks on Monday"*. The implication is of course that if one is to sell stocks, any other day (he suggests Friday) is preferable. As to buying and selling, there is no round trip guidance. In the Irish context, over the period under investigation, the high level of commissions and charges would have rendered such round tripping unviable. Thus, the existence, if real and significant, of these regularities would provide us not with an investment strategy but with an investment *timing* strategy. This approach, of seeking a guidance in terms of timing, is exemplified in for example papers such as Kato (1990),Maberly (1995)and Chan, Khanthavit and Thomas (1996).

Second, as a challenge to the prevailing paradigm the existence of unexplained (not inexplicable, as there remains no doubt hypotheses untested or even unformulated which are quite possibly an explanation) daily seasonality is at best mixed. The evidence presented above indicates that it is possible that there do exist daily seasonal patterns in the Irish market, but that this evidence is weak and that the existing hypotheses are at best partial explanations for this. Consequently, either there exists another set of explanations congruent with existing financial economic theory and which is capable of explaining these daily seasonal, or these daily regularities must be classed as truly anomalous.

Third, if we accept the possibility that there exists daily seasonality, why this exists is unclear. The hypotheses posed are inadequate as explanations for the Irish case as they have proved to be so for others. The main area of potential hypotheses that I have not examined, for lack of a clear testable hypothesis, is the area of psychology. Until an explanation arises which is rooted in the psychological domain and which uses the data available to financial economic researchers such a test remains unfeasible. Regardless of this, the philosophy of science literature urges general, testable, falsifiable hypotheses. While the Irish results presented here are, it appears, novel, they are part of a more general set of 'anomalies'. Thus any hypothesis that seeks only to explain the Irish results, be it drawn fròm psychology or otherwise, is deemed ad hoc and partial. A more general explanation of asset price formation, which allows for both the general pattern of calendar regularities, especially daily seasonals, and for the particular manifestation of this daily seasonal in the Irish context is required. This thesis has not attempted to do this, contenting itself with data analysis and testing rather than theory formation.

Bibliography & References

Aboudi, R. and D. Thon (1994). "Efficient Algorithms for Stochastic Dominance: Tests Based on Financial Market Data." Management Science 40(4): 508-515.

Abraham, A. and D. Ikenberry (1994). "The Individual Investor and the Weekend Effect." Journal of Financial and Quantitative Analysis **29**(2): 263-277.

Adrangi, B. and F. Ghazanfari (1996). "Corporate Bond Returns and Weekday Seasonality." Journal of Applied Business Research **13**(1).

Aggarwal, R. and P. Rivol (1989). "Seasonal and Day-of-the-Week Effects in Four Emerging Stock Markets." The Financial Review **24**(4): 541-550.

Aggarwal, R. and J. Schatzberg (1997). "Day of the Week Effects, Information Seasonality and Higher Moments of Security Returns." Journal of Economics and Business **49**: 1-20.

Agrawal, A. and K. Tandon (1994). "Anomalies or Illusions? Evidence from Stock Markets in Eighteen Countries." Journal of International Money and Finance **13**: 83-106.

Alexakis, P. and M. Xanthakis (1995). "Day of the Week Effect on the Greek Stock Market." Applied Financial Economics **5**: 43-50.

Andrade, I., A. Clare, R. O'Brien and S. Thomas (1999). "Tests for Stochastic Seasonality Applied to Daily Financial Time Series." The Manchester School **67**(1): 39-59.

Anon (1998). "Holiday Trading Revisited." Futures(July): 46-48.

Ariel, R. (1987). "A Monthly Effect in Stock Returns?" Journal of Financial Economics **18**: 161-174.

Ariel, R. (1990). "High Stock Returns before Holidays: Evidence and Possible Causes." Journal of Finance **45**(September): 1611-1626.

Arsad, Z. and J. A. Coutts (1996). "The Weekend Effect, Good News, Bad News and the Financial Timès Ordinary Shares Index: 1935:1994." Applied Economics Letters 3: 797-801.

--- (1997). "Security Price Anomalies in the London International Stock Exchange; a 60 Year Perspective." Applied Financial Economics 7: 455-464.

Associates, Bacon. (1999). Strategic Development Options for Irelands Capital Markets in a Comparative Context. Dublin, The Irish Stock Exchange: 134.

Atchinson, M., K. Butler and R. Simonds (1987). "Nonsynchronous Security Trading and Market Index Autocorrelation." Journal of Finance **42**(1): 111-118.

Athanassakos, G. and S. Foerster (2000). Canadian Security Market Anomalies. In Security Market Imperfections in World Wide Equity Markets. D. Keim and W. Ziemba. Cambridge, Cambridge University Press: 297-336.

Athannasakos, G. (1997). "Firm Size, Stock Return Seasonality and the Trading Pattern of Individual And Institutional Investors: The Canadian Experience." Journal of Investing(Fall): 75-86.

Athannasakos, G. and J. Schnabel (1994). "Professional Portfolio Managers and the January Effect." Review of Financial Economics **4**(1): 79-91.

Bachelier, L. (1900). Theory of Speculation. Paris, Paris Dauphine IX.

Bagehot, pseud. for Treaynor, J (1971). "The Only Game in Town." Financial Analysts Journal **27**(March/April): 12-17.

Baker, R. and R. Limmack (1998). "Firm Size, Monthly Seasonalities and Tax Loss Selling: Further Evidence from the UK." British Accounting Review **30**: 221-248.

Balaban, E., A. Bayar and O. B. Kan (1998). Day of the Week Effects and Asymmetric Conditional Volatility in World Stock Markets. Research Series. Ankara, Central Bank of the Republic of Turkey.

Ball, C., W. Torous and A. Tschoegl (1982). "Gold and the Weekend Effect." Journal of Futures Markets 2(2): 175-182.

Ball, R. (1996). "The Theory of Stock Market Efficiency: Accomplishments and Limitations." Journal of Financial Education 22: 1-13.

Ball, R. and P. Brown (1968). "An Empirical Evaluation of Accounting Income Numbers." Journal of Accounting Research 6: 103-126.

Banz, R. (1981). "The Relationship between Return and Market Value of Common Stocks." Journal of Financial Economics 9(1): 3-18.

Barone, E. (1990). "The Italian Stock Market: Efficiency and Calendar Anomalies." Journal of Banking and Finance 14: 483-510.

Bell, D. and E. Levin (1998). "What Causes Intra-Week Regularities in Stock Returns: Some Evidence from the Uk." Applied Financial Economics 8: 353-357.

Beller, K. and J. Nofsinger (1998). "On Stock Return Seasonality and Conditional Hetroskedasticity." Journal of Financial Research 21(2): 229-246.

Berges, A., J. McConnell and G. Schlarbaum (1984). "The Turn of the Year in Canada." Journal Of Finance 39(1): 185-192.

Berk, J. (1995). "A Critique of Size Related Anomalies." Review of Financial Studies 8(2): 275-286.

Bernstein, P. (1992). Capital Ideas: The Improbable Origins of Modern Wall Street. New York, Free Press.

Berry, T. and K. Howe (1994). "Public Information Arrival." Journal of Finance 49(4): 1331-1347.

Bhardwaj, R. and L. Brooks (1992). "Stock Price and Degree of Neglect as Determinants of Stock Returns." Journal of Financial Research 15: 101-112.

Bishara, H. (1989). "Stock Returns and the Weekend Effect in Canada." American

Business and Economic Review **20**(2): 62-71.

Blaug, M. (1992). The Methodology of Economics ; or How Economists Explain. Cambridge, Cambridge University Press.

Blume, M. and R. Stambaugh (1983). "Biases In Computed Returns: An Application Of The Size Effect." Journal of Financial Economics **12**: 387-404.

Board, J. and C. Sutcliffe (1988). "The Weekend Effect in UK Stock Market Returns." Journal of Business, Finance & Accounting **15**(2): 199-213.

Boland, L. (1979). "A Critique of Friedman's Critics." Journal of Economic Literature **17**: 503-522.

Bollerslev, T. (1986). "Generalised Autoregressive Conditional Hetroskedasticity." Journal of Econometrics **31**: 307-322.

Booth, D. and D. Keim (2000). Is There Still a January Effect? In Security Market Imperfections in World Wide Equity Markets. D. Keim and W. Ziemba. Cambridge, Cambridge University Press: 169-178.

Bossert, W., M. Fleurbaey and D. Van de gaer (1999). "Responsibility, Talent, and Compensation: A Second-Best Analysis." Review of Economic Design **4**(1): 35-55.

Branch, B. (1977). "A Tax Loss Trading Rule." Journal of Business **50**(2): 198-207.

Branch, B. and D. Echevarria (1991). "The Impact of Bid-Ask Prices on Market Anomalies." Financial Review **26**(2): 249-268.

Brockman, P. (1995). "A Review and Analysis of the Holiday Effect." Financial Markets, Institutions and Instruments **4**(5): 37-58.

Brockman, P. and D. Michayluk (1997). "The Holiday Anomaly; an Investigation of Firm Size Versus Share Effects." Quarterly Journal of Business and Economics **36**(Summer): 23-35.

Brockman, P. and D. Michayluk (1998). "The Persistent Holiday Effect: Additional

Evidence." Applied Economics Letters(5): 205-209.

Brown, P., D. Keim, W. Kleidon and T. Marsh (1983). "Stock Return Seasonalities and the Tax Loss Selling Hypothesis: Analysis of the Arguments and Australian Evidence." Journal of Financial Economics **12**(1): 105-123.

Brown, S., W. Goetzmann and A. Kumar (1998). "The Dow Theory: William Peter Hamilton's Track Record Reconsidered." Journal of Finance **53**(4): 1311-1333.

Bume, M. and R. Stambaugh (1983). "Biases in Computed Returns: An Application of the Size Effect." Journal of Financial Economics **12**: 387-404.

Cadsby, C. and M. Ratner (1992). "Turn of the Month and Pre Holiday Effects on Stock Returns: Some International Evidence." Journal of Banking and Finance **16**: 497-509.

Campbell, R. and T. Vinci (1983). "Novel Confirmation." British Journal for the Philosophy of Science **34**: 315-341.

Canestrelli, E. and W. Ziemba (2000). Seasonal Anomalies in the Italian Stock Market 1973-1993. in Security Market Imperfections in World Wide Equity Markets. D. Keim and W. Ziemba. Cambridge, Cambridge University Press: 332-363.

Chamberlain, T., C. S. Cheun and C. Kwan (1990). "Day of the Week Patterns in Futures Prices: Some Further Results." Quarterly Journal Of Business And Economics **29**(2): 68-89.

Chamberlain, T., C. S. Cheung and C. Kwan (1991). "The Friday the Thirteenth Effect: Myth or Reality." Quarterly Journal of Business and Economics **30**(2): 111-118.

Chan, K. and N.-F. Chen (1988). "An Unconditional Asset Pricing Test and the Role of Firm Size as an Instrumental Variable for Risk." Journal Of Finance **43**(2): 309-325.

Chan, M., A. Khanthavit and H. Thomas (1996). "Seasonality and Cultural Influences on Four Asian Stock Markets." Asia Pacific Journal of Management **13**(2): 1-24.

Chang, E. and C. Kim (1988). "Day of the Week Effects and Commodity Price Changes." Journal of Futures Markets(April): 229-241.

Chang, E., J. Pinegar and R. Ravichandran (1993). "International Evidence on the Robustness of the Day-of-the-Week Effect." Journal of Financial and Quantitative Analysis **26**(4): 497-513.

Chang, E. and J. M. Pinegar (1989). "Seasonal Fluctuations in Industrial Production and Stock Market Seasonals." Journal of Financial and Quantitative Analysis **24**(1): 59-74.

--- (1990). "Stock Market Seasonals and Prespecified Multifactor Pricing Relationships." Journal Of Financial And Quantitative Analysis **25**(4): 517-533.

Chang, E., J. M. Pinegar and R. Ravichandran (1993). "International Evidence on the Robustness of the Day-of-the-Week Effect." Journal of Financial and Quantitative Analysis **26**(4): 497-513.

--- (1995). "European Day-of-the-Week Effects, Beta Asymmetries and International Herding." European Journal of Finance **1**(2): 173-200.

--- (1998). "US Day-of-the-Week Effects and Asymmetric Responses to Macroeconomic News." Journal of Banking and Finance **22**: 513-534.

Chelley-Steeley, P. (1996). "Risk, Seasonality and the Asymmetric Behaviour of Stock Returns." Journal of Business, Finance and Accounting **23**(1): 145-154.

Chen, L.-L. and R. Fishe (1994). "Seasonal Money Movements and the January Effect." Atlanta Economic Journal **22**(4): 26-42.

Chen, N.-F., R. Roll and S. Ross (1986). "Economic Forces and the Stock Market: Testing the APT and Alternative Asset Pricing Theories." Journal of Business **59**:

383-403.

Cheung, Y.-L., R. Ho and K.-F. Wong (1994). "Risk and Return Seasonalities in Three Emerging Asian Markets: Hong Kong, Korea and Taiwan." Journal of International Financial Management and Accounting **5**(3).

Choudhry, T. (2000). "Day of the Week Effects in Emerging Asian Stock Markets: Evidence from the GARCH Model." Applied Financial Economics **10**(235-242).

Chow, E., P. Hsian and M. Solt (1997). "Trading Returns for the Weekend Effect Using Intraday Data." Journal Of Business, Finance And Accounting **24**(3 & 4): 425-444.

Choy, A. and J. O'Hanlon (1989). "Day of the Week Effects in the UK Equity Market: A Cross Sectional Analysis." Journal of Business, Finance and Accounting. **16**: 89-104.

Clare, A., M. Ibrahaim and S. Thomas (1998). "The Impact of Settlement Procedures on Day-of-the-Week Effects: Evidence from the Kuala Lumpur Stock Exchange." Journal of Business, Finance & Accounting **25**(3/4): 401-418.

Comolli, L. and W. Ziemba (2000). Japanese Security Market Regularities. In Security Market Imperfections in World Wide Equity Markets. D. Keim and W. Ziemba. Cambridge, Cambridge University Press: 458-491.

Condoyanni, L., J. O'Hanlon and C. Ward (1987). "Day of the Week Effects on Stock Returns: International Evidence." Journal of Business, Finance & Accounting **14**(2): 159-174.

Conine, T. and M. Tamarkin (1981). "On Diversification Given Asymmetry in Returns." Journal of Finance **36**(5): 1143-1153.

Connolly, R. (1989). "An Examination of the Robustness of the Weekend Effect." Journal of Financial and Quantitative Analysis **24**(2): 133-169.

Connolly, R. (1991). "A Posterior Odds Analysis of the Weekend Effect." Journal of Econometrics **49**: 51-104.

Constatinides, G. (1984). "Optimal Stock Trading with Personal Taxes; Implications for Prices and the Abnormal January Returns." Journal of Financial Economics **13**(1): 65-89.

Cooper, J. C. B. (1982). "World Stock Markets: Some Random Walk Tests." Applied Economics **14**(5): 515-531.

Cootner, P., Ed. (1964). The Random Character of Stock Prices. Cambridge, MIT Press.

Corhay, A. (1991). "Daily Seasonalities on the Brussels Spot Equity Market." Cahiers Economiques de Bruxelles **132**(4eme Trimestre): 415-430.

Corhay, A., G. Hawawini and P. Michel (1987). "Seasonality in the Risk-Return Relationship: International Evidence." Journal Of Finance **32**(1): 49-68.

Cotter, J. (1998). "Testing Distributional Models for the Irish Equity." Economic and Social Review **29**(4): 369-382.

Coursey, D. and E. Dyl (1990). "Price Limits, Trading Suspensions and the Adjustment of Prices to New Information." Review of Futures Markets: 342-360.

Coutts, J. A. and P. Hayes (1999). "The Weekend Effect, the Stock Exchange Account and the Financial Times Industrial Ordinary Shares Index 1987-1994." Applied Financial Economics **9**: 67-71.

Coutts, J. A. and M. Sheik (2000). "The January Effect and Monthly Seasonality in the All Gold Index on the Johannesberg Stock Exchange 1987-1997." Applied Economics Letters 7: 489-492.

Cowles, A. (1933). "Can Economic Forecasters Forecast ?" Econometrica **7**(3): 229-263.

Cowles, A. I. (1944). "Stock Market Forecasting." Econometrica **12**: 206-214.

Cowles, A. I. and H. Jones (1937). "Some *a posteori* Probabilities in Stock Market Action." Econometrica **5**: 280-294.

Cross, F. (1973). "The Behaviour of Stock Prices on Fridays and Mondays." Financial Analysts Journal **29**(November/December): 67-69.

Cuthbertson, K. (1996). Quantitative Financial Economics. Chichester, John Wiley & Sons.

Damodaran, A. (1989). "The Weekend Effect in Information Releases: A Study of Earning and Dividend Announcements." Review of Financial Studies **2**(4): 607-623.

DeFusco, R., G. McCabe and K. Yook (1993). "Day of the Week Effects: A Test of the Information Timing Hypothesis." Journal Of Business, Finance And Accounting **20**(6): 835-842.

DeGennaro, R. (1990). "The Effect of Payment Delays on Stock Prices." Journal of Financial Research **13**(2): 133-145.

Devine, M. (1996). The Macroeconometrics of the Irish Stock Market: An Investigation into the Influence of Macroeconomic Variables on Irish Stock Prices. Business Studies. Dublin, M.Litt., Trinity College: 167.

Dewit, G. (2001). "Intervention in Risky Export Markets: Insurance, Strategic Action or Aid?" European Journal of Political Economy **17**(3): 575-92.

Diaconis, P. and B. Efron (1983). "Computer-Intensive Methods in Statistics." Scientific American(May): 116-130.

Dimson, E. (1988). Stock Market Anomalies. Cambridge, Cambridge University Press.

Dimson, E. and P. Marsh (1999). "Murphy's Law and Market Anomalies." Journal of Portfolio Management **25**(2): 53-69.

Dimson, E. and A. Mussavian (1998). "A Brief History of Market Efficiency." European Financial Management **4**(1): 91-103.

Doan, T. (2000). Users Guide to Rats V 5.01. Evaston, Ill., ESTIMA.

Donnelly, R. (1991). "Seasonality in the Irish Stock Market." Irish Business and Administrative Research **12**: 39-51.

Doornik, J. and H. Hansen (1994). An Omnibus Test for Univariate and Multivariate Normality. Oxford, Nuffield College.

Draper, P. and K. Paudyal (1997). "Microstructure and Seasonality in the UK Equity Market." Journal Of Business, Finance And Accounting **24**(7 & 8): 1177-1204.

Dubois, M. and P. Louvet (1996). "The Day-of-the-Week Effect: The International Evidence." Journal of Banking and Finance **20**: 1463-1484.

Dunne, P. G. (1994). "The Implicit Costs of Trading in a Jointly Listed Irish Equity." Economic and Social Review **26**(1): 31-43.

Durham, J. B. (2001). "Sensitivity Analysis of Anomalies in Developed Stock Markets." Journal of Banking and Finance **25**: 1503-1541.

Dyl, E. (1977). "Capital Gains Taxation and Year End Stock Market Behaviour." Journal of Finance **32**: 165-175.

Dyl, E. and C. Holland (1990). "Why a Weekend Effect: Comment." Journal of Portfolio Management (Winter): 88-89.

Dyl, E. and E. Maberly (1988). "The Anomaly That Isn't There: A Comment on Friday the Thirteenth." Journal of Finance **43**(5): 1285-1286.

Dyl, E. and S. Martin (1985). "Weekend Effects on Stock Returns: A Comment." Journal of Finance **40**: 347-352.

Dyl, E. A. and E. D. Maberly (1986). "The Weekly Pattern in Stock Index Futures: A Further Note." Journal of Finance **41**(5): 1149-52.

Eakins, S. and S. Sewell (1993). "Tax Loss Selling, Institutional Investors and the January Effect: A Note." Journal of Financial Research **16**(4): 377-384.

Easton, S. and R. Faff (1994). "An Investigation of the Robustness of the Day-of-the-Week Effect in Australia." Applied Financial Economics **4**: 99-110.

Edgington, E. S. (1995). Randomization Tests. New York, M Dekker.

Efron, B. and R. Tibshirani (1993). An Introduction to the Bootstrap. New York, Chapman & Hall.

Elyasiani, E., P. Perera and T. Puri (1996). "Market Efficiency and Calendar Anomalies in Emerging Capital Markets: Evidence from the Colombo Stock Exchange." Journal of International Financial Markets, Institutions and Money **6**(4): 59-77.

Engle, R. (1982). "Autoregressive Conditional Hetroskedasticity with Estimates of the Variance of United Kingdom Inflation." Econometrica **50**: 987-1007.

Engle, R., D. Lilien and R. Robins (1987). "Estimating Time Varying Risk Premia in the Term Structure - the Arch-M Model." Econometrica **55**: 391-407.

Fabozzi, F., C. Ma and J. Briley (1994). "Holiday Trading in Futures Markets." Journal of Finance **51**(1): 307-324.

Fama, E. (1963). "Mandlebrot and the Stale Paretian Hypothesis." Journal of Business **36**.

--- (1965). "The Behaviour of Stock Market Prices." The Journal of Business **38**: 34-105.

--- (1970). "Efficient Capital Markets: A Review of Theory and Empirical Work." Journal of Finance **25**(2): 383-417.

--- (1976). Foundations of Finance. New York, Basic Book.

Fama, E., L. Fisher, M. Jensen and R. Roll (1969). "The Adjustment of Stock Prices to New Information." International Economic review **10**: 1-21.

Fama, E. and K. French (1992). "The Cross-Section of Expected Returns." Journal of Finance **47**: 427-465.

Fama, E. and J. MacBeth (1973). "Risk, Return and Equilibrium." Journal of Political Economy **81**: 607-636.

Fatemi, A. and J. Park (1996). "Seasonal Patterns in Japanese ADR Returns and the Us Stock Market Influence." Japan and the World Economy **8**: 65-79.

Fields, M. (1931). "Stock Prices: A Problem in Verification." Journal of Business **October**: 415-418.

--- (1934). "Security Prices and Stock Exchange Holidays in Relation to Short Selling." Journal of Business **7**: 328-338.

Fishe, R., T. Gosnell and D. Lasser (1993). "Good News, Bad News, Volume and the Monday Effect." Journal Of Business, Finance And Accounting(November): 881-892.

Flannery, M. and A. Protopapadakis (1988). "From T-Bills to Common Stocks: Investigating the Generality of Intra-Week Return Seasonality." Journal of Finance **43** (2): 431-450.

Flavin, T. J. and M. G. Limosani (2000). "Fiscal Policy and the Term Premium in Real Interest Rate Differentials." Applied Financial Economics **10**(4): 413-17.

Fletcher, J. (2000). "On the Conditional Relationship between Beta and Returns in International Stock Returns." International Review of Financial Analysis **9**: 235-245.

Fortune, P. (1998). Weekends Can Be Rough; Revisiting the Weekend Effect in Stock Prices. Working Papers. Boston, Federal Reserve Bank of Boston: 19.

Fosback, N. (1976). Stock Market Logic. Fort Lauderdale, Florida, Institute for Econometric Research.

Frankfurter, G. and E. McGoun (1999). "Ideology and The Theory of Financial

Economics." Journal of Economic Behaviour and Organization **39**: 159-177.

--- (2001). "Anomalies in Finance: What Are They and What Are They Good For?" International Review of Financial Analysis **10**: 407-429.

French, K. (1980). "Stock Returns and the Weekend Effect." Journal of Financial Economics **8**: 55-69.

Friedman, M. (1953). The Methodology of Positive Economics. Chicago, University of Chicago Press.

Gahan, S. (1993). The January Effect: Is There Evidence of Its Existence on the Irish Stock Exchange? Business. Dublin, Dublin City University.

Gallagher, L. (1995). "Interdependencies between the Irish, British and German Stock Markets." Economic and Social Review **26**(2): 131-147.

Gallagher, L. A. and C. E. Twomey (1998). "Identifying the Source of Mean and Volatility Spillovers in Irish Equities: A Multivariate GARCH Analysis." Economic and Social Review **29**(4): 341-356.

Gamble, R. (1993). "The January Effect and Intergenerational Transfers." Quarterly Review of Economics and Finance **33**(3): 295-304.

Garza-Gomez, X., J. Hodoshima and M. Kunimura (1998). "Does Size Really Matter in Japan." Financial Analysts Journal **54**(November/December): 22-34.

Geary, R. (1944). "Some Thoughts on the Making of Irish Index Numbers." Journal of the Statistical And Social Inquiry Society of Ireland **17**: 345-380.

Gibbons, M. and P. Hess (1981). "Day of the Week Effects and Asset Returns." Journal of Business **54**(4): 579-596.

Glosten, R., R. Jagannathan and D. Runkle (1993). "On the Relationship between the Expected Value and the Volatility of the Nominal Excess Return on Stocks." Journal of Finance **48**: 1779-1801.

Graham, B. and D. Dodd (1934). Security Analysis. New York, McGraw Hill.

Granger, C. and O. Morgenstern (1963). Spectral Analysis of New York Stock Exchange Prices. The Random Character of Stock Prices. P. Cootner. Cambridge, MIT Press.

Gultekien, M. and N. Gultekien (1983). "Stock Market Seasonality: International Evidence." Journal of Financial Economics **12**: 469-481.

Han, L. M., J. L. Kling and C. W. Sell (1999). "Foreign Exchange Futures Volatility: Day-of-the-Week, Intraday, and Maturity Patterns in the Presence of Macroeconomic Announcements." Journal of Futures Markets **19**(6): 665-93.

Han, L, Johnston and D. Dyl (1999). ": Foreign Exchange Futures Volatility: Day-of-the-Week, Intraday, and Maturity Patterns in the Presence of Macroeconomic Announcements

: Day-of-the-Week Effects in Financial Futures: An Analysis of Gnma, T-Bond, T-Note, and T-Bill Contracts

: The Weekly Pattern in Stock Index Futures: A Further Note.": Journal-of-Futures-Markets; 19(6), September 1999, pages 665-93.

Hansen, L. (1982). "Large Sample Properties of Generalized Method of Moments Estimators." Econometrica **50**: 1029-1054.

Harris, L. (1986). "A Transaction Data Study If Weekly and Intraday Patterns in Stock Returns." Journal of Financial Economics **16**: 99-117.

Haugen, R. and P. Jorion (1996). "The January Effect; Still Here after All These Years." Financial Analysts Journal(January-February): 27-31.

Haugen, R. and J. Lakonishok (1988). The Incredible January Effect: The Stock Markets Unsolved Mystery. Holmwood, Illinois, Dow Jones - Irwin.

Hausman, D., Ed. (1994). The Philosophy of Economics: An Anthology. Cambridge,

Cambridge University Press.

Hawawini, G. and D. Keim (2000). The Cross Section of Common Stock Returns - a Review of the Evidence and Some New Findings. Security Market Imperfections in World Wide Equity Markets. D. Keim and W. Ziemba. Cambridge, Cambridge University Press: 3-44.

Henry, O. (1998). "Modelling the Asymmetry of Stock Market Volatility." Applied Financial Economics **8**: 145-153.

Heston, S., K. Rouwenhorst and R. Wessels (1999). "The Role of Beta and Size in the Cross Section of European Stock Returns." European Financial Management **5**: 9-23.

Hilliard, J. and A. Tucker (1992). "A Note on Weekday, Intraday, and Overnight Patterns in the Interbank Foreign Exchange and Listed Currency Options Markets." Journal of Banking and Finance **16**: 1159-1171.

Hiraki, T. and E. Maberly (1995). "Are Preholiday Returns in Tokyo Really Anomalous ? If So, Why?" Pacific-Basin Finance Journal **3**: 93-1111.

Hirsch, Y. (1986). Dont Sell Stocks on Monday ! New York, Basic Books.

Hirshleifer, D. (2001) "Investor Psychology and Asset Pricing." Journal of Finance **56**(4): 1533-1597.

Ho, R. Y.-K. and Y.-L. Cheung (1994). "Seasonal Patterns in Volatility in Asian Stock Markets." Applied Financial Economics **4**: 61-67.

Ho, Y.-K. (1990). "Stock Return Seasonalities in Asia Pacific Markets." Journal of International Financial Management and Accounting **2**(1): 47-77.

Ho, Y.-K. and Y.-L. Cheung (1991). "Behaviour of Intra-Daily Stock Returns on an Asian Emerging Market." Applied Economics **23**: 957-966.

Howlett, D. (1998). Dually-Traded Securities: An Examination of Equities Traded on Both the Dublin and London Stock Exchanges, M.Sc. Dublin City University.

Jacobs, B. L. K. (1988). "Calendar Anomalies: Abnormal Returns at Calendar Turning Points." Financial Analysts Journal(November-December): 28-39.

Jacobsen, B. and D. Bouman (2002). "Sell in May and Go Away; the Halloween Indicator Revisited." American Economic Review **2002**.

Jaffe, J. and R. Westerfield (1985). "The Weekend Effect in Common Stock Returns; the International Evidence." Journal of Finance **30**(2): 433-454.

--- (1985). "Patterns in Japanese Common Stock Returns; Day of the Week and Turn of the Year Effects." Journal of Financial and Quantitative Analysis **20**(2): 261-272.

Jaffe, J., R. Westerfield and C. Ma (1989). "A Twist on the Monday Effect in Stock Prices." Journal of Banking and Finance: 641-650.

Jensen, M. (1978). "Some Anomalous Evidence Regarding Market Efficiency." Journal of Financial Economics **6**(95-101).

Johnston, E. and W. M. J. Kracaw (1991). "Day of the Week Effects in Financial Futures: An Analysis of Gnma, T-Bond, T-Note and T-Bill Contracts." Journal Of Financial And Quantitative Analysis **26**(1): 23-44.

Johnston, E. T., W. A. Kracaw and J. J. McConnell (1991). "Day-of-the-Week Effects in Financial Futures: An Analysis of Gnma, T-Bond, T-Note, and T-Bill Contracts." Journal of Financial and Quantitative Analysis **26**(1): 23-44.

Jones, C., W. Lee and R. Apenbrink (1991). "New Evidence on the January Effect before Income Taxes." Journal Of Finance **46**: 1909-1924.

Jones, C., D. Pearse and J. Wilson (1987). "Can Tax Loss Selling Explain the January Effect: A Note." Journal of Finance **42**(2): 453-461.

Jones, C. and J. Wilson (1989). "An Analysis of the January Effect in Stocks and Interest Rates under Varying Monetary Regimes." Journal of Financial Research **12**(4): 341-354.

Jones, L. (1993). The Development of Irish Capital Markets. Irish Stock Exchange Conference for Quoted Companies and Investors: 7.

Jordan, S. and B. Jordan (1991). "Seasonality in Daily Bond Returns." Journal Of Financial And Quantitative Analysis **26**(2): 269-285.

Kallunki, J.-P. and T. Martikainen (1997). "Trading Patterns of Small and Large Traders: Implications for the Weekend Effect in Finland." Applied Financial Economics **4**: 595-597.

Kamara, A. (1997). "New Evidence on the Monday Seasonal in Stock Returns." Journal of Business: 63-84.

Kamath, R., R. Chakornpipat and A. Chatrath (1998). "Return Distributions and the Day-of-the-Week Effects in the Stock Exchange of Thailand." Journal of Economics and Finance **22**(2-2): 97-106.

Kamstra, M., L. Kramer and M. Levi (2000). "Losing Sleep at the Market: The Daylight Saving Anomaly." American Economic Review **90**(4): 1005-1012.

Kato; K. (1990). "Being a Winner in the Tokyo Stock Market." Journal of Portfolio Management(Summer): 52-56.

Kato, K. and J. Schallheim (1985). "Seasonal and Size Anomalies in the Japanese Stockmarket." Journal Of Financial And Quantitative Analysis **20**(2): 243-260.

Kearney, C. (1998). "The Causes of Volatility in a Small, Internationally Integrated Stock Market: Ireland 1975-1994." Journal of Financial Research **21**(1): 85-105.

Keim, D. (1983). "Size Related Anomalies and Stock Market Seasonality; Further Empirical Evidence." Journal of Financial Economics **12**: 12-32.

Keim, d. and R. Stambaugh (1984). "A Further Investigation of the Weekend Effect in Stock Returns." Journal of Finance **39**(3): 819-835.

Kleidon, A. (1986). "Anomalies in Financial Economics: Blueprint for Change."

Journal of Business 59(4): S469-S499.

Kelly, F. (1930). Why You Win or Lose. New York, Fraser Publishing.

Kendall, M. (1953). The Analysis of Economic Time Series: Part 1: Prices. The Random Character of Stock Prices. P. Cootner. Cambridge, MIT Press.

Kendall, M. and A. Stuart (1958). The Advanced Theory of Statistics. New York, Hafner.

Kennedy, T., M. MacCormac and J. Teeling (1995). Financial Management. Dublin, Gill & Macmillan.

Kim, C.-W. and J. Park (1994). "Holiday Effects and Stock Returns: Further Evidence." Journal of Financial and Quantitative Analysis **29**(1): 145-157.

Kim, S.-w. (1988). "Capitalizing on the Weekend Effect." Journal of Portfolio Management(Spring): 59-63.

Kirwan, F. and J. McGilvray (1983). Irish Economic Statistics. Dublin, Institute of Public Administration.

Koenker, R. (1982). "Robust Methods in Econometrics." Econometric Reviews **1**: 213-255.

Koh, S.-K. and k. A. Wong (2000). Anomalies in Asian Emerging Stock Markets. In Security Market Imperfections in World Wide Equity Markets. D. Keim and W. Ziemba. Cambridge, Cambridge University Press: 433-457.

Kohers, T. and G. Kohers (1995). "The Impact of Size Differences on the Day-of-the-Week Effect: A Comparison of Major Stock Exchanges." Applied Financial Economics **5**: 151-160.

Kohers, T. and J. Patel (1996). "An Examination of the Day of The Week Effect in Junk Bond Returns over Business Cycles." Review of Financial Economics **5**(1): 31-46.

Kolb, R. (1993). "Theory Succession, the CAPM and the APT." Managerial Finance **19**(3/4): 1-23.

Kolb, R. and R. Rodriguez (1987). "Friday the Thirteenth Part Vii: A Note." Journal of Finance **42**(5): 1385-1387.

Kramer, C. (1994). "Macroeconomic Seasonality and the January Effect." Journal of Finance **49**(5): 1883-1891.

Kramer, W. R. R. (1996). "Stochastic Properties of German Stock Returns." Empirical Economics **21**: 281-306.

Kuhn, T. (1970). The Structure of Scientific Revolutions. chicago, University of Chicago Press.

Lakatos, I. (1978). The Methodology of Scientific Revolutions. Cambridge, Cambridge University Press.

Lakonishok, J. and M. Levi (1982). "Weekend Effects on Stock Returns: A Note." Journal of Finance **37**: 883-889.

Lakonishok, J. and E. Maberly (1990). "The Weekend Effect: Trading Patterns of Individual and Institutional Investors." Journal of Finance **45**(1): 231-243.

Lakonishok, J. and A. Shapiro (1984). "Stock Returns, Beta, Variance and Size: An Empirical Analysis." Financial Analysts Journal **40**: 36-41.

Lakonishok, J. and S. Smidt (1988). "Are Seasonal Anomalies Real ? A Ninety Year Perspective." Journal of Financial Studies **1**(4): 403-425.

Larsen, G. A., Jr. and B. G. Resnick (1995). "Refining the Bootstrap Method of Stochastic Dominance Analysis: The Case of the January Effect." Review of Quantitative Finance and Accounting **7**(1): 65-79.

Lauterbach, B. and M. Ungar (1991). "Stock Return Regularities; Evidence from the Israeli Stock Market." Review of Business and Economic Research **26**: 70-84.

--- (1992). "Calendar Anomalies; Some Perspectives from the Behaviour of the Israeli Stock Market." Applied Financial Economics **2**: 57-60.

Leamer, E. (1983). "Lets Take the 'Con' out of Econometrics." American Economic Review **73**: 31-43.

Lee, C. F. and C. Wu (1985). "The Impact of Kurtosis on Risk Stationarity; Some Empirical Evidence." Financial Review **20**(4): 262-269.

Lee, I. (1992). "Stock Market Seasonality: Some Evidence from the Pacific Basin Countries." Journal Of Business, Finance And Accounting **19**(2): 199-210.

Lee, I., R. R. Pettit and M. Swankoski (1990). "Daily Return Relationships among Asian Stock Markets." Journal of Business, Finance & Accounting **17**(2): 265-284.

LeRoy, S. (1973). "Risk Aversion and the Martingale Properties of Stock Prices." International Economic Review **14**(2): 436-446.

--- (1989). "Efficient Capital Markets and Martingales." Journal of Economic Literature **27**(December): 1583-1621.

Levis, M. (1985). Are Small Firms Large Performers? Investment Analyst **76:** 21-27.

Liano, K. (1995). "A Preholiday Effect in the Currency Futures Market: A Note." International Review of Economics and Finance **4**(3): 299-304.

Liano, K. and B. Gup (1989). "The Day-of-the-Week Effect in Stock Returns over Business Cycles." Financial Analysts Journal(July-August): 74-77.

Liano, K., P. Marchand and G.-C. Huang (1992). "The Holiday Effect in Stock Returns:Evidence from the Otc Market." Review of Financial Economics(Fall): 45-55.

Liano, K. and L. White (1994). "Business Cycles and the Pre Holiday Effect in Stock Returns." Applied Financial Economics **4**: 171-174.

Ligon, J. (1997). "A Simultaneous Test of Competing Theories Regarding the January

Effect." Journal of Financial Research **20**(1): 64-70.

Lindley, D. (1957). "A Statistical Paradox." Biometrika **44**: 187-192.

Lo, A., H. Mamayasky and J. Wang (2000). "Foundations of Technical Analysis: Computational Algorithims, Statistical Inference and Empirical Implementation." Journal of Finance **55**(4): 1701-1770.

Lucey, B. (1994). "Some Empirics of the ISEQ Index." Economic and Social Revew **25**(2): 157-179.

--- (2000a). "Anomalous Daily Seasonality in Ireland?" Applied Economics Letters **7**(10): 637-640.

--- (2000b). "Friday the 13th and the Philosophical Basis of Financial Economics." Journal of Economics and Finance **24**(3): 294-302.

--- (2001). "Friday the 13th in International Equity Markets." Applied Economics Letters **8**(4).

--- (2002). "Is the Pre-Holiday Effect in the Irish Stock Market Caused by Local or International Influences?" Applied Financial Economics **forthcoming**

Lucey, B. and S. F. Whelan (2002). "A Simple Strategy to Outperform the Stock Market." Journal of the Statistical and Social Inquiry Society of Ireland **Forthcoming**: 31.

Ludbrook, J. and H. Dudley (1998). "Why Permutations Are Superior to T and F Tests in Biomedical Research." American Statistician **52**: 127-132.

Ma, C. (1986). "A Further Investigation of the Day-of-the-Week Effect in the Gold Market." Journal of Futures Markets **6**(3): 409-419.

Maberly, E. (1995). "Eureka ! Eureka ! Discovery of the Weekend Effect Belongs to the Ancient Scribes." Financial Analysts Journal **September-October**: 10-11.

Mandlebrot, B. (1964). The Variation of Certain Speculative Prices. The Random

Character Of Stock Prices. P. Cootner. Cambridge, M.A., MIT Press.

--- (1966). "Forecasts of Future Prices, Unbiased Markets and Martingale Models." Journal of Business **39**(1): 242-255.

Martikainen, T. (2000). Security Market Anomalies in Finland. In Security Market Imperfections in World Wide Equity Markets. D. Keim and W. Ziemba. Cambridge, Cambridge University Press: 390-415.

McKillop, D. and R. Hutchinson (1989). "The Small Firm Effect, Seasonality and Risk in Irish Equities." Irish Business and Administrative Research **9**: 21-29.

Mehra, R. and Prescott (Prescott, Edward). "The Equity Premium: A Puzzle." Journal of Monetary Economics **15**(2): 145-161.

Mehra, R. and E. Prescott (1980). "The Equity Premium: A Puzzle." Journal of Monetary Economics **15**(2): 145-161.

Merrill, A. (1966). The Behaviour of Prices on Wall Street. Chappaqua, New York, Analysis Press.

Miller, E. (1988). "Why a Weekend Effect?" Journal of Portfolio Management(Summer): 43-48.

--- (1990). "Explaining the January Small Firm Effect by the Interaction of Procedurally Rational Investors and Seasonal Traders." Quarterly Journal of Business and Economics **29**(3): 36-55.

Mills, T. and J. Coutts (1995). "Calendar Effects in the London Stock Exchange Ft-Se Indices." The European Journal of Finance **1**: 79-93.

Murray, C. (1960). "Some Aspects of the Industrial Capital Market in Ireland." Journal of the Statistical And Social Inquiry Society of Ireland **20**: 97-131.

Nelson, D. (1991). "Conditional Hetroskedasticity in Asset Returns: A New Approach." Econometrica **59**: 347-370.

Newton-Smith, W. (1981). The Rationality of Science. London, Routledge & Paul Keenan.

Officer, R. (1975). "Seasonality in Australian Capital Markets." Journal of Financial Economics **2**: 29-51.

Ogden, J. (1990). "Turn of the Month Evaluations of Liquid Profits and Stock Returns; a Common Explanation of the Monthly and January Effects." Journal of Finance **45**(4): 1259-1272.

Ohlsen, J. (1977). "Risk Aversion and the Martingale Properties of Stock Prices: Comment." International Economic Review **18**(1): 229-234.

O'Rourke, K. and J. Williamson (1999). Globalization and History: The Evolution of a Ninetheenth Century Atlantic Economy. London, MIT Press.

Papandreou, A. (1958). Economics as a Science. Chicago, Lippincotte.

Patell, J. and M. Wolfson (1982). "Good News, Bad News and the Intraday Timing of Corporate Disclosures." The Accounting Review **47**(3): 509-527.

Pearce, D. (1996). "The Robustness of Calendar Anomalies in Daily Stock Returns." Journal of Economics and Finance **20**(3): 69-80.

Peiro, A. (1994). "Daily Seasonality in Stock Returns: Further International Evidence." Economics Letters **45**: 227-232.

Peña, J. I. (1995). "Daily Seasonalities and Stock Market Reforms in Spain." Applied Financial Economics **5**: 419-423.

Penman, S. (1987). "The Distribution of Earnings News over Time and Seasonalities in Aggregate Stock Returns." Journal of Financial Economics **18**: 199-228.

Persons, W. (1919). "An Index of General Business Conditions." Review of Economics and Statistics **1**(2): 111-205.

Peterson, D. (1990). "Stock Return Seasonalities and Earnings Information." Journal

Of Financial And Quantitative Analysis **25**(2): 187-202.

--- (1990). "A Transaction Data Study of Day-of-the-Week and Intraday Patterns in Option Returns." Journal of Financial Research **13**(2): 117-131.

Peterson, I. (1991). "Pick a Sample, Any Sample." Science News **140**: 56-58.

Pettengill, G. (1986). "A Non Tax Cause for the January Effect: Evidence from Early January." Quarterly Journal of Business and Economics **25**(3): 15-33.

--- (1989). "Holiday Closings and Security Returns." Journal of Financial Research **22**(1): 57-67.

Pettengill, G. and D. Buster (1994). "Variation in Return Signs: Announcements and the Weekday Anomaly." Quarterly Journal of Business and Economics **33**(3): 81-93.

Pettengill, G. and B. Jordan (1988). "A Comprehensive Analysis of Volume Effects and Seasonality in Daily Security Returns." Journal of Financial Research **11**(1): 57-70.

Pettengill, G., S. Sundaram and I. Mathur (1995). "The Conditional Relationship between Beta and Returns." Journal of Financial And Quantitative Analysis **30**(1): 101-116.

Pettengill, G. N. (1993). "An Experimental Study of the "Blue Monday" Hypothesis." Journal of Socio-Economics **22**(3): 241-57.

Phillips-Patrick, F. and T. Schneeweis (1988). "The Weekend Effect for Stock Indices and Stock Index Futures: Dividend and Interest Rate Effects." Journal of Futures Markets **8**(1): 115-121.

Pickering, D. (1991). A Dictionary of Superstitions. London, Cassell.

Popper, K. (1959). The Logic of Scientific Discovery. New York, Basic Books.

Praetz, P. (1973). "Analysis of Australia Share Prices." Australian Economic Papers **20**(12): 70-78.

Quenouille, M. (1949). "Approximate Tests of Correlation in Time Series." Journal of the Royal Statistical Society, Series B **11**: 18-84.

Ramcharran, H. (1997). "Seasonality in the Jamaican Stock Market: An Examination of Stock Returns and the Volume Traded." Journal of Emerging Markets **2**(1): 23-35.

Redman, A. (1997). "Real Estate Investment Trusts and Calendar Anomalies." Journal of Real Estate Research **14**(1/2): 19-29.

Redman, D. (1989). Economic Methodology: A Bibliography with References to Works in the Philosophy of Science. New York, Greenwood Press.

--- (1990). Economics and the Philosophy of Science. Oxford, Oxford University Press.

--- (1994). "Karl Popper's Theory of Science and Econometrics: The Rise and Decline of Social Engineering." Journal of Economic Issues **28**(1): 67-99.

Reinganum, M. (1981). "Misspecification of Capital Asset Pricing; Empirical Anomalies Based on Earnings Yield and Market Values." Journal of Financial Economics **9**: 19-46.

Reinganum, M. (1983). "The Anomalous Stockmarket Behaviour of Small Firms in January." Journal of Financial Economics **12**(1): 89-104.

Reinganum, M. and A. Shapiro (1987). "Taxes and Stock Return Seasonality: Evidence from the London Stock Exchange." Journal of Business **60**(2): 281-295.

Riepe, M. (1998). "Is Publicity Killing the January Effect?" Journal of Financial Planning **11**(February): 64-70.

--- (2001). "The January Effect; Not Dead yet but Not at All Well." Journal of Financial Planning **14**(January): 44-47.

Ritter, J. (1988). "They Buying and Selling Behaviour of Individual Investors at the Turn of the Year." Journal of Finance **43**: 701-719.

--- (1988). "The Buying and Selling Behaviour of Individual Investors at the Turn of the Year." Journal of Finance **43**: 701-719.

Ritter, J. and N. Chopra (1989). "Portfolio Rebalancing and the Turn of the Year Effect." Journal Of Finance **44**(1): 169-177.

Roberts, H. (1957). Stock Market Patterns and Financial Analysis: Methodological Considerations. The Random Character of Stock Prices. P. Cootner. Cambridge, MIT Press.

Rogalski, R. (1984). "New Findings Regarding Day of the Week Returns over Trading and Non-Trading Periods: A Note." Journal Of Finance (December): 1603-1614.

Roll, R. (1983). "Vas Is Das?" Journal of Portfolio Management **9**: 18-28.

Rozeff, M. and W. Kinney (1976). "Capital Market Seasonality - the Case of Stock Returns." Journal of Financial Economics **3**: 379-402.

Ryan, J. and M. Donnelly (1998). The Overreaction Hypothesis ; an Examination in the Irish Stock Market. Irish Accounting and Finance Association, Colerain.

Rystrom, E. and E. Benson (1989). "Investor Psychology and the Day-of-the-Week Effect." Financial Analysts Journal(September-October): 74-77.

Sala-i-martin, X. (1997). "I Just Ran Two Million Regressions!" American Economic Review **87**(January): 178-183.

Salyer, K. (1988). "Risk Aversion and Stock Prices When Dividends Are Difference Stationary." Economic Letters **28**(3): 251-254.

Samuelson, P. (1965). "Proof That Properly Anticipated Prices Fluctuate Randomly." Industrial Management Review **6**: 41-49.

--- (1973). "Proof That Properly Discounted Present Values of Assets Vibrate Randomly." Bell Journal of Economics **4**(2): 369-372.

Santesmaes, M. (1986). "An Investigation of Spanish Stock Market Seasonalities." Journal of Business, Finance & Accounting **13**(2): 267-276.

Saunders, E. (1993). "Stock Prices and Wall Street Weather." American Economic Review **83**(5): 1337-1345.

--- (1994). "Testing the Efficient Markets Hypothesis without Assumptions." Journal of Portfolio Management(Summer): 28-30.

Schatzberg, J. and P. Datta (1992). "The Weekend Effect and Corporate Dividend Announcements." Journal of Financial Research **15**(1): 69-76.

Schultz, P. (1985). "Personal Income Taxes and the January Effect: Small Firm Stock Returns before the War Revenue Act of 1917: A Note." Journal of Finance **40**(1): 79-86.

Scott, R. and R. Horvath (1980). "On the Direction of Preferences for Moments Higher Than the Variance." Journal of Finance **35**(4): 915-919.

Scott, R. and R. Horvath (1980). "On the Direction of Preferences for Moments Higher Than the Variance." Journal of Finance **35**(4): 915-919.

Sehun, H. N. (1993). "Can Omitted Risk Factors Explain the January Effect ? A Stochastic Dominance Approach." Journal of Financial and Quantitative Analysis **28**(2): 195-211.

Seiler, M. (1997). "Stock Market Inefficiencies: Fortune or Folly?" Review of Business(Summer): 16-19.

--- (1997). "Historical Pre and Post Special Closing Effects." Studies in Economics and Finance: 59-72.

Sharpe, W. (1964). "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." Journal of Finance **19**(4): 425-442.

Shiller, R. (1992). Market Volatility. Cambridge, MIT Press.

Shiller, R. J. (1987). Investor Behaviour in the October 1987 Stock Market Crash: Survey Evidence. Yale, Cowles Foundation Discussion Paper: 41.

Sias, R. and L. Starks (1995). "The Day-of-the-Week Anomaly: The Role of Institutional Investors." Financial Analysts Journal (May-June): 58-67.

Simon, J. (1997). Resampling - the New Statistics.

Singleton, J. C. and J. Wingender (1994). "The Nonparallel Weekend Effect in the Stock and Bond Markets." Journal of Financial Research **27**(4): 531-538.

Smirlock, M. and L. Starks (1986). "Day-of-the-Week and Intraday Effects in Stock Returns." Journal of Financial Economics **17**: 197-210.

Solnik, B. and L. Bousquet (1990). "Day-of-the-Week Effect on the Paris Bourse." Journal of Banking and Finance **14**: 461-468.

Steeley, J. (1999). Information Seasonality and the Disappearance of the Weekend Effect in the UK Stock Market. Stirling, University of Stirling, Department of Accountancy, Finance and Law: 33.

--- (2001). "A Note on Information Seasonality and the Disappearance of the Weekend Effect in the UK Stock Market." Journal of Banking and Finance **25**(October): 1941-1956.

Stephenson, S. (1998). Simple Tests of Market Efficiency: The Example of the Dublin Stock Exchange: WP 98-01. Centre for the study of Financial Markets. Dublin, University College Dublin: 28.

Sullivan, R., A. Timmerman and H. White (1999a). Scientific Progress with Data Sharing. San Diego, University of California, San Diego: Department of Economics: 17.

--- (1999b). "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap." Journal of Finance **54**(5): 1647-1671.

Sullivan, R., A. Timmermann and H. White (2002). "Dangers of Data Mining: The Case of Calendar Effects in Stock Returns." Journal of Econometrics **105**(1): 249-86.

Tang, G. (1997). "Weekly Pattern in Higher Moments; an Empirical Test in Hong Kong Market." Journal of Economics and Business **21**(1): 51-59.

Tang, W. (1992). "An Analysis of the Janaury Effect of United States, Taiwan and South Korea Stock Rturns." Asia Pacific Journal of Management **9**(2): 189-207.

Teeling, J. and M. Lynch (1985). Modern Irish Business. Dublin, ETA Publishers.

Thaler, R. (1987). "Anomalies; Seasonal Movements in Security Prices Ii: Weekend, Holiday, Turn of the Month and Intraday Effects." Economic Perspectives **1**(1): 169-177.

Theobald, M. and V. Price (1984). "Seasonality Estimation in Thin Markets." Journal of Finance **39**(2): 377-392.

Thomas, W. A. (1986). The Irish Stock Exchanges. London, Redwood Burn ltd.

Thompson, B. and P. Snyder (1997). "Statistical Significance Testing Practice in the Journal of Experimental Eductation." Journal of Experimental Education **66**: 75-83.

Tinic, S., G. Barone-Adesi and R. West (1987). "Seasonality in Canadian Stock Prices: An Investigation of the Tax Loss Selling Hypothesis." Journal Of Financial And Quantitative Analysis **22**(1): 51-64.

Tinic, S. and R. West (1984). "Risk and Return - January V the Rest of the Year." Journal of Financial Economics **13**: 561-574.

Tong, W. (1992). "An Analysis of the January Effect of United States, Taiwan and South Korean Stock Returns." Asia Pacific Journal of Management **9**(2): 189-207.

Treynor, J. (1961). Towards a Theory of Market Value of Risky Assets. Foundations of Finance: Asset Pricing. E. Dimson and M. Mussavian. Dartmouth, Dartmouth Publishing 1998. **II**.

Tukey, J. W. (1958). "Bias and Confidence in Not Quite Large Samples." Annals of Mathematical Statistics **29**: 614-618.

Van de gaer, D., N. Funnell and T. McCarthy (1999). "Statistical Inference for Two Measures of Inequality When Incomes Are Correlated." Economics Letters **64**(3): 295-300.

van den Berg, W. and R. Wessels (1985). "Stock Market Seasonality and Taxes: An Examination of the Tax Loss Selling Hypothesis." Journal of Business, Finance and Accounting **12**(4): 515-530.

Wachtel, S. B. (1942). "Certain Observations on Seasonal Movements in Stock Prices." Journal of Business **15**: 184-193.

Whelan, S. (1999a). From Canals to Computers: The Friends First Guide to Long Term Investment in Ireland. Dublin, Friends First.

--- (1999b). The Frequency of Extreme Movements in the Irish Equity Market. Investment Conference of the Faculty and Institute of Actuaries, Edinburgh.

Whelan, S. (2002). The Tail Index of the Irish Equity Market. Annual conference of the Irish Economic Association, Mullingar.

White, H. (1997). A Reality Check for Data Snooping. San Diego, NRDA Technical Report 97-01.

Williams, J. (1938). The Theory of Investment Value. Cambridge, Harvard University Press.

Wilson, J. and C. Jones (1993). "Comparison of Seasonal Anomalies across Major Equity Markets: A Note." The Financial Review **28**(1): 107-115.

Wingender, J. and J. Groff (1989). "On Stochastic Dominance Analysis of Day-of-the-Week Return Patterns." Journal of Financial Research **12**(1): 51-55.

Wong, K. (1995). "Is There an Intra-Month Effect on Stock Returns in Developing

Stock Markets?" Applied Financial Economics **5**: 285-289.

Wong, K., T. Hui and C. Chan (1992). "Day-of-the-Week Effects: Evidence from Developing Stock Markets." Applied Financial Economics **2**: 49-56.

Wong, P. L., Neoh, S, K. Lee and Thjong, T (1990). "Seasonality in the Malaysian Stock Market." Asia Pacific Journal of Management **7**(Special Issue): 43-63.

Working, H. (1934). "A Random Difference Series for Use in the Analysis of Time Series." Journal of The American Statistical Association **29**: 11-24.

--- (1960). "A Note on the Correlation of First Differences of Averages in a Random Chain." Econometrica **4**(28): 916-918.

Yadav, P. and P. Pope (1992). "Intraweek and Intraday Seasonalities in Stock Market Risk Premia: Cash and Futures." Journal of Banking and Finance **16**: 233-270.

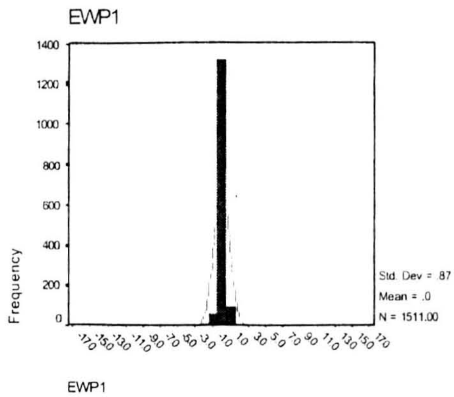
Yu, C.-h. (2002). Resampling Methods.

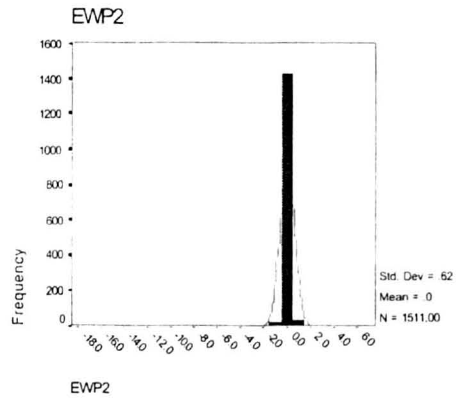
Ziemba, W. (1991). "Japanese Security Market Regularities: Monthly, Turn of the Month and Year, Holiday and Golden Week Effects." Japan and the World Economy **3**: 119-146.

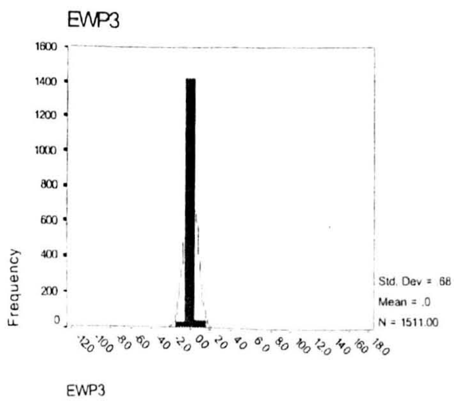
--- (1993). "Comment on 'Why a Weekend Effect'." Journal of Portfolio Management(Winter): 93-99.

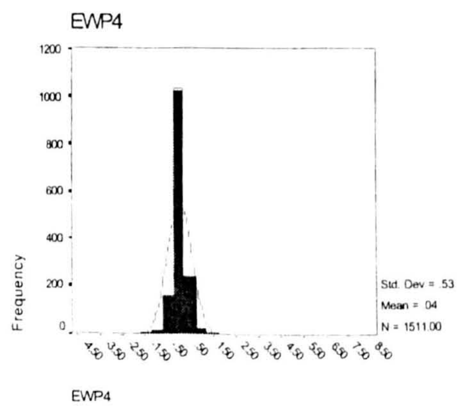
Zinberger, E. (1964). "The Stock Market's Seasonal Pattern." Financial Analysts Journal **20**: 53.

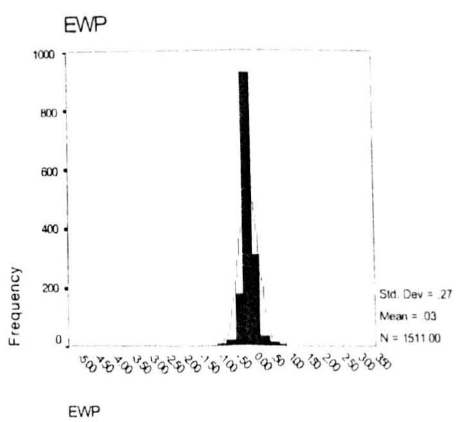
Appendix I. Empirical Histograms & Normal Curves



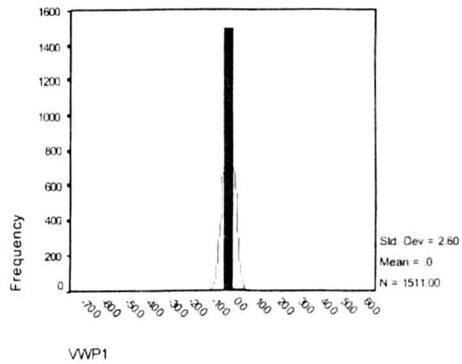




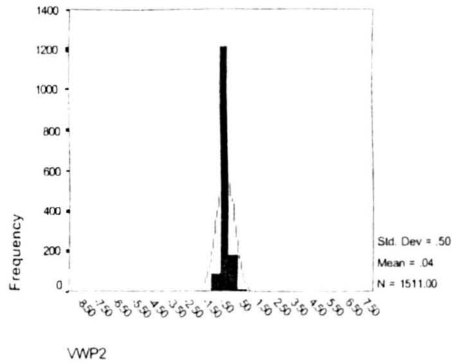




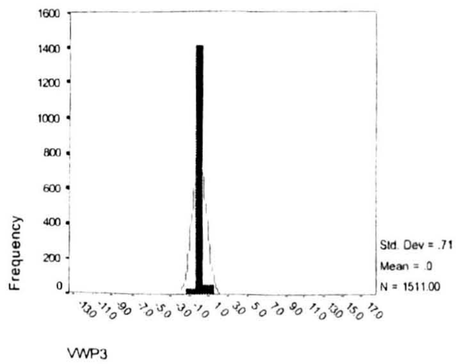
VWP1



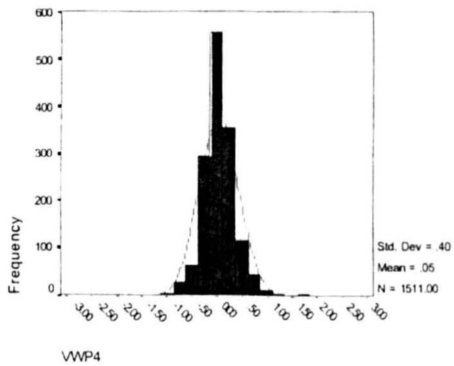
VWP2



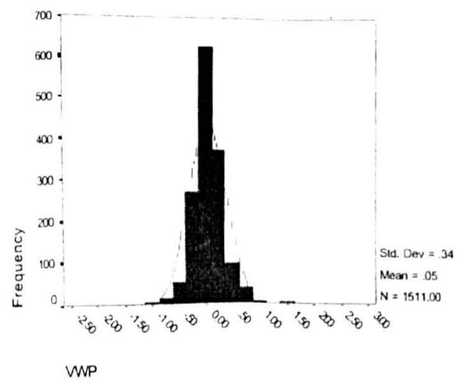
VWP3

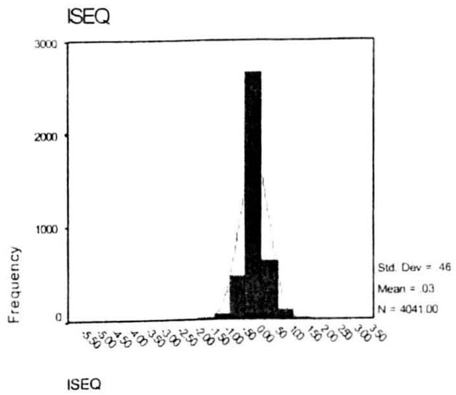


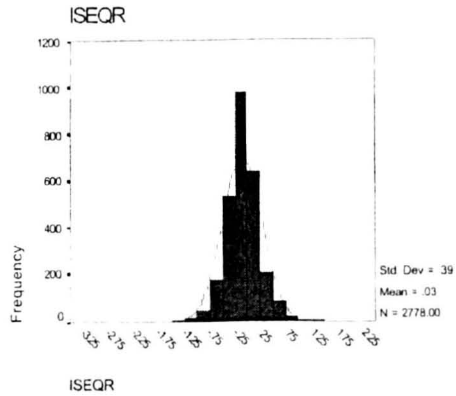
VWP4

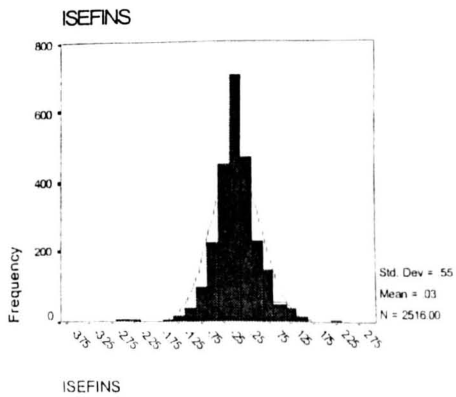


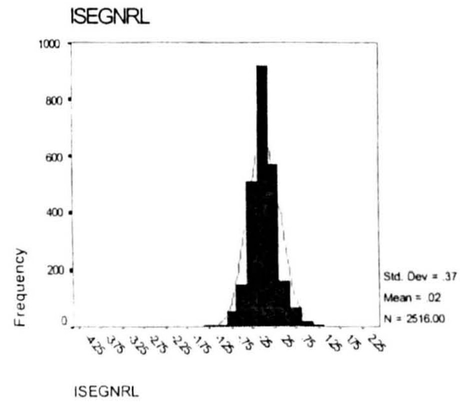
VWP



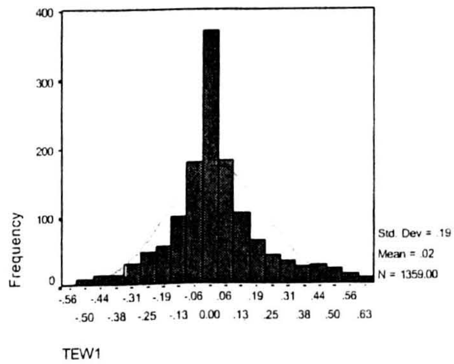

ISEQ
Frequency
Std. Dev = .46
Mean = .03
N = 4041.00
ISEQ


ISEQR
Frequency
Std. Dev = .39
Mean = .03
N = 2778.00
ISEQR

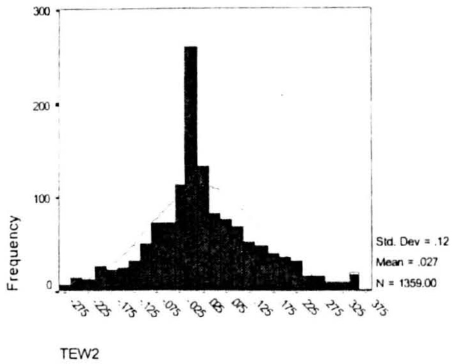

ISEFINS
Frequency
Std. Dev = .55
Mean = .03
N = 2516.00
ISEFINS


ISEGNRL
Frequency
Std. Dev = .37
Mean = .02
N = 2516.00
ISEGNRL

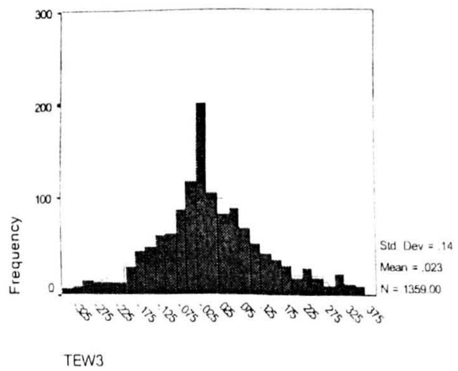
TEW1



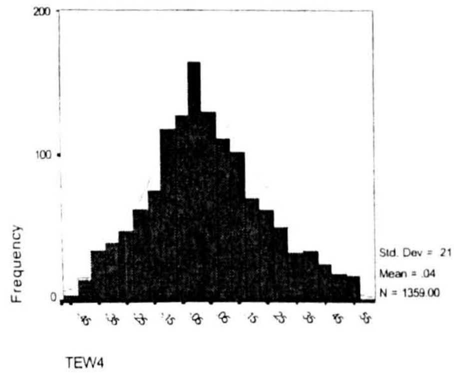
TEW2



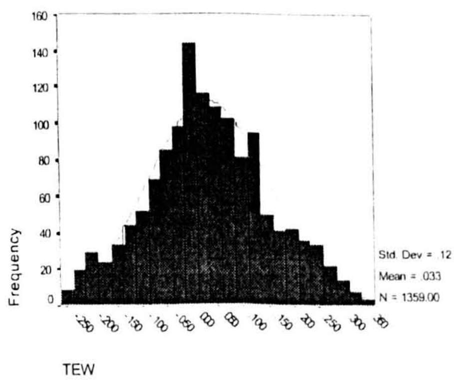
TEW3



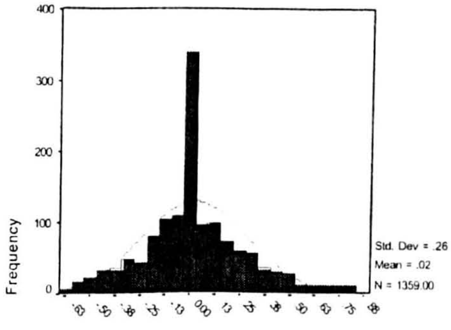
TEW4



TEW

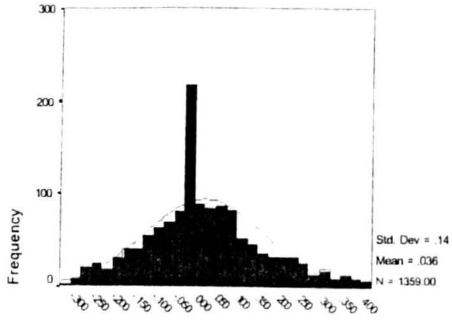


TVW1



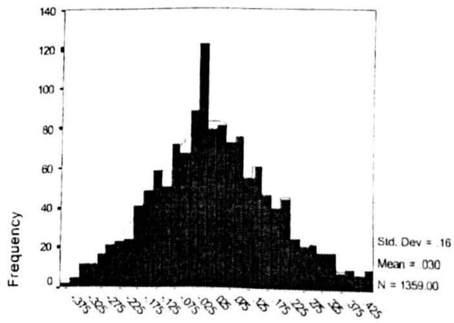
TVW1

TVW2



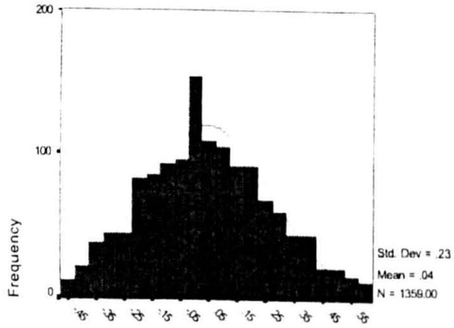
TVW2

TVW3



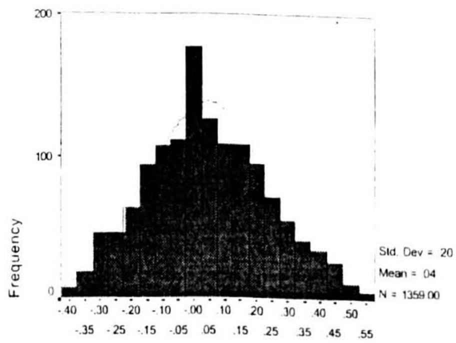
TVW3

TVW4



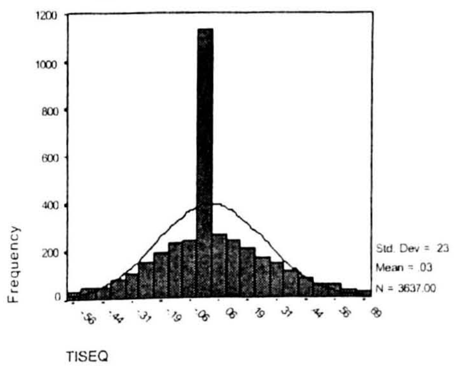
TVW4

TVW

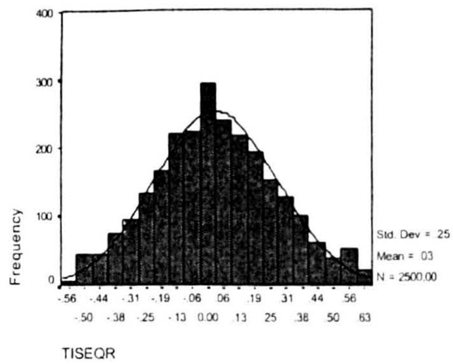


TVW

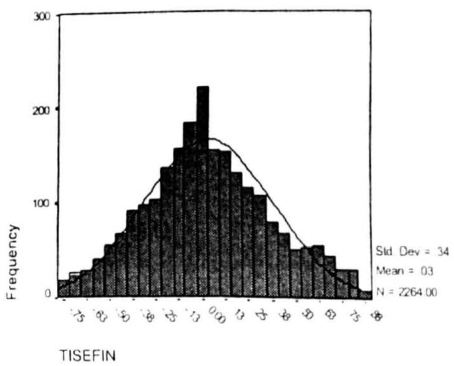
TISEQ



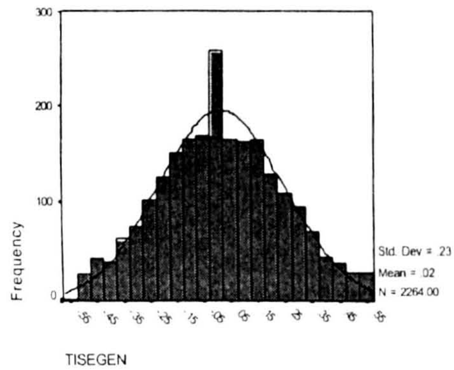
TISEQR



TISEFIN



TISEGEN



Appendix II. Partial Autocorrelation Function Data

LAG	P_EWP
1	1.000000000000
2	0.162929037095
3	0.080962260107
4	0.107475000142
5	0.065039156114
6	0.019899942299
7	0.012719496679
8	-0.022970289329
9	-0.007253200655
10	-0.039327337681

LAG	P_EWP4
1	1.000000000000
2	-0.133428123165
3	-0.015288573173
4	0.068190851910
5	0.027750070757
6	0.015713446687
7	0.019126156445
8	-0.026950704281
9	0.022497042986
10	-0.025756792665

LAG	P_ISEFIN
1	1.000000000000
2	0.089392338548
3	-0.008927233589
4	0.038492995421
5	0.046676696351
6	-0.024459004851
7	-0.029121649778
8	-0.001134337920
9	0.000614282553
10	-0.022687844543

LAG	P_ISEGEN
1	1.000000000000
2	0.117465746872
3	0.057558139397
4	0.049092488664
5	0.051082991629
6	0.003799833519
7	0.020301668410
8	-0.012755325638
9	-0.000158921048
10	0.022128335657

LAG	P_ISEQ
1	1.000000000000
2	0.160250167318

3	0.001674912332
4	0.067841930409
5	0.037870586544
6	-0.020420896337
7	0.009181395154
8	-0.008166344109
9	0.013954004691
10	-0.000357304957

LAG	P_ISEQR
1	1.000000000000
2	0.153512601518
3	0.020564040915
4	0.048972818903
5	0.044403421400
6	-0.014967593520
7	0.006542022834
8	-0.008220127065
9	0.010462567004
10	-0.007343140961

LAG	P_TEW
1	1.000000000000
2	0.178201574289
3	0.129353516486
4	0.057018447404
5	0.059688533620
6	0.055680868082
7	0.015153773763
8	0.032659880652
9	0.018489732095
10	0.041682815958

LAG	P_TEW1
1	1.000000000000
2	0.019377942649
3	0.026358981823
4	0.010520908474
5	0.054038716476
6	0.031665242848
7	0.028684795650
8	0.019042137140
9	0.055093161127
10	0.032862311785

LAG	P_TEW2
1	1.000000000000
2	0.053380717064
3	0.033799245708
4	0.032380905321
5	0.006706445471
6	0.055211856993
7	-0.006521126504
8	-0.015025016877

9	0.068589889112
10	-0.003130962715

LAG	P_TEW3
1	1.000000000000
2	0.061673850835
3	0.114291211928
4	0.114856430613
5	0.065044263595
6	0.049338922884
7	0.034003259085
8	0.047014984123
9	0.041117177952
10	0.052644541396

LAG	P_TEW4
1	1.000000000000
2	0.093435249079
3	0.066656053930
4	0.044725668717
5	0.007927066759
6	0.000880999259
7	0.062368513409
8	-0.016753379014
9	-0.021689119882
10	-0.001593055797

LAG	P_TISEFIN
1	1.000000000000
2	0.135000309682
3	0.016387589988
4	-0.026333024056
5	0.020555048752
6	0.008158174579
7	-0.024981853078
8	0.008154629727
9	0.009985465723
10	0.016303514558

LAG	P_TISEGEN
1	1.000000000000
2	0.167512187050
3	0.058660797389
4	0.015963625636
5	-0.027844361987
6	-0.018002094890
7	-0.007074655957
8	0.003515165558
9	0.024118346278
10	0.057906428217

LAG	P_TISEQ
1	1.000000000000
2	0.178293321177
3	0.034892902053

4	-0.003623943572
5	0.015159307623
6	0.014849391995
7	-0.013376540639
8	-0.022110888950
9	0.032128541453
10	0.043592685976
LAG	P_TISEQR
1	1.000000000000
2	0.173767679216
3	0.028914102652
4	-0.021628850938
5	0.009368119049
6	0.002168481733
7	-0.028117332185
8	-0.036138585668
9	0.034230301104
10	0.061586075690
LAG	P_TVW4
1	1.000000000000
2	0.069049779265
3	0.013426243379
4	0.031155572128
5	0.012737799532
6	-0.006169243003
7	0.048077805205
8	0.009954281688
9	0.000221190565
10	0.030390892098
LAG	P_VWP4
1	1.000000000000
2	0.064305723401
3	0.036602466780
4	0.108499927338
5	0.031975148103
6	0.017860154136
7	0.005205395070
8	-0.023499474559
9	-0.032681655257
10	-0.030171502823

Appendix III. LB Q Statistics

EWP1				
Autocorrelations				
-0.0161551	0.0231248	0.0046353	-0.0182414	-0.0122661
Ljung-Box Q-Statistics				
	Q(1)	0.3954	Sig.	0.52947666
	Q(2)	1.2061	Sig.	0.54714241
	Q(3)	1.2387	Sig.	0.74374140
	Q(4)	1.7438	Sig.	0.78274592
	Q(5)	1.9724	Sig.	0.85295741
EWP2				
Autocorrelations				
0.0050026	-0.0069058	0.0063580	0.0044417	0.0178536
Ljung-Box Q-Statistics				
	Q(1)	0.0379	Sig.	0.84561615
	Q(2)	0.1102	Sig.	0.94638440
	Q(3)	0.1715	Sig.	0.98204787
	Q(4)	0.2015	Sig.	0.99525373
	Q(5)	0.6857	Sig.	0.98374571
EWP3				
Autocorrelations				
0.02691984	0.05586521	0.02620303	0.04801457	0.02711478
Ljung-Box Q-Statistics				
	Q(1)	1.0979	Sig.	0.29473008
	Q(2)	5.8292	Sig.	0.05422514
	Q(3)	6.8708	Sig.	0.07613188
	Q(4)	10.3704	Sig.	0.03462935
	Q(5)	11.4872	Sig.	0.04253104
EWP4				
Autocorrelations				
-0.1334281	0.0027867	0.0686236	0.0087827	0.0102433
Ljung-Box Q-Statistics				
	Q(1)	26.9717	Sig.	0.00000021
	Q(2)	26.9835	Sig.	0.00000138
	Q(3)	34.1274	Sig.	0.00000019
	Q(4)	34.2444	Sig.	0.00000066
	Q(5)	34.4038	Sig.	0.00000198
EWP				
Autocorrelations				
0.16292904	0.10535892	0.13290353	0.10526070	0.06206615
Ljung-Box Q-Statistics				
	Q(1)	40.2170	Sig.	0.00000000

	Q(2)	57.0455	Sig.	0.00000000
	Q(3)	83.8409	Sig.	0.00000000
	Q(4)	100.6603	Sig.	0.00000000
	Q(5)	106.5119	Sig.	0.00000000
VWP1				
Autocorrelations				
0.0130291	-0.0024139	0.0014458	0.0007056	0.0036974
Ljung-Box Q-Statistics				
	Q(1)	0.2572	Sig.	0.61206258
	Q(2)	0.2660	Sig.	0.87545816
	Q(3)	0.2692	Sig.	0.96571541
	Q(4)	0.2699	Sig.	0.99167094
	Q(5)	0.2907	Sig.	0.99781418
VWP2				
Autocorrelations				
0.0243498	-0.0145087	0.0128904	0.0324934	0.0215393
Ljung-Box Q-Statistics				
	Q(1)	0.8983	Sig.	0.34324847
	Q(2)	1.2174	Sig.	0.54406194
	Q(3)	1.4695	Sig.	0.68933798
	Q(4)	3.0722	Sig.	0.54581548
	Q(5)	3.7769	Sig.	0.58195599
VWP3				
Autocorrelations				
0.04007561	0.02123318	0.03679794	0.00312089	0.02864918
Ljung-Box Q-Statistics				
	Q(1)	2.4332	Sig.	0.11879202
	Q(2)	3.1167	Sig.	0.21048691
	Q(3)	5.1708	Sig.	0.15970717
	Q(4)	5.1856	Sig.	0.26877700
	Q(5)	6.4324	Sig.	0.26638824
VWP4				
Autocorrelations				
0.06430572	0.04058633	0.11277465	0.04615456	0.02969795
Ljung-Box Q-Statistics				
	Q(1)	6.2649	Sig.	0.01231548
	Q(2)	8.7621	Sig.	0.01251211
	Q(3)	28.0556	Sig.	0.00000354
	Q(4)	31.2894	Sig.	0.00000267
	Q(5)	32.6291	Sig.	0.00000446
VWP				
Autocorrelations				
0.10546474	0.05686152	0.14733611	0.05982147	0.04373571
Ljung-Box Q-Statistics				
	Q(1)	16.8511	Sig.	0.00004043

	Q(2)	21.7527	Sig.	0.00001890
	Q(3)	54.6838	Sig.	0.00000000
	Q(4)	60.1162	Sig.	0.00000000
	Q(5)	63.0218	Sig.	0.00000000
ISEQ				
Autocorrelations				
0.1408339	0.0023291	0.0600222	0.0824637	-0.0077989
Ljung-Box Q-Statistics				
	Q(1)	30.0488	Sig.	0.00000004
	Q(2)	30.0571	Sig.	0.00000030
	Q(3)	35.5223	Sig.	0.00000009
	Q(4)	45.8453	Sig.	0.00000000
	Q(5)	45.9376	Sig.	0.00000001
ISEQR				
Autocorrelations				
0.1359151	0.0027543	0.0696093	0.0758495	-0.0080464
Ljung-Box Q-Statistics				
	Q(1)	27.9865	Sig.	0.00000012
	Q(2)	27.9980	Sig.	0.00000083
	Q(3)	35.3486	Sig.	0.00000010
	Q(4)	44.0820	Sig.	0.00000001
	Q(5)	44.1803	Sig.	0.00000002
ISEFIN				
Autocorrelations				
0.0811027	-0.0121592 -	0.0635611	0.0585758	0.0049337
Ljung-Box Q-Statistics				
	Q(1)	9.9652	Sig.	0.00159531
	Q(2)	10.1893	Sig.	0.00612948
	Q(3)	16.3180	Sig.	0.00097582
	Q(4)	21.5265	Sig.	0.00024894
	Q(5)	21.5635	Sig.	0.00063367
ISEGEN				
Autocorrelations				
0.10389490	0.03658174	0.04778299	0.07081900	0.00727465
Ljung-Box Q-Statistics				
	Q(1)	16.3532	Sig.	0.00005257
	Q(2)	18.3819	Sig.	0.00010196
	Q(3)	21.8456	Sig.	0.00007024
	Q(4)	29.4589	Sig.	0.00000631
	Q(5)	29.5393	Sig.	0.00001817
TEW1				
Autocorrelations				
0.01937794	0.02672459	0.01152465	0.05509216	0.03411501
Ljung-Box Q-Statistics				
	Q(1)	0.5689	Sig.	0.45070022

	Q(2)	1.6516	Sig.	0.43787868
	Q(3)	1.8531	Sig.	0.60344585
	Q(4)	6.4605	Sig.	0.16729548
	Q(5)	8.2284	Sig.	0.14408900
TEW2				
Autocorrelations				
0.05338072	0.03655244	0.03594122	0.01138999	0.05818026
Ljung-Box Q-Statistics				
	Q(1)	4.3170	Sig.	0.03773340
	Q(2)	6.3425	Sig.	0.04195103
	Q(3)	8.3021	Sig.	0.04016324
	Q(4)	8.4991	Sig.	0.07491541
	Q(5)	13.6409	Sig.	0.01805895
TEW3				
Autocorrelations				
0.06167385	0.11766015	0.12640093	0.08814515	0.08063945
Ljung-Box Q-Statistics				
	Q(1)	5.7626	Sig.	0.01637122
	Q(2)	26.7500	Sig.	0.00000155
	Q(3)	50.9876	Sig.	0.00000000
	Q(4)	62.7819	Sig.	0.00000000
	Q(5)	72.6597	Sig.	0.00000000
TEW4				
Autocorrelations				
0.09343525	0.07480428	0.05688972	0.02147224	0.01024679
Ljung-Box Q-Statistics				
	Q(1)	13.2262	Sig.	0.00027606
	Q(2)	21.7093	Sig.	0.00001931
	Q(3)	26.6190	Sig.	0.00000708
	Q(4)	27.3189	Sig.	0.00001714
	Q(5)	27.4784	Sig.	0.00004602
TEW				
Autocorrelations				
0.17820157	0.15700159	0.10169391	0.10074972	0.09692252
Ljung-Box Q-Statistics				
	Q(1)	48.1101	Sig.	0.00000000
	Q(2)	85.4789	Sig.	0.00000000
	Q(3)	101.1673	Sig.	0.00000000
	Q(4)	116.5759	Sig.	0.00000000
	Q(5)	130.8456	Sig.	0.00000000
TVW1				
Autocorrelations				
0.03908109	0.05711735	0.03694667	0.05176179	0.03134539
Ljung-Box Q-Statistics				
	Q(1)	2.3139	Sig.	0.12822114

	Q(2)	7.2597	Sig.	0.02651999
	Q(3)	9.3305	Sig.	0.02520443
	Q(4)	13.3977	Sig.	0.00948747
	Q(5)	14.8902	Sig.	0.01084194
TVW2				
Autocorrelations				
0.03962648	0.02153004	0.06301396	0.05413627	0.06863078
Ljung-Box Q-Statistics				
	Q(1)	2.3789	Sig.	0.12298066
	Q(2)	3.0817	Sig.	0.21420144
	Q(3)	9.1054	Sig.	0.02792239
	Q(4)	13.5543	Sig.	0.00886235
	Q(5)	20.7091	Sig.	0.00091921
TVW3				
Autocorrelations				
0.09038122	0.09900077	0.06948407	0.10689884	0.09282775
Ljung-Box Q-Statistics				
	Q(1)	12.3757	Sig.	0.00043496
	Q(2)	27.2343	Sig.	0.00000122
	Q(3)	34.5585	Sig.	0.00000015
	Q(4)	51.9054	Sig.	0.00000000
	Q(5)	64.9948	Sig.	0.00000000
TVW4				
Autocorrelations				
0.0690498	0.0181301	0.0331636	0.0172640	-0.0031709
Ljung-Box Q-Statistics				
	Q(1)	7.2233	Sig.	0.00719619
	Q(2)	7.7216	Sig.	0.02105065
	Q(3)	9.3901	Sig.	0.02452982
	Q(4)	9.8425	Sig.	0.04316545
	Q(5)	9.8578	Sig.	0.07936606
TVW				
TVW				
Autocorrelations				
0.11865265	0.04275836	0.05123570	0.01516528	0.01635609
Ljung-Box Q-Statistics				
	Q(1)	21.3289	Sig.	0.00000387
	Q(2)	24.1006	Sig.	0.00000584
	Q(3)	28.0829	Sig.	0.00000349
	Q(4)	28.4320	Sig.	0.00001019
	Q(5)	28.8384	Sig.	0.00002494
TISEQ				
Autocorrelations				
0.1523240	0.0245955	0.0032290	0.0047481	-0.0305215
Ljung-Box Q-Statistics				

	Q(1)	35.1520	Sig.	0.00000000
	Q(2)	36.0691	Sig.	0.00000001
	Q(3)	36.0849	Sig.	0.00000007
	Q(4)	36.1191	Sig.	0.00000027
	Q(5)	37.5342	Sig.	0.00000047
TISEQR				
Autocorrelations				
0.1420381	0.0283749	-0.0041924	-0.0134726	-0.0413911
Ljung-Box Q-Statistics				
	Q(1)	30.5649	Sig.	0.00000003
	Q(2)	31.7855	Sig.	0.00000013
	Q(3)	31.8121	Sig.	0.00000057
	Q(4)	32.0877	Sig.	0.00000184
	Q(5)	34.6901	Sig.	0.00000173
TISEFIN				
Autocorrelations				
0.1523737	0.0645355	-0.0185768	0.0177041	0.0028274
Ljung-Box Q-Statistics				
	Q(1)	35.1749	Sig.	0.00000000
	Q(2)	41.4888	Sig.	0.00000000
	Q(3)	42.0123	Sig.	0.00000000
	Q(4)	42.4881	Sig.	0.00000001
	Q(5)	42.5003	Sig.	0.00000005
TISEGEN				
Autocorrelations				
0.1368267	0.0426248	0.0110561	-0.0342030	-0.0478560
Ljung-Box Q-Statistics				
	Q(1)	28.3632	Sig.	0.00000010
	Q(2)	31.1176	Sig.	0.00000017
	Q(3)	31.3030	Sig.	0.00000073
	Q(4)	33.0789	Sig.	0.00000115
	Q(5)	36.5577	Sig.	0.00000073