# AN ANALYSIS OF THE TURN-OF-THE-YEAR EFFECT IN SOUTH AFRICAN EQUITY RETURNS.

A thesis submitted in partial fulfilment of the requirements for the degree of



**MASTERS IN COMMERCE (Financial Markets)**

of

RHODES UNIVERSITY

by

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December 2006

# ABSTRACT

This study investigates FTSE/JSE All Share Index monthly and daily equity returns for evidence of the January and TY effect. Four different measures of monthly return are analysed for the 1995-2006 period, whilst daily returns are analysed during the 1995-2005 period. In addition to this, analysis is conducted on monthly Fama-MacBeth risk premium estimates for the FTSE/JSE All Share Index. Descriptive statistics are first analysed, followed by ANOVA or Kruskal-Wallis tests, the paired t-test and finally dummy variable regression analysis in investigating the seasonality of FTSE/JSE All Share Index returns and risk premia.

Analysis on monthly returns reveals an absence of the January effect, however a positive slightly statistically significant December effect is found. Thus, investors earn abnormal returns on equity during the month of December. The results from the Fama-MacBeth risk premia estimates reveals highly statistically significant negative risk premia seasonal patterns during March, July and September. Thus, investors are in fact penalised for investing in equities during these months. In addition, the analysis reveals an absence of a December effect in risk premia, which contradicts the risk-return trade-off central to modern finance. The daily return analysis reveals a highly significant Turn-of-the-Year effect (TY), which suggests that investors earn abnormal returns on days at the turn of the year.

Therefore, it is concluded that a December effect is apparent in South African equity monthly returns, whilst a March, July and September effect is apparent in South African equity risk premia contradicting the risk-return trade-off central to modern finance. In addition to this, a TY effect is present in South African equity daily returns.

# ACKNOWLEDGEMENTS

Numerous people have helped in the production of this dissertation. I would like to thank Mr E. Seedat, my supervisor, for his patience, invaluable advice and encouragement throughout the duration of the dissertation. To Mr M. Ackerman of Citadel Asset Managers for providing a significant portion of data that was required in order to carry out the study. Also to Mr J. Dawood of Rand Merchant Bank and the JSE for additional data and information supplied. Finally, I would like to extend my thanks to my wife, Roxanne, and family for providing the encouragement needed to ensure the completion of this dissertation.

## DECLARATION

I certify that this thesis has not been submitted for a degree at any other university and that it is my original work except for where referenced within the document.

Signed........................

Date: 18 December 2006

**AN ANALYSIS OF THE TURN-OF-THE-YEAR EFFECT IN SOUTH AFRICAN EQUITY RETURNS.**

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# CHAPTER ONE
# INTRODUCTION

## 1.1 BACKGROUND, CONTEXT AND RATIONALE FOR THE RESEARCH

The weak form of the Efficient Market Hypothesis (WEMH) precludes the prediction of future returns on securities like equities by economic agents using relevant information on equities. Information available to these economic agents includes prices, volumes traded and bid-ask spreads. Conclusive evidence of the WEMH's validity still eludes economists, given numerous examples of deviations from the WEMH in both securities and associated derivatives markets. Such deviations comprise anomalies which include seasonal patterns in data series. In turn, a form of seasonal pattern often detected across countries is the January effect and cognate Turn-of-the-Year (TY) effect.

The phenomenon of exceptionally high equity returns during the month of January (January effect) is first identified by Wachtel (1942), while the related TY effect is first identified by Reinganum (1983). The TY effect occurs during the last trading day of December and the first four trading days of January, where abnormal returns are obtained by investors (Keim, 1983; Roll, 1983 and Al-Rjoub, 2005).

Studies on time-series, cross-section and panel data published in peer-reviewed journals contain analyses of whether stock markets are efficient in this form. Of the studies done on the January effect and TY effect, appearing in Appendix 1 Panel 1-6, more than a third have been published in the top ten Institute for Scientific Information (ISI)-ranked journals[1] whilst more than a half are published in other journals. Approximately a tenth of these studies are working papers.

[1] ISI ranked journals are ranked according to impact, which is calculated by dividing the number of current year citations to the source items published in that journal during the previous two years. Refer to Garfield (1994) for further information.

Besides detection, much of this research consists of explaining the presence or absence of seasonal patterns. Two such explanations include the tax-loss selling hypothesis and the small-firm effect. Tax-loss selling consists of the sale of equities on which losses are incurred in December to offset tax liabilities. The small-firm effect is the phenomenon of higher returns accruing to low market capitalisation equities. However, any explanation of a seasonal pattern must depend on the securities like equities to which the analysis is applied, the markets in which these equities trade and the laws that constrain issuers of such securities (Berges et al. 1984 and Gao & Kling 2005).

Most studies of seasonal patterns in equity markets are done with Organisation for Economic Co-operation & Development (OECD) nations data sets, especially the United States of America (USA). There are fewer examples of studies of "emerging" equity markets like those of South Africa. The few extant studies using South African equity data include Bradfield (1990), Hattingh & Smit (1993), Coutts & Sheikh (2000) and le Roux & Smit (2001).

## 1.2 THE SIGNIFICANCE OF SEASONAL PATTERNS

Seasonal patterns in equity markets contradict the WEMH. Such seasonal patterns admit the prediction of future price changes based on past price information. If the present still depends on the past, the exploitation of such weak-form market inefficiency through the purchase and sale of equities when appropriate, may present profitable trading opportunities for an astute economic agent.

## 1.3 GOALS OF THE RESEARCH

The primary objective is to detect the January and TY effect whilst the secondary objective of the study is to detect a seasonal pattern in risk premium and whether the risk and return seasonal patterns exist for the same month.

## 1.4 METHODOLOGY

A seasonal effect is detected in equity market indices or a large portfolio of equities more easily than in the case of individual equities (Officer, 1975; Boudreaux, 1995 and Chotigeat & Pandey, 2005). Thus, monthly return data on the FTSE/JSE All Share Index is used during the 1995-2006 period to detect a January effect. The FTSE/JSE All Share Index daily returns are then used to detect a Turn-of-the-Year (TY) effect during the 1995-2005 period. The Fama-MacBeth (1973) procedure is used to estimate values of the risk premium, from 255 equities during the 1997-2005 period.

Four different measures of monthly returns are analysed for the January effect. These measures include the continuously compounded return (log return), log real return, log realised return and log realised real returns. Realised returns are calculated from the FTSE/JSE All Share Total Return Index, whilst real returns are returns deflated with the South African PPI. With regard to the TY effect, daily continuously compounded returns are used.

Preliminary examination of the data is first conducted on the various data sets, before advancing to regression analysis. Preliminary examination includes analysis of the first four moments of each data set, normality testing and tests for differences in mean returns. Regression analysis includes dummy variable models in order to detect seasonal patterns in return and risk. For the TY effect the regression analysis includes a GARCH model, which allows for a more accurate estimation of the effect.

## 1.5 ORGANISATION OF THE STUDY

This study consists of five chapters. The next chapter contains a review of the theoretical and empirical literature on the issue of the January and TY effect, including an evaluation of the various approaches described. Chapter three comprises the derivation of an apt model to detect the January and TY effects for South African equities. The results of these models appear in Chapter four. Chapter five concludes the study.

# CHAPTER TWO
# LITERATURE REVIEW

## 2.1 INTRODUCTION

This chapter consists of a review and evaluation of the extant literature on seasonality like the January effect and Turn-of-the-Year (TY) effect in equity markets and is divided as follows. Section 2.2 contains a descriptive of theory for the January and TY effect. A discussion and evaluation of the empirical literature is presented in Section 2.3. Finally the chapter is concluded in Section 2.4.

## 2.2 THEORETICAL ISSUES

### 2.2.1 Introduction

If equity prices incorporate information implied by all preceding price changes, the market is weak-form efficient. Changes in prices now are independent of prices before, which obviates price patterns which can be used for prediction. The weak-form efficient market hypothesis (WEMH) precludes the use of trading rules like buying (selling) an equity if its price increases (decreases) by *x*% greater (less) than a certain price. Thus prices change only in response to new information or new economic events. One of the world's leading financial economists, Thaler (1987: 199), states that "it should be impossible to predict changes in equity prices based on past price behaviour". Beside past prices, volumes and other historical information also cannot predict future equity price movements (Boudreaux, 1995: 15). Thus, the WEMH implies that equity prices follow a random walk.

After Fama (1970) describes the WEMH, many authors test this hypothesis for the randomness of equity price movements (Boudreaux, 1995: 15). Among the many approaches to testing WEMH, seasonal patterns in equity returns are often detected around the world. Proof of systematic variation in equity returns implies pecuniary gains from the use of such knowledge.

The WEMH implies that equity returns are time-invariant. In addition, short-term time-based patterns are absent. However, equity market anomalies abound for individual equity returns, portfolio returns and index returns.

Thaler (1987: 198) mentions that anomalies can easily be found in equity markets since substantial data on these markets are available. These markets are considered the most efficient of all markets, because they are well regulated and highly liquid. Thus, if anomalies are found in the equity market, high transactions costs or other market failures could be eliminated as causes of these phenomena. Secondly, numerous well-developed theories exist for assigning prices to securities. Therefore, structured approaches to potential tests of efficiency in its various forms are available.

There is significant evidence suggesting that a January effect, in which returns are consistently higher in January than any other month, is present in numerous equity markets across the world. Some explanations of this seasonal pattern include the tax-loss selling hypothesis, the size-effect, the information hypothesis and the parking-the-proceeds hypothesis.

Investors behave in a peculiar manner in late December by selling losing equities in order to offset capital losses against their capital gains, thereby decreasing their tax liability. This peculiarity is referred to as the tax-loss selling or the bed-and-breakfasting hypothesis. International evidence of tax-loss selling partially explains the January effect (Thaler, 1987: 200). The parking-the-proceeds hypothesis is a slight variation of the tax-loss selling hypothesis and is first suggested by Ritter (1988) as a possible explanation of the January effect. As the end of the year approaches, individuals sell equities in order to offset tax liabilities. Some of the proceeds made from these sales are not immediately reinvested and instead are "parked" until January. When the funds are reinvested, this buying pressure pushes up the prices of small firms in which individual investors typically invest. Three assumptions form the basis of this hypothesis. Firstly, it is assumed that individual investors have low-priced, low capitalisation equity more intensive portfolios than the institutional investors and buy a disproportionate number of small equities. Secondly, for small equity buying and selling, pressures affect equity prices and finally, the proceeds from December tax-motivated selling is not immediately reinvested in the same or other equities, i.e. individuals are net buyers of small equities in January (Ritter, 1988). Ritter (1988: 705-706) provides evidence in support of these assumptions, suggesting that this hypothesis is valid.

Central to the parking-the-proceeds hypothesis is the effect of small firm equity buying and selling. This is referred to as the size-effect in the anomalies literature, in which small firm equities experience proportionately larger changes in price. Thus, these equities can have a significant impact on equity returns observed in December and January if the tax-loss selling or parking-the-proceeds hypotheses are valid. For this reason value-weighted indices are preferred to equally-weighted indices[2] in analysing market returns for seasonality.

The gradual dissemination of information during January may have a greater impact on small firm equity prices relative to large firm equities (Keim, 1983: 30). This is known as the information hypothesis and is also identified as a possible explanation of the January effect.

These are the various hypotheses surrounding the cause of the January effect. Various other equity market anomalies have been identified; however, they are not the focus of this research. For this reason literature reviewed in this chapter concentrates significantly on the January effect and the TY effect, which is the focus of this research. Section 2.2.2 contains a brief description on anomalies / seasonality before proceeding with Section 2.2.3 and Section 2.2.4 in which the January effect and the TY effect are discussed.

### 2.2.2 Anomalies / seasonality

Anomalies include seasonal patterns in individual equity returns, portfolio returns and index returns. These consist of day-of-the-week effects, the weekend effect (Connolly, 1989), the holiday effect (Barone, 1990) and the turn-of-the-month effect (Barone,

[2] Value-weighted indices are constructed according to market capitalisation value of each equity. Thus small firm equities have a proportionately smaller influence on the index value as compared to an equally-weighted index in which small firm equities would have a proportionatly larger influence. Therefore if a January effect is present in a value-weighted index, one cannot invoke the small-firm effect in explaining the seasonal pattern.

1990). The day-of-the-week effect refers to the anomaly where excess returns accrue to a particular day of the week; the weekend effect is an anomaly where returns on Monday are negative and positive on Friday; the holiday effect refers to an anomaly where excess returns accrue to equities a few days preceding a public holiday and the turn-of-the-month effect refers to an anomaly where equity returns show a clear difference between the first and second halves of any given month.

### 2.2.3 The January effect

The January effect of exceptionally high equity returns during the month of January is first identified by Wachtel (1942), contradicting the WEMH. Wachtel asserts that the cause is tax-loss selling behaviour. Rozeff & Kinney (1976) suggest that the January effect applies mainly to small firms' equity returns which are greater than the monthly average in January. The January effect is conspicuous in equally-weighted equity indices but remains when indices are value-weighted, which implies the absence of the small-firm effect. Value-weighted indices are constructed according to market capitalisation value of each equity. Thus, small firm equities have a proportionately smaller influence on the index value as compared to an equally-weighted index in which small firm equities would have a proportionately larger influence. Therefore, if a January effect is present in a value-weighted index, one cannot invoke the size effect in explaining this seasonal pattern.

### 2.2.4 The turn of the year (TY) effect

The TY effect is an anomaly where abnormal returns on equities are earned on the last trading day of December and the first four trading days of January (Keim, 1983; Roll, 1983 and Al-Rjoub, 2005). This anomaly is distinct from the January effect which is observed in monthly rather than daily equity returns. Like the analysis of the January effect the TY effect is analysed in relation to tax-loss selling and the size-effect. Evidence in favour of these hypotheses as explanations of the TY effect is inconclusive.

## 2.3 EMPIRICAL LITERATURE

### 2.3.1 Introduction

This section comprises a review of the international and domestic empirical literature on the January and TY effect including the various approaches used in detecting these patterns and is divided as follows.

Section 2.3.2 consists of various international literature that focuses on testing for seasonal effects using descriptive techniques. Section 2.3.3 contains the bulk of the literature reviewed and consists of inferentially based work. Section 2.3.3 is sub-divided into three, with the first sub-section, Section 2.3.3.1, consisting of all international literature on the developed equity markets of the world. The second sub-section, Section 2.3.3.2, consists of literature on the emerging markets of the world, some of which include China, India and Malaysia. Section 2.3.3.3 comprises the extant literature on the South African equity market.

### 2.3.2 Descriptive

Wachtel (1942) first identifies the January effect in the American equity market. Wachtel examines the Dow Jones Industrial Average for the 1927-1942 period and finds that this index, comprising thirty equities, is frequently "bullish" during the December-January period. Wachtel further finds a marked tendency for January advances in the index's value during this period. Thus there may be a stimulus to equity prices during the month of January (Wachtel, 1942: 185). In explaining the January effect, Wachtel (1942: 186) mentions that tax-loss selling, an unusual demand for cash, pre-holiday increases, future expectation of better business in spring and a sense of good cheer could all be responsible.

Wachtel's focus is on explaining the January effect in relation to the tax-loss selling hypothesis. Wachtel (1942) assumes that the best equities to sell in order to obtain the greatest realisable losses are the high yielding equities, and that individuals and corporations sell these equities for tax-saving towards the middle of December. Wachtel also assumes that the increase in the index's value at the year's end is a normal "recovery" from troughs.

To prove the theory of tax-loss selling Wachtel (1942: 188) combines thirteen separate indices, during the period 1928-1940, of a different group of the twenty highest-yielding industrial common equities listed on the New York Stock Exchange (NYSE). The values of these thirteen indices are added together at dates equidistant from the bases in December. The total is then divided by thirteen. This same procedure is followed to obtain the mean values for the thirty Dow-Jones Industrial equities. Wachtel finds that the late December increase in the value of high-yielding equities is greater than that of the low-yielding Dow-Jones equities. This pattern continues until the third Saturday of January. Thus, tax-loss selling is the cause of the January anomaly in the thirteen indices examined by Wachtel (1942).

Wachtel's study is deficient in that tax-loss selling pressure ends in mid-December. Theoretically, it should continue until the end of December (Shin, 2003: 3). Wachtel's study also lacks statistical tests of significance, thus it can only be tentatively asserted that the differences between the high-yielding and low-yielding equities are significant. The value of Wachtel's study is that several hypotheses on the causes of this phenomenon are propounded. The most significant of these hypotheses relates to tax-loss selling. Wachtel's explanation is so cogent that numerous authors have since tested the tax-loss selling hypothesis as a possible cause of the January effect.

Bonin & Moses (1974) examine thirty, individual, seasonally-adjusted Dow-Jones industrial equity prices adjusted for capital changes every month during the period 1962-1971. Of the thirty equities examined, seasonal patterns are apparent for seven equities. Given the use of a few equity prices rather than equity indices or large portfolios of equities, it is difficult to assert that seasonal patterns apply generally to other equities listed on the Dow-Jones.

Berges et al. (1984) offer a novel perspective on the issue of tax-loss selling using Canadian equity market data for the period 1951-1980. This data includes month-end prices, equity splits, equity dividends, cash dividends[3], and the number of equities outstanding at the end of each month for 391 companies listed on the Toronto Equity Exchange and the Montreal Equity Exchange.

Berges et al. (1984: 186) seek confirmation or rejection of the tax-loss selling hypothesis as an explanation of the size-effect in turn-of-the-year equity returns. The Canadian situation is particularly amenable to the analysis from this perspective because Capital Gains Tax (CGT) was only introduced after 1972 and the tax-year end falls in December. For the tax-loss selling hypothesis to hold it is necessary for the tax structure to include some form of CGT. Thus, the presence of the January effect in a jurisdiction free of CGT means that this hypothesis cannot explain the January effect. Therefore, Berges et al. (1984) split the data set into the period 1951-1972 and the period 1973-1980. Berges et al. (1984) propound the hypothesis that if the tax-selling hypothesis holds, the January effect should be absent during the 1951-1972 period. To test the foregoing hypothesis, equities are assigned to five different portfolios, containing an equal number of equities, based on their total market value. The total market value of each equity is determined by multiplying the month-end price by the number of equities outstanding. Berges et al. (1984) then compute an equally-weighted average for each of the five portfolios for each month of the year beginning with January 1951. The findings from this analysis reveal a size-effect in monthly returns.

Berges et al. (1984: 188) compare the mean monthly equity returns for January to the mean return for the remaining months of the year for both periods. A January effect is present prior to 1972 and afterwards; thus tax-loss selling only partially explains this equity market anomaly since investors lack an incentive to sell equities at the end of the year. To further test the tax-loss selling hypothesis, Berges et al. (1984) analyse the relationship between January returns and a measure of potential tax-loss selling (PTS), using Reinganum's (1983) PTS measure. Berges et al. (1984) adjust

[3] Equity dividends and cash dividends are two separate items; the difference is not explicitly stated by Berges et al. (1984: 187).

the PTS measure to incorporate extra data compared to Reinganum's (1983) study. The PTS measure used by Berges et al. (1984: 189) is the ratio of the year-end price and the highest transaction price during a period which would permit the registration of losses as short-term in nature for tax purposes in the USA. This measure's range is from 0.0, where there is the absence of PTS, to 1.0, where PTS is complete. Equities are assigned to ten portfolios; the original five portfolios that have been split into two PTS categories, high and low. Thus, the high PTS portfolio contains half of the equities with the highest PTS measure. The other half is assigned to a low PTS portfolio. Berges et al. (1984) suggest that the mean equity returns are greater for the high PTS group than the low PTS group. However, this holds at lower statistical significance levels than conventionally used. There is slight evidence in favour of the tax-loss selling hypothesis. Berges et al. (1984: 191) therefore conclude that the tax-loss selling is a dubious explanation of the January effect.

### 2.3.3 Inferential

#### 2.3.3.1 Evidence from developed markets

Granger & Morgenstern (1963, 1970) examine aggregate monthly American equity price data for the period 1875-1956. This data includes the Standard & Poor's Equity Index, Securities and Exchange Commission's (SEC) Equity Price Index, Dow-Jones Industrial Average and individual company equities. Using spectral analysis, Granger & Morgenstern find the absence of a seasonal peak in the spectra. They also reveal small peaks in the spectra corresponding to seasonal harmonics; however none of these cycles is significant (Granger & Morgenstern, 1970: 130-131 in Shin 2003: 3). Bonin & Moses (1974: 966), impugn Granger & Morgenstern's conclusions, as the method yields seasonal patterns by default.

Officer (1975) focuses on Australian equity returns for 1958-1970, sourced from an unpublished price file of 651 equities listed on the now-defunct Melbourne Equity Exchange. Officer uses a mixed Auto-Regressive Moving-Average (ARMA) linear stochastic model, which includes seasonal elements. Officer finds a 6-month seasonal and to some extent a 9-month and 12-month seasonal in the autocorrelation function. Forecasts are then made using the Box & Jenkins method. The forecast errors from the seasonal model are lower than the forecast errors from the simple random walk model, suggesting that the seasonal model better explains equity returns than the simple random walk model.

Officer (1975: 49) concludes that a seasonal pattern exists in the Australian equity market but one cannot reject the WEMH. No mention is made of a possible cause; however it is stated that this is an area for research if continued testing leads to the conclusion of seasonality.

Rozeff & Kinney (1976) investigate seasonality in the tradeoff between risk and return with equity indices listed on the NYSE during the period 1904-1974[4] and are compared against Officer's (1975) study on the Australian market and Granger & Morgenstern's (1963, 1970) spectral analysis on USA data. They examine the behaviour of the estimates obtained from the two-parameter Capital Asset Pricing Model (CAPM). On visual inspection of the return data, seasonal patterns are absent. Rozeff & Kinney (1976: 383) state that "returns seem to have been generated by a stochastic process that is mean stationary." Rozeff & Kinney divide the time series into four periods[5].

The autocorrelation function, constructed on returns, is consistent with the findings of Granger & Morgenstern (1963, 1970) that there is a tendency for seasonal peaks at four months and less. However, this analysis reveals a six month seasonal and the absence of a January effect. Thus the seasonal patterns observed by Officer (1975) are unimportant in USA data. However, upon testing the average monthly returns, high returns during January are responsible for the observed seasonality. Rozeff & Kinney (1976) then use the Kruskal-Wallis test statistic, a distribution-free test, to detect seasonality in equity returns assuming that the random variables are continuous and measurable on an ordinal scale. When this test is applied, a seasonal pattern in

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[4] For the 1904-1909 period, rates of return are computed from the aggregate Cowles Commission equity price index. For the 1910-1925 period these rates of return are derived from the Standard & Poor's aggregate index value relatives. The 1926-1974 period includes equally weighted total returns for all common equities listed on the NYSE. These are computed from Standard & Poor's 1975 version of the CRSP file. The year 1914 is omitted from the study due to the exchange being closed for four months during this year.

[5] 1904-1928, 1929-1940, 1941-1974 and 1904-1928 plus 1941-1974 for analysis. The entire time period as well (1904-1974) is also considered.

each of the equity index's rate of return is apparent. In order to identify the months of the year during which there is seasonality, Rozeff & Kinney (1976: 391) compare across months in a pair-wise manner using rank sums for each month, and investigate the differences. This analysis reveals significantly greater mean returns during the month of January than in every other month of the year, except November, July and December.

When Rozeff & Kinney use the distribution-free Siegel-Tukey test of differences in scale, a rank test designed to detect differences in dispersion, in conjunction with the Kruskal-Wallis and pair-wise analysis suggests that the month of January may be the source of the distributional difference in equity returns. Parametric tests also confirm the non-parametric analysis. Rozeff & Kinney (1976) also find a positive seasonal pattern in equity returns for July, November and December as well as negative seasonal patterns for February and June. Applying the same techniques to the risk premium estimates from the Fama-MacBeth (1973) CAPM reveals a January effect. Thus returns in January are significantly greater than any other month's return, and the January risk premium is relatively greater than in other months for America.

Research done by Banz (1981) and Reinganum (1981) initiates research into the link between the January effect and the size of firms (Bentzen & Hansson, 2005: 9) by explaining the relationship between abnormal returns and firm size. It is expected that low capitalisation equities cause the January effect since a change in the price of a low capitalisation equity is significantly greater proportionately than a change in price of a high capitalisation equity.

Banz (1981) analyses the relationship between equity returns and market value of all common equities listed on the NYSE during the 1926-1975 period, i.e. the size-effect. Monthly price and return data and the number of shares outstanding are obtained from the CRSP monthly returns file. Three different market indices are used. Two of these are pure common equity price indices, the CRSP equally- and value-weighted indices. The third is a value-weighted combination of the CRSP value-weighted index and return data on corporate and government bonds. Banz (1981: 16) suggests that the CAPM is mis-specified and that "small NYSE firms have had significantly larger risk adjusted returns than large NYSE firms over a forty year period.".

Keim (1983) documents the size-effect in relation to the January effect. Keim's study examines the month-to-month stability of the size-effect on the NYSE and American Equity Exchange (AMEX) during the 1963-1979 period. The data is obtained from the CRSP daily equity price files. Keim assigns these various equities to ten portfolios according to market value (size) and then regresses daily excess returns (R) on eleven dummy variables (D) which is specified as:

$$R_t = a_1 + a_2 D_{2t} + a_3 D_{3t} + ... + a_{12} D_{12t} + e_t \qquad (2.1)$$

The subscripts attached to the dummy variables appearing in Equation (2.1) denote days corresponding to a particular month of the year besides January which each dummy variable represents. The intercept measures the excess return obtained during the month of January. Keim (1983) finds that returns for small-firms during the month of January are significantly greater than those of large firms. In fact "nearly fifty percent of the average magnitude of the risk-adjusted premium of small firms relative to large firms ... is due to anomalous January abnormal returns." (Keim, 1983: 31). Reinganum (1983: 90) states that this may indicate an anomaly within an anomaly. Keim's (1983) study therefore suggests a relationship between the January effect and the size-effect. Keim (1983: 29-31) explains this effect in terms of the tax-loss selling and information hypothesis.

Reinganum (1983) examines equity returns for equities listed on the NYSE and AMEX for the 1962-1979 period and this data is obtained from the December 1980 CRSP daily price files. Reinganum's focus is on whether the January size effects documented by Keim (1983), are associated with tax-loss selling. To test for size effects Reinganum (1983: 91) creates portfolios based on year-end market capitalisations for the firms included in the sample. Firms in the top decile belong to the large firm portfolio and firms in the bottom decile belong to the small firm portfolio. A relationship between the January effect and the size-effect is found from this analysis.

In order to test for year-end tax effects Reinganum (1983: 92) devises a measure for potential tax-loss selling (PTS). The PTS is calculated by dividing the equity's price on the penultimate trading day of the year by the maximum price from the beginning of July. Following this, each equity is jointly ranked according to its year-end market capitalisation and its PTS measure. Four PTS categories are created; thus each equity is assigned to one of forty portfolios. Due to data constraints, Reinganum (1983: 92) constructs the PTS from price data. Reinganum (1983: 93) states that this categorisation permits one to test for tax-loss selling effects within each portfolio as well as to test for differences in tax-loss selling effects between portfolios. Reinganum (1983) expects portfolios with a lower market capitalisation value and the greatest PTS to be associated with the January effect.

Reinganum (1983) finds that equities of small firms have high returns, after controlling for tax-loss-selling pressures. In addition, January abnormal returns for small firms are consistent with the tax-loss selling hypothesis. However, this partially explains the January effect. Reinganum also identifies systematic variation during the first trading days of January (Bentzen & Hansson, 2005: 9).

Gultekin & Gultekin (1983) examine seasonality in equity indices for major industrialised countries[6] for the period 1959-1979. Gultekin & Gultekin (1983: 470) state that the Capital International Perspective (CIP) indices, which are value-weighted and expressed in local currencies, represent sixty percent of the total market value of all equities traded in the foregoing countries.

Gultekin & Gultekin (1983: 471) first use visual and descriptive techniques to analyse the data before they use non-parametric tests, such as the Kruskal-Wallis test. Among the descriptive measures analysed the autocorrelations reveal that most autocorrelations are not statistically different from zero, only Austria, Denmark and Norway have serially dependent equity returns. The descriptive measures reveal high positive skewness in several countries, due to extremely large outliers (Gultekin & Gultekin, 1983: 471). The descriptive measures also reveal that equity returns for several countries are non-normally distributed. Gultekin & Gultekin (1983: 471) test

[6]These countries are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK and the USA.

for seasonality using both non-parametric and parametric tests. Similar findings are achieved from this analysis, thus they only discuss the non-parametric Kruskal-Wallis test results.

Monthly equity returns differ for twelve of the seventeen countries; at the ten percent level of significance. Gultekin & Gultekin (1983) also find a persistent January effect for most of the countries in the sample. This contradicts the tax-loss selling hypothesis, since these countries have different tax laws and tax year ends. However, Gultekin & Gultekin acknowledge that a single market index cannot distinguish the size-effect from the January effect (Kato & Schallheim, 1985: 245).

Gultekin & Gultekin (1983: 474) find the absence of seasonality for the American equity market, which contradicts research done by Bonin & Moses (1974) and Rozeff & Kinney (1976). Gultekin & Gultekin (1983:474) mention that their use of a value-weighted index rather than an equally-weighted index accounts for this difference. The reason is that the equally-weighted index weights small firms more heavily. Gultekin & Gultekin (1983) then test the equally-weighted NYSE index for the periods 1959-1979 and 1947-1979, subsequently confirming the work done by Rozeff & Kinney (1976). This is consistent with Keim (1983) in that the main cause of seasonality is due to the size-effect during January.

Brown et al. (1983) find a link between the tax-loss selling hypothesis and the size-effect in their study using Australian equities, obtained from a merged version of three monthly data files[7], during the 1958-1981 period. A value-weighted market index is created using the merged data file with the weights based on the previous month-end equity market value. Australia's tax year ends on the 30th of June, thus, *a priori*, if the tax-loss selling hypothesis holds, a July seasonal for small equities will be apparent. To incorporate the size-effect, Brown et al. (1983) assign the equities to ten portfolios based on equity market value in month *t*-2. Equities are then equally-weighted within each portfolio. Average returns of the smallest firms are 6.754

[7] The merged database consists of 1924 equities. The first file, Brown's N=909 file, covers the 1958-1973 period and comprises all industrial equities, par value not less than one million American dollars, listed on the Australian stock exchange. The second file, ADSM/CRA, covers the 1958-1979 and consists of all listed mining and oil equities, where a company's main operations are in Australia. The third file, AGSM Share Data File, covers the 1974-1981 period and comprises all Australian equities (Brown et al., 1983: 111).

percent, while the average returns of the largest firms are 1.023 percent (Brown et al. 1983:113). Greater returns are also found during the December-January period and July-August period, which contradicts the tax-loss selling hypothesis. Brown et al. (1983: 125) mention arbitrage and international market integration as explanations for the observation of such seasonals. They conclude that the January effect is ascribed to factors beside tax-loss selling in general.

Tinic & West (1984) examine seasonality in the relationship between expected equity return and risk on the NYSE for the period 1935-1982. Tinic & West (1984) extend Rozeff & Kinney's (1976) study on seasonality. They demonstrate that January is the only month when there is a consistently positive, statistically significant relationship between expected return and risk. Tinic & West (1984), like Rozeff & Kinney (1976), use monthly estimates of risk and return obtained from the two-parameter Fama & MacBeth (1973) CAPM for the NYSE, based on an equally-weighted index. Estimates of risk for the month of January are positive in twenty-four of the twenty-eight years analysed. To understand the seasonal behaviour of Fama & MacBeth's (1973) estimates they use the following model:

$$\tilde{\gamma}_{j\tau} = \beta_1 + \sum_{i=2}^{12} \beta_i D_i + \tilde{e}_{j\tau} \qquad (2.2)$$

where:

| | | |
|---|---|---|
| | $\tilde{\gamma}_{j\tau}$ | = mean equity return or market risk premium |
| | $D_2 \dots D_{12}$ | = a set of dummy variables representing months of the year from February to December. |
| | $\beta_1$ | = the mean $\gamma_0$ or $\gamma_1$ for January. |
| | $j$ | = 0 and 1 |

The difference in monthly mean return ($\gamma_0$) or market risk premia ($\gamma_1$) from the January average is therefore captured by the dummy variable regression coefficients. The regression analysis suggests that the coefficient for January is positive and significant for all three periods, only July is not statistically different from January.

This interests Tinic & West (1984: 567) as Officer (1975) and Brown et al. (1984) also identify a July seasonal in Australian equity prices.
Tinic & West (1984) then add data for December 1982. This supplementary analysis confirms the findings from analysis on the previous data set. Tinic & West (1984: 573) mention that "[r]ecent textbooks dealing with portfolio management and investment selection build heavily on the idea of a relatively consistent risk-return trade-off". This basic risk-return trade-off, central to modern finance, only appears in January. Thus, investors can gain from transacting during January.

Jaffe & Westerfield (1985) analyse daily prices of equities listed on the Nikkei-Dow (ND) Index, the Tokyo Equity Exchange (TSE) Index and Standard & Poor's Composite 500 Equity Price Index (S&P 500) for the 1970-1983 period. The ND consists of 225 equities and is similar in construction to the Dow-Jones Index. The TSE is a value-weighted index of 1000 equities and is similar to the S&P 500. The focus is on the day-of-the-week effect; however the January effect is analysed as well. The findings suggest a January daily mean return of 0.13 percent, which is significantly greater than the daily average return of 0.035 percent. This indicates a significant January seasonal in Japan. This is of interest since Japanese firms can set their tax year arbitrarily and in fact approximately fifty percent of Japanese firms have tax years ending in March (Lee, 1992: 200). Additionally, individual investors in Japan are exempt from CGT and cannot offset tax losses (Kato & Schallheim, 1985: 245 and Lee, 1992: 200). This means that the tax-loss selling hypothesis is invalid for Japan.

Kato & Schallheim (1985: 245) on the other hand suggest that the potential integration of American and Japanese equity markets precludes the total rejection of the tax-loss selling hypothesis. Kato & Schallheim (1985) study the Japanese equity market, with the emphasis on identifying a January and size-effect in this market. They also test the tax-loss selling hypothesis as a possible explanation for the cause of these anomalies. Kato & Schallheim (1985: 243) observe that the Japanese equity market is apt for testing the tax-selling hypothesis due to the differences between the Japanese and American tax systems.

The data used is obtained from the Nissho Monthly Equity Returns file and includes all firms listed on the TSE's First Section. Equity prices are obtained from the Nissho Monthly Equity Price file in order to construct size portfolios. The data spans the period between 1952 and 1980. The number of each firm's equities and total assets are obtained from the Nikkei Needs Financial Data file for the period 1964-1981. Thus, aggregation of the data means the exclusion of certain companies from the sample.

Kato & Schallheim (1985) test for the January and size effects by creating ten portfolios based upon equity market capitalisation. These portfolios are rearranged each year given changes in the market value of each equity contained in the sample. Due to data constraints, Kato & Schallheim (1985) use seventeen years of data for portfolio analysis and twenty-nine years of data for index analysis. Two methods are used for the analysis of the data. First, the raw return data for the January and size effects are analysed. Secondly, Kato & Schallheim (1985: 246) adjust returns for systematic risk by use of a market model. The market model is estimated on the basis of a moving procedure of the prior sixty months of data for each equity included in the sample. Kato & Schallheim (1985: 246) use this method since many financial economists assert that the market model is not stationary during long time horizons. The market model's specification is:

$$R_{it} = a_i + b_i R_{mt} + e_{it} \qquad (2.3)$$

where: $R_{it}$ = return on an equity.

$R_{mt}$ = return on an equity market index.

$t$ = $(t-60), (t-59), \ldots, (t-1)$

$i$ = $1,2,\ldots,n$ is the number of firms

Kato & Schallheim (1985) use return data from the Nissho Monthly Stock file to calculate an equally-weighted index (EWI). They use the conventional dummy variable model, Equation (2.1), as specified by Keim (1983), to test for the January effect in the EWI and VWI.

A January seasonal is observed for both indices, but the January average return for the EWI is greater than that of the VWI. This reveals that there may be a small firm effect since the EWI is affected more by small firms than the VWI (Gultekin & Gultekin, 1983 and Kato & Schallheim, 1985). When Equation (2.1) is estimated for each of the ten size portfolios to identify any size effects, small firms' returns on average are greater than those of large firms during January. In addition, when the non-parametric Kruskal-Wallis test is applied to Japanese equity returns to detect seasonal patterns in equity returns, a statistically significant difference for all of the portfolios except for the three largest portfolios is found. Thus the January effect is mainly a small firm effect. The dummy variable coefficients also indicate a significant January effect across all portfolios. Kato & Schallheim (1985: 251) find after supplementary analysis that the January-size effect "may be very sensitive to the choice of the market index." The remarkable similarity between the American and Japanese equity markets to these anomalies may indicate that international capital markets are well integrated. Kato & Schallheim's analysis impugns the tax-loss selling hypothesis as an explanation of the January effect.

Tinic et al. (1987) investigate the seasonality of equity index returns on the value-weighted Toronto Stock Exchange 300 Index (TSE 300[8]) for the 1956-1981 period. In order to test the January effect in relation to the size-effect, equities are assigned to five portfolios based on market capitalisation as obtained from the Laval-Wood Gundy data file[9]. Equity returns for each portfolio are equally-weighted in order to obtain the portfolio's return. In determining whether the January effect is related to the size-effect Tinic et al. (1987: 55) use the following regression model:

$$R_{pt} = \beta_0 + \beta_1 D_{1t} + \beta_2 D_{12t} + \beta_3 Q_{0t} + \beta_4 Q_{1t} + \beta_5 Q_{12t} + e_t \quad \text{.......(2.4)}$$

where: $R_{pt}$ = return on portfolio $p$ in month $t$

$D_1$ and $D_{12}$= dummy variables for January and December

$Q_{0t}$ = dummy variable equalling zero during 1950-1972, one thereafter

$Q_{1t} = D_{1t} \cdot Q_{0t}$

[8] The TSE 300 is a value-weighted index comprising 300 common equities listed on the Toronto and Montreal Stock Exchanges, some of which are also listed on the NYSE and AMEX.

[9] All but eighty-four of the equities in the TSE 300 are contained in the Laval-Wood Gundy data file. In addition to this, the file includes 175 smaller Canadian equities.

$$Q_{12t} = D_{12t} \cdot Q_{0t}$$

Tinic et al. (1987) expect that if the introduction of CGT in 1972 has a conspicuous effect on December and January equity returns, then the coefficients of $\beta_4$ and $\beta_5$ should capture this effect. This analysis reveals that tax-loss selling is among the causes of the January effect in Canada. However, there is slight evidence that equity returns on Canadian equities are slightly greater after CGT is imposed. To test for this possibility, Tinic et al. (1987) specify the following model:

$$R_{i,J} = \beta_0 + \beta_1 R_{i,12-t} + e_t \qquad (2.5)$$

where $t$ is equal to 0, 1, 2, ..., 11, $R_{i,J}$ is the return on equity $i$ in January and $R_{i,12-t}$ is returns of the equity over successive shorter intervals in the preceding year. Thus $R_{i,12}$ is the return during the preceding twelve months and $R_{i,11}$ is the return over the preceding eleven months and so on. It is found that when the CGT is introduced returns on equity traded in Canada are greater during January.

Tinic et al. (1987) then analyse the extent to which Americans trading in Canadian equity influence the January effect. The same equities are split into two portfolios. One portfolio consists of 317 equities traded only in Canada with the remaining seventy-four equities being assigned to another portfolio which consists of equities listed on both the Canadian and American exchanges. Tinic et al. (1987) analyse the seasonality of trading volume of these two portfolios, due to data limitations, and specifying their model as:

$$V_{pt} = \beta_0 + \beta_1 D_{1t} + \beta_2 D_{12t} + e_{pt} \qquad (2.6)$$

where $D_{1t}$ and $D_{12t}$ are dummy variables corresponding to the months of January and December. The coefficients of these dummy variables, $\beta_1$ and $\beta_2$, measure the incremental percentage trading volumes in January and December. Canadian-traded CGT equities trade more often during January but not December. The trading volumes of these equities comprise approximately a tenth of annual trading volume.

On the other hand, significant seasonal patterns in trading activity are absent in the case of dually-listed equities. After CGT is introduced seasonal patterns are absent in the case of both portfolios. Tinic et al. (1973: 59) state that their findings are inconsistent with the tax-loss selling hypothesis. This is because seasonality is absent in trading activity around the turn of the year for dually-listed equities, and the January effect disappears after the introduction of CGT. Tinic et al. (1987) findings are consistent with that of Berges et al. (1984) in that tax-loss selling is among the causes of the January effect, and is a factor that must be considered (Tinic et al. 1987: 62).

Corhay et al. (1987) examine the relationship between average returns and risk in the USA, the United Kingdom (UK), France and Belgium to determine whether the estimated risk-return coefficients exhibit a January seasonal similar to that observed by Tinic & West (1984) for the American equity market. Corhay et al. (1987: 50) state that the analysis of equity price behaviour in markets other than the USA is essential as it again proves the validity of security-pricing models, allows the comparison of the pattern of risk-premium seasonality across equity markets and enhances understanding as to why the market risk premium exhibits seasonalities. The specific aim of this study is to find out whether the risk-premium seasonality is linked to return seasonality. Their hypothesis is that any potential explanation for return seasonality is then an explanation for risk-premium seasonality.

For all markets the 180 monthly equity returns for each equity span the 1969-1983 period. For the USA, the data is obtained from the CRSP tape. The UK data is obtained from the London Equity Price Data Base and data for the French and Belgian equities are collected by the authors. Equally weighted total return equity indices are used. The index used for the American market is given by the CRSP tape, whereas the indices for the European markets are an average of those domestic equities included in the sample.

Corhay et al. (1987: 54) analyse the four market indices and discover a significant positive January seasonal in equity returns for all four countries. The USA is the only country where equity returns are significantly positive only in January. Corhay et al. (1987: 54) document an April seasonal for the UK, a July seasonal for France and a

February, April, June and July seasonal for Belgium as well as a January seasonal. For the UK the observed April seasonal can be likened to the January effect since the tax year-end in the UK is the sixth of April. The findings for France are inconsistent with the January effect since the tax year-end is the 31st of December. The application of the Kruskal-Wallis test further yields differences in mean monthly equity returns for France at the ten percent level, and Belgium at the one percent level. Corhay et al. (1987: 56) then test for seasonality in the month-to-month behaviour of portfolio returns. Twenty equally-weighted domestic portfolios based on the estimated beta of each equity are constructed. These findings are similar to those obtained from the market indices analysis. A significant finding is that the analysis of portfolios yields an April seasonal in the UK and the July seasonal in France dominates the January seasonal. The January seasonal dominates all other months in the USA and Belgium.

To estimate each month's risk premium Corhay et al. (1987) use Fama & MacBeth's (1973) method to estimate the two-parameter CAPM specified as:

$$R_{pt} = \gamma_{0t} + \gamma_{1t}\beta_{p,t-1} + \mu_{pt} \qquad (2.7)$$

where $\gamma_{1t}$ represents the risk premium based on the systematic risk (beta). To estimate the intercept coefficient $\gamma_{0t}$ and the slope coefficient $\gamma_{1t}$ in Equation (2.7) Corhay et al. (1987: 56) use the first year of monthly equity returns to assign equities to twenty portfolios based on equity betas. The second year of data is then used to calculate the systematic risks of the equities. The estimated betas for each portfolio are then calculated by averaging the beta of each equity in the portfolio. The returns for the twenty portfolios are then calculated and cross-sectionally regressed on estimated betas according to regression (2.7). This then provides Corhay et al. (1987) with twelve monthly estimates of return and risk. They then drop the earliest year of data and add the next and repeat this process until they reach the year 1983, obtaining 156 monthly estimates of risk and return.

This analysis suggests that investors in the USA, UK and Belgian equity markets bear greater risk during the 1971-1983 period without compensation in the form of greater average equity returns. Indeed, investors in equities listed on the Paris Equity Exchange are penalised. This confirms and reinforces Tinic & West's (1984) finding since the absence of a positive risk-return relationship applies in countries other than the USA. In addition, Corhay et al. (1987) find a significant January risk-premium for the USA and Belgium. For the UK and France, they observe a positive January risk-premium; however it is not statistically significant. Unlike the USA, the risk premium is significantly negative during the remaining eleven months, -0.39 percent for Belgium, -0.61 percent for the UK and –0.93 percent for France. Corhay et al. (1987:60) test the hypothesis that the risk premium in January equals the average risk premium during the rest of the year, by estimating:

$$\gamma_{1t} = a_1 + a_2 D_2 + e_t \qquad (2.8)$$

where: $\gamma_{1t}$ = monthly estimate of the risk premium,

$D_2$ = a dummy variable representing the rest of the year,

$a_1$ = the difference between the average risk premium in January and the rest of the year.

Estimation of Equation (2.8) yields an average risk premium that is significantly less from February to December than January's risk premium. The UK's risk premium is also free of a January seasonal. Corhay et al. (1987) analyse the month-to-month seasonality of the risk premium to identify a seasonal pattern other than the January seasonal. An April seasonal in the UK risk premium confirms the previous findings for the USA and Belgium, and a weak January seasonal for France.

Ritter (1988) examines the arithmetic mean daily buying and selling behaviour of individuals at the turn-of- the-year in order to test the parking-the-proceeds hypothesis during the 1971-1985 period.

Ritter (1988) obtains the buy/sell ratios of the cash-account customers of Merrill Lynch, Pierce, Fenner and Smith (America's largest retail brokerage firm). Ritter (1988) also obtains the daily volume of sales and purchases of NYSE-listed common equities denominated in American dollars. Ritter (1988) uses a ratio of these purchases and sales as a measure of the net buying activity of investors. An analysis of the mean buy/sell ratios for each month of the year reveals that the ratio is low in late December and high in early January. This means that there is relatively more selling in December than buying, which implies that there is downward pressure on prices during December. Ritter (1988: 707) further tests the hypothesis whether the yearly changes from one sub-period to another are non-zero. Ritter (1988) suggests that this is a more powerful test for seasonal patterns in the presence of highly auto-correlated daily levels than a simple comparison-of-means test. The analysis reveals that in every single year during the fifteen year period the December buy/sell ratio is lower than the preceding mid-January to mid-December buy/sell ratio and that the January buy/sell ratio is at least as high as the preceding December value.

Ritter (1988) further analyses the differences in mean daily returns, obtained from the 1986 CRSP daily returns file, on small and large equity portfolios. The smallest and largest equity portfolios correspond to the smallest and largest market capitalisation deciles of equities listed on the NYSE. The portfolios are formed on the November rankings of market capitalisation of the NYSE and are rebalanced annually. Ritter (1988: 711) mentions that the portfolios are formed in this way in order to keep portfolio composition constant over the December-January period; however Ritter (1988: 711) does mention that the same analysis is carried out with rebalancing taking place in December. Thus, conclusions reached by Ritter (1988) are not sensitive to the portfolio formation date. The data used in this analysis is obtained from the CRSP daily files. To avoid bid-ask spread bias, Ritter (1988) computes daily portfolio returns as follows:

$$r_{p,t} = \left[ \sum_{i=1}^{n} (1 + r_{i,t-1})(1 + r_{i,t}) \Big/ \sum_{i=1}^{n} (1 + r_{i,t-1}) \right] - 1 \quad \text{.......(2.9)}$$

Equation (2.9) weights the current day's return on equity $i$, $r_{p,t}$, by the previous day's relative return (Ritter, 1988: 711). From this Ritter (1988) calculates the daily small-firm premium ($r_{small} - r_{large}$) in order to understand the influence of size effect in relation to the January effect. Seasonal patterns in daily small-firm premium values are observed from this analysis. Additionally daily returns for small-firm equities are extremely high with average daily return for the first day of January equaling 2.4 percent. Ritter (1988) states that the year-to-year buy/sell ratio is related to the magnitude of the turn-of-the-year effect and that the analysis of the buy/sell ratio provides evidence in support of the park-the-proceeds hypothesis. In effect, as Ritter (1988: 716) states, "the turn-of-the-year effect can be best understood in terms of a framework where the small-stock sector is subject to predictable price patterns due to price pressure resulting from predictable portfolio-rebalancing behaviour by individual investors.".

Barone (1990) examines the Milan Equity Exchange's MIB Storico Equity Index (value-weighted) for various calendar anomalies during the period 1975-1989. These calendar anomalies include the weekend effect, the holiday effect, the turn-of-the-month effect, the settlement effect and the January effect. Barone (1990) assumes that equity prices within each monthly account follow a geometric random walk and therefore returns are calculated as continuously compounded rates of change. Barone (1990:505) reports a conspicuous seasonal pattern in mean monthly equity returns. It is expected that a January effect will be present in Italian equity returns since the tax year ends in December and CGT is applicable to equity returns. Daily changes in equity prices during January are on average 0.33 percent and significantly different from zero at a confidence level of less than 0.001. In addition, positive seasonal patterns for the months of February, May and August are observed. This is consistent with previous studies done on the American market. Barone (1990) propounds the causes of the various effects analysed as portfolio adjustment, where investors systematically rearrange their portfolios at the end of the year and the window dressing hypothesis, where investors sell securities that they exclude from their year-end portfolios and then re-buy these equities in January. Although Barone's (1990) secondary objective is to analyse and explain the January effect, the study provides another view of the January effect, and confirms other seasonal effects outside of the USA. This, as well as various other studies, confirms that the January effect, and indeed seasonality in equity markets, is an international equity market phenomenon.

Seyhun (1993) tests the hypothesis that large January returns may be due to omitted risk factors with American equity return data from the daily and monthly CRSP tapes. Seyhun (1993: 199) assigns equities to ten portfolios according to the previous year-end market capitalisation provided by CRSP. The portfolios are formed by equally-weighting each equity within each decile and are rebalanced each year according to market capitalisation. Seyhun (1993) examines both weekly and monthly equity return data. The weekly data is generated by the amalgamation of the NYSE-AMEX files with the NASDAQ files of CRSP. The data spans the 1926-1991 period.

Seyhun (1993: 199) examines the mean returns for the ten portfolios as a preliminary investigation into the January effect. This examination identifies and confirms the previously documented January effect for the period 1929-1991 with the highest average monthly return, 13.12 percent, occurring in January in the smallest decile of firms. January average returns exceed the non-January returns across all deciles with the exception of the largest decile. Seyhun (1993) introduces the stochastic dominance approach to test the hypothesis that large January returns can be attributed to omitted risk factors. The stochastic dominance tests compare distributions of total portfolio returns and implicitly incorporate the differences in expected returns and risk (Seyhun, 1993: 199). Seyhun (1993: 199) hypothetically compares two portfolios A and B. If Portfolio A's expected return is greater than Portfolio B's then the greater return of A represents compensation for greater risk. Thus, Portfolio A's returns are more extreme positive and negative and would not stochastically dominate portfolio B.

To examine the stochastic dominance in January returns across firm deciles Seyhun (1993: 201) constructs a cumulative density function (CDF) of the realised total returns in January form 1926-1991. To construct the CDF Seyhun (1993: 201) takes the sixty-six monthly January returns and ranks them in increasing order. The occurrence of each observation is equi-probable; thus each realised return is assigned a probability of 1/66. The least realised return then has a cumulative probability of 1/66 whilst the highest realised return has a cumulative probability of 66/66 or one. Plotting these points yields an empirical CDF. January returns in the smallest decile have a first-order stochastic dominance over the January returns in larger deciles. Similar analysis is done for equally-weighted and value-weighted indices of the NYSE, AMEX and NASDAQ. January returns in small firms dominate the January returns in all other decile groups as well as both value- and equally-weighted indices. The stochastic dominance of January returns is rarer for the larger firm size portfolios.

Seyhun (1993) thus suggests that the small firm portfolio in January is dominant over all other portfolios. Analysis by Seyhun (1993: 202) reveals that January returns exhibit dominance over non-January returns for each portfolio. Thus, the stochastic dominance results confirm that greater returns during January for small firms cannot be attributed to omitted risk factors (Seyhun, 1993: 209). This is irrespective of investors' attitudes toward risk and degree of risk aversion, or seasonal variations in risk or risk premia. For the period 1926-1991, January returns are too high to be considered equilibrium returns.

Griffiths & White (1993) test the tax-loss selling hypothesis as an explanation of the turn-of-the-year effect using intra-day data during the 1977-1989 period for Canada and the 1984-1989 period for America. The Canadian intra-day data comprises all date- and time-stamped bid-ask quotes, transaction prices, and volumes for all equities listed on the Toronto Equity Exchange. For America the data comprises 311 NYSE and AMEX equities obtained from a direct data feed. However, these American equity indices include relatively few low-priced equities thus there is a bias towards high-priced equities. Therefore the American data is biased against finding a turn-of-the-year effect (Griffiths & White, 1993: 577).

Griffiths & White (1993) examine two hypotheses. Firstly, they test whether the turn-of-the-year effect is advanced by five trading days in Canada to accommodate settlement day regulations, in which settlement takes place five days after any particular trade. Secondly, they test whether the turn-of-the-year taxation year dummy variables act as good proxies for variables representing buying and selling pressure. Alternatively this second hypothesis can be interpreted as detecting seasonal patterns of transactions at or above the ask and transactions at or below the bid prices (Griffiths & White, 1993: 579). Griffiths & White (1993) then test Ritter's (1988) parking-the-proceeds hypothesis by repeating the analysis on the first hypothesis with bid-to-bid equity returns. To test these hypotheses equities are assigned to five portfolios according to November month end prices[10] to allow for

[10] Bhardwaj & Brooks (1992 in Griffiths & White, 1993: 579) show that the January anomaly is primarily a low price effect and less so a market value effect. Thus the reason that Griffiths & White assign equities to portfolios according to month end prices.

comparisons between portfolios over the December-January period[11]. Portfolio rates of return are calculated as an equally-weighted average of the logarithm of the price relatives of each equity using daily closing prices.

Griffiths & White (1993) use the following dummy variable regression model to test for the turn-of-the-year effect for both Canada and America.

$$R_{pt} = a_{p0} + a_{p1}CDNDUM_t + a_{p2}USDUM_t + e_{pt} \text{ .......................................(2.10)}$$

where $R_{pt}$ is the equally-weighted logarithmic portfolio return on portfolio $p$ on day $t$, $CDNDUM_t$ and $USDUM_t$ are dummy variables with a value of one for each of the five trading days starting one day prior to the tax year-end and zero otherwise. The data used in this analysis data is obtained from the Toronto Equity Exchange / WESTERN database for Canada and from the CRSP files for the USA. A statistically significant turn-of-the year effect is revealed for the three smallest Canadian price portfolios. The analysis also suggests that a turn-of-the-year effect is present in the smallest quintile American portfolio. Griffiths & White's study strongly supports the hypothesis that the Canadian turn-of-the-year effect is advanced by five trading days due to settlement day tax regulation. Thus American investors, holding Canadian equity, should sell their equities to Canadian investors in the last five days of December. When Griffiths & White (1993) augment the analysis with statistical tests, the turn-of-the-year effect is associated with taxation rather than the calendar year-end[12].

Raj & Thurston (1994) test for the TY effect in the New Zealand equity market. Using daily price data for the 1983-1993 period, collected from the New Zealand Herald, the authors analyse larger equities and smaller equities separately. The larger equities are represented by the New Zealand Stock Exchange 40 (NZSE 40) Index while the smaller equities are represented by the smallest forty equities listed on this exchange. The focus of this research is to prove or refute the tax-loss selling hypothesis. New Zealand's tax year ends in March and the only form of CGT applies

[11] As suggested by Ritter (1988).

[12] Griffiths & White (1993: 596-597) provide numerous other findings and conclusions which are beyond the focus of this literature review.

to regular traders of equity, or where equity is purchased for the purpose of resale or disposal. Thus, if these investors affect returns to equities through their tax-loss selling, then an April effect is expected in equity returns rather than a January effect, assuming that the tax-loss selling hypothesis is valid (Raj & Thurston, 1994: 81).

Raj & Thurston (1994: 82) use two models to test for the January effect, a weak test and strong test model. The weak test model is specified as:

$$R_{it} = \beta_0 + \beta_1 D_{it} + e_{it} \quad \text{(2.11)}$$

where $R_{it}$ is the equity return in month $i$ in year $t$, $\beta_0$ is the average return for the remaining months, excluding January, $\beta_1$ is the difference in January returns relative to other months and $D_{it}$ is a dummy variable where January = 1 and February-December = 0. Thus, if $\beta_1$ is statistically significantly greater than zero it can be concluded that a January effect is present in New Zealand equity returns. The strong test model is specified as Equation (2.11), but where $\beta_0$ is the average return for January, $\beta_1$ is the difference in average return for each month relative to January returns and $D_{it}$ is a dummy variable, where $D_{2t}...D_{12t} = 1$ for February-December, and January = 0. Thus, all $\beta_1$'s should be negative for a January effect to be detected in New Zealand equity returns. If the tax-loss selling hypothesis is to hold a statistically significant positive $\beta_1$ coefficient should be observed for the month of April. Both models find an absent January effect in New Zealand equity returns for both large and small firms. In addition to this, the models find an absence of an April effect in both large and small firms. Thus, it is concluded by Raj & Thurston (1994) that these findings directly contradict the tax-loss selling hypothesis.

Pearce (1995) examines the robustness of calendar anomalies in America equity returns with respect to the choice of return measure, estimation procedure and time period. These calendar anomalies include the January effect, the weekend effect, the turn-of-the-month effect, the pre-holiday effect and serial dependence of returns across days of the week. The existence of these anomalies is well known; however their robustness remains a controversial issue. Pearce (1995: 1) states that evidence on whether the anomalies are universal or they appear only in certain time periods or for small equities is contradictory. In addition, the robustness of these anomalies is dubious as previous studies ignore econometric problems and rely on OLS. As a result, Pearce (1995) re-investigates the major calendar anomalies, introducing a more comprehensive approach that embeds all the calendar anomalies into two models.

The major calendar anomalies are examined simultaneously by embedding them into two alternative models for daily returns. The first model is specified as:

$$R_t = a_0 + a_1 WD_t + b_1 M_t^* R_{t-1} + b_2 Tu_t^* R_{t-1} + b_3 W_t^* R_{t-1} + b_4 Th_t^* R_{t-1} + b_5 F_t^* R_{t-1} + b_6 POSTH_t^* R_{t-1}$$

$$+ dPH_t + eJAN_t + fTOM_t + e_t \qquad \text{(2.12)}$$

| | | |
|---|---|---|
| where: | $R$ | = return on equity portfolio |
| | $WD$ | = 1 if day is Monday or Tuesday after a Monday holiday, 0 otherwise. |
| | M, Tu, W, Th, F | = 1 if day is Monday, Tuesday, Wednesday, Thursday or Friday, 0 otherwise. |
| | $POSTH$ | = 1 if the day follows a holiday, 0 otherwise. |
| | $PH$ | = 1 if the day after is a holiday, 0 otherwise. |
| | $JAN$ | = 1 if the day is in January, 0 otherwise. |
| | $TOM$ | = 1 if the day is the last day of the month or one of the first 5 days of the month, 0 otherwise. |

The second model is then specified as:

$$R_t = \alpha_0 + \alpha_1 WD_t + \beta_1 M_t^* R_{t-1} + \beta_2 Tu_t^* R_{t-1} + \beta_3 W_t^* R_{t-1} + \beta_4 Th_t^* R_{t-1} + \beta F_t^* R_{t-1} + \beta_6 POSTH_t^* R_{t-1}$$

$$+ \delta PH1_t + \gamma TOY_t + \lambda TOMR_t + e_t \qquad \text{(2.13)}$$

| | | |
|---|---|---|
| where: | $TOY$ | = 1 if the return falls on last trading day of the year or one of the first 5 trading days of the new year, 0 otherwise. |
| | $TOMR$ | = 1 if the day is the last day of the month or one of |

the first 5 days of the month, excluding TOY, 0 otherwise.

To examine the sensitivity of the anomalies to firm size, models are estimated for six measures of equity returns that vary according to the weight given to smaller firms. The temporal stability of the anomalies is also investigated by splitting the data into shorter sub-periods. In order to test the robustness of calendar anomalies across return measures, the models are estimated using daily returns from six portfolios for the period 1974-1991, obtained from the CRSP tapes. Equally-weighted and value-weighted portfolios of equities traded on formal equity exchanges like the NYSE and AMEX are formed concurrently with that of the over-the-counter NASDAQ exchange.

Pearce (1995: 8) employs OLS, Least Absolute Error and GARCH models to test whether results vary for estimation methods given the uncertainty about the appropriate distributional assumption for equity returns; hence these different estimation techniques are used. Pearce finds for the entire period that inferences about calendar anomalies differ more across return measures than across estimation techniques. Firm size may be more important for estimates of the January effect but the January effect is not statistically significant for the value-weighted NYSE portfolio, but is generally positive and statistically significant for the value-weighted AMEX portfolio and the value-weighted NASDAQ portfolio, with returns in January being greater by about 0.08 percent.

In analysing sub-periods Pearce (1995: 13) finds that there is an absence of compelling evidence of the January effect except for the last sub-period of AMEX and OTC returns. With regard to the estimation techniques, the threshold GARCH (TARCH) model indicates that the distribution of equity returns appears to have become even fatter-tailed in the last sub-period. This again impugns the assumption of normally-distributed equity returns. Analysis on the value-weighted indices suggests that the January effect appears more in the return of smaller equities (Pearce: 1995:13) which is consistent with Keim (1983) and Reinganum (1983). Calendar anomalies like the January effect are stronger both in magnitude and statistical significance when the analysis is done with equally-weighted indices. Again the TARCH model indicates the non-normal distribution of equity returns. Pearce (1995) reveals the robustness of the calendar anomalies and how return measures affect the detection of such anomalies.

Bentzen & Hansson (2005) investigate the January effect on the New York Equity Exchange. Monthly data is obtained from the NYSE for the period 1966-2002 and includes five indices, namely: the Composite, Industrial, Transportation, Utility and Finance indices. Bentzen & Hansson (2005: 12) note that the data is far from optimal and acknowledge aggregation problems in previous research. The return from a market index is:

$$R_{kt} = \mu + \delta_k + e_{kt} \qquad (2.14)$$

where: $\mu$ = mean return in period 1966-2002,

$\delta_k$ = main effects from months $k$=1,...,12

$t$ = 1,...,444 months

The analysis on Equation (2.14) suggests that the hypothesis of equality between months could be rejected, and hence analysis is required. A simple regression on Equation (2.14) is estimated for each month of the year to identify possible monthly effects. Significant positive monthly effects for January, March, April, November and December are observed. Of these months, monthly return during January is slightly greater.

The problem with this approach is that it only incorporates systematic variations between months, and omits systematic variations from years and from portfolios; therefore the model must be expanded to incorporate these factors (Bentzen & Hansson, 2005: 13).

The expanded model subsumes important effects other than monthly effects, thus Bentzen & Hansson (2005: 14) can investigate the effect from months and years using the following:

$$R_{ijk} = \mu + \alpha_i + \beta_j + \delta_k + (\alpha\beta)_{ij} + (\alpha\delta)_{ik} + (\beta\delta)_{jk} + e_{ijk} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.15)$$

where:

$\mu$ = mean return in period 1966-2002

$\alpha_i$ = main effect of index $i$, $i$=1,...,5

$\beta_j$ = main effect of year $j$, $j$=1966,...,2002

$\delta_k$ = main effect of month $k$, $k$=January...December

$(\alpha\beta)_{ij}$ = interaction between index $i$ and year $j$

$(\alpha\delta)_{ik}$ = interaction between index $i$ and month $k$

$(\beta\delta)_{jk}$ = interaction between year $j$ and month $k$

$e_{ijk}$ = 3 factor interaction, that is the random variation assumed to be independent $N(0,\sigma^2)$.

Using model (2.15), the authors test the hypotheses of (i) equal returns between indices, (ii) returns are equal between years, (iii) returns are equal between months, (iv) interaction between indices and years are zero, (v) interaction between indices and months are zero and (vi) interaction between years and months are zero.

This analysis indicates that returns between indices are equal and therefore an investment in one index is just as good as an investment in another. Investments between years differ; thus it is better to invest in some years than others. In addition, returns between months are significantly different from zero indicating a monthly effect; therefore investors can earn more through investing, when propitious, across months. Analysis on the interaction hypotheses indicates an absence of interaction between an index and years and an index and months, but there is a significant relationship between a year and month. The year and month interaction can explain sixty-eight percent of total variation in equity returns and indicates that an investment depends to a considerable extent on the chosen year and month (Bentzen & Hansson, 2005: 16).

Bentzen & Hansson (2005: 17) then estimate:

$$R_{j,t} = \beta_0 + \beta_1 D_t + e_{j,t} \quad \text{(2.16)}$$

where: $D_t$ = dummy variable equal to 1 in January, 0 otherwise.

$R_{j,t}$ = the return from portfolio $j$ at time $t$

$\beta_1$ = extra return above or below the rest of the year (January effect)

In line with previous research and this analysis, the January effect is significant for small size portfolios. The data used by Bentzen & Hansson (2005) includes ten size portfolios obtained from Ken French for the period 1993-2004, constructed according to market value. Portfolio one, the smallest portfolio, indicates a significant positive January return of 6.188 percent. Bentzen & Hansson expand the model again to incorporate other main effects.

$$R_{ijk} = \mu + \alpha_i + \beta_j + \delta_k + (\alpha\beta)_{ij} + (\alpha\delta)_{ik} + (\beta\delta)_{jk} + e_{ijk} \quad \text{(2.17)}$$

where: $\mu$ = mean return in period 1993-2004

$\alpha_i$ = main effect from portfolio $i$, $i$=1,...,10

$\beta_j$ = main effect of year $j$, $j$=1993,...,2004

$\delta_k$ = main effect of month $k$, $k$=January...December

$(\alpha\beta)_{ij}$ = interaction between portfolio $i$ and year $j$

$(\alpha\delta)_{ik}$ = interaction between portfolio $i$ and month $k$

$(\beta\delta)_{jk}$ = interaction between year $j$ and month $k$

$e_{ijk}$ = three-factor interaction, that is the random variation assumed to be independent $N(0,\sigma^2)$.

The analysis reveals that size explains very little of the total variation of equity returns. Of interest is that the interaction between year and month remains significant and explains seventy-four percent of the total variation of equity returns. The expanded model also shows an absence of the January effect; however, statistically significant negative April, June, July and August effects are observed. Statistically significant positive effects during September, October and December are also observed. Bentzen & Hansson's (2005) findings are contradictory to previous literature in the area of seasonality and the January effect.

**2.3.3.2 Evidence from Emerging Markets**

Lee (1992) examines the Chinese (Hong Kong), Japanese, South Korean, Singaporean and Taiwanese equity markets for evidence of seasonality in equity index returns. For China (Hong Kong), Taiwan and Singapore the study is done for the 1970-1989 period, thus providing monthly observations for a twenty-year period. The South Korean and Japanese equity market data covers the 1975-1989 period, providing fifteen years of monthly observations. The indices used in the analysis are as follows: the Hang Seng index, a value-weighted index on the thirty-three largest firms, for China (Hong Kong); the Nikkei-Dow Average Share Price Index, computed on the price weighting basis of more than 250 firms, for Japan; The South Korea Composite Equity Price Index, a value-weighted index, for South Korea; the Straits Times Industrial Index, an equally-weighted index of thirty firms, for Singapore and the Taiwan Equity Exchange Index, a value-weighted index, for Taiwan. The monthly-closing equity index values are collected directly from each country's respective equity exchange. Monthly equity returns are calculated as the percentage change between sequential closing index values for months $t$ and $t-1$. Lee (1992) uses a similar dummy variable model as specified by Keim (1983), Equation (2.1) to test that monthly returns are equal across months of the year.

For all the Asian markets except South Korea, the average returns for January are higher than any other month of the year. Thus a January effect is present in these markets. January returns in South Korea are positive; however, average monthly returns for March are the highest followed by returns for December. Lee (1992) suggests that seasonality is present in all of these Asian equity markets and that since there is an absence of CGT in these countries, tax-loss selling cannot be responsible for the observed seasonal patterns.

Tan & Tat (1998) examine daily equity returns on the value-weighted Singaporean Equity Exchange (SES) All-Singapore Index during the 1975-1994 period for the January effect. The SES All-Share Index is not used due to the delisting of Malaysian companies from the SES in January 1990. To eliminate the influence of suspended trading from the second of December 1985 to the fifth of December 1985 and the global equity market crash on the nineteenth of October 1989, two trading weeks before and after the 2nd of December 1985 and the 19th of October 1989 are excluded from the sample data (Tan & Tat, 1998: 118).

Tan & Tat (1998) use the conventional dummy variable regression model as specified by Keim (1983) to test for the January effect. This regression analysis is run across the entire period and across two sub-periods, 1975-1984 and 1985-1994. For the entire period January returns are significantly higher than any other month, thus indicating a January effect for the entire period. However, the sub-period regression analysis reveals that January average returns during the 1985-1994 sub-period are only significantly greater than four other months, thus indicating a weakening January effect in SES All-Singapore Index equity returns. Tan & Tat (1998: 125) also suggest that this weakening of the January effect reveals that investors are timing their trades accordingly, thereby negating whatever advantage is gained through knowledge of equity market seasonalities. The January effect is not the sole focus of Tan & Tat's (1998) research; however, the other anomalies analysed do not add to the discussion on the January or turn-of-the-year effect and are thus not reviewed here.

Ayadi et al. (1998) test for the January effect[13] in the low-income equity markets of Africa. Three low-income African countries are examined; Ghana, Nigeria and Zimbabwe. The data used in the study is monthly market value-weighted indices for the Ghanaian Equity market (GSE), Nigerian Equity market (NSE) and the Zimbabwean Equity (ZSE) market for the 1991-1996, 1984-1995 and 1987-1995 periods respectively. This data is obtained from the IFC Emerging Markets Database,

[13] Incorrectly referred to as the turn-of-the-year effect by Ayadi et al. (1998).

Bloomburg Financial markets, Commodities, and News Services and the Nigerian Equity Exchange. Ayadi et al. (1998) use the Kruskal-Wallis and Friedman test to test whether the rates of return in each month are equal, i.e. to test for seasonality in equity returns. Ayadi et al. (1998) also use the conventional dummy variable regression model specified by Keim (1983) to test for the January effect in equity returns in each respective country.

The Kruskal-Wallis test reveals an absence of any seasonality in equity returns for all three markets; however, the Friedman test reveals the presence of equity return seasonality on the GSE at the ten percent level of significance. The Wilcoxon-Mann-Whitney pair-wise test is used to test whether average January returns are statistically significant from each of the other months. A significant difference between January equity returns and other months for the NSE and ZSE is absent. For the GSE, however, a January effect is found, but the months of February and May present statistically significantly greater equity returns. The conventional dummy variable regression model reveals an absence of a January effect for both Nigeria and Zimbabwe; however, there is evidence of a slightly statistically significant January effect for Ghana.

Cheung & Coutts (1999) examine China's (Hong Kong) Hang Seng index for the period 1985-1997 for the January effect and any other monthly seasonalities. The Hang Seng index is a value-weighted index comprising thirty-three actively traded blue-chip equities. The data consists of daily closing values during the 1985-1997 period with a total of 3561 observations after excluding holidays. Monthly seasonality is tested for the entire period plus two sub-periods, 1 Jan 1985 – 30 June 1991 and 1 July 1991 – 30 June 1997. Given that bias from the exclusion of dividend payments in the computation of index returns will be minimal (Cheung & Coutts, 1999: 122; Mills & Coutts, 1995 and Draper & Paudyal, 1997), daily logarithmic non-dividend adjusted returns are computed.

Cheung & Coutts (1999: 122) specify the conventional dummy variable model, equation (2.1), to test for monthly seasonal patterns. Both the parametric t-statistic and F-statistic and the non-parametric Kruskal-Wallis test are used in order to determine the significance of the regression estimates. Cheung & Coutts (1999) find that the mean return for January in all three periods is similar to the other months of the year, thus the January effect is absent. This is consistent with the tax-loss selling hypothesis; since there is no CGT in China it is expected that the January effect would be absent from equity index returns. Monthly seasonalities are absent in the Hang Seng index as well. This is a peculiar result since most authors find monthly seasonals in equity returns and directly contradicts the findings of Lee (1992). The two periods investigated by Cheung & Coutts (1999) and Lee (1992) are different and only overlap slightly, suggesting that the market has incorporated the January effect. The index also consists of high market capitalisation blue-chip equities, and numerous studies have linked the January effect to the behaviour of small firm equities. This implies that if the proportion of total equity market capitalisation ascribed to small equities is minimal, seasonals would seldom be observed in that market. Thus, that market is efficient. This suggests that economic agents err in assigning prices to the equities of small firms. In itself, ascertaining an appropriate threshold at which a firm is to be designated "small" or "large" must be done very carefully. Comparisons across equity markets in various jurisdictions should also denominate prices and index values in a standard currency like the American dollar.

Fountas & Segredakis (2002) test for the January effect in relation to the tax-loss selling hypothesis using monthly equity returns in eighteen[14] emerging equity markets during the 1987-1995 period. Weekly and monthly equity return data is used on equity index returns. This return data is calculated using the value-weighted total return (includes dividend yields and capital gains) equity market indices provided by the Emerging Markets Data Base constructed by the IFC, and covers the 1989-1996 period for weekly returns while monthly equity return data covers the 1987-1995 period.

The conventional dummy variable model, Equation (2.1), is used in testing for the January effect and any other monthly seasonal effects for each country considered in the sample. Seasonal effects for all countries in the sample are detected; however, the evidence is relatively weak for Jordan, Pakistan, Taiwan and Venezuela. The

[14] The countries included in the study are Argentina, Chile, Colombia, Greece, India, Jordan, South Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela and Zimbabwe.

strongest evidence of significant monthly effects is Chile, Colombia, India, Malaysia, Mexico, Nigeria and Zimbabwe. The absence of the January effect is also detected in these countries; however there is evidence in favour of the January effect and the tax-loss selling hypothesis for Chile, where average equity returns during January exceed the average equity return over the rest of the year. These findings are consistent with Ayadi et al. (1998) for the countries of Nigeria and Zimbabwe.

Balbina & Martins (2002) examine the existence of persistent seasonal effects in daily equity returns for the Portuguese equity market. Daily data on the BVL Geral Index (BVLG)[15], a value-weighted total return index (adjusted for stock splits and dividends), during the 1988-2001 period is used in the analysis. The analysis includes testing for the weekend effect, the holiday effect and the monthly effect. In testing for the monthly effect the following regression model is used:

$$R_t = \beta_1 Jan_t + \beta_2 Feb_t + ... + \beta_{12} Dec_t + \sum_{l=1}^{3} \phi_l R_{t-l} + \eta_t \qquad (2.18)$$

where $R_t$ is the daily return data and $Jan_t$ through $Dec_t$ are dummy variables representing months of the year. Thus $Jan_t$ takes a value of one if daily equity returns are in January and zero otherwise, and so on. Balbina & Martins (2002) also consider the first three lags of the dependent variable as explanatory variables. No monthly seasonal pattern is observed for Portuguese equity returns during the 1988-2001 period. This provides evidence that the tax-loss selling hypothesis may not be solely responsible for the observed January effect in numerous markets across the world since CGT applies to the Portuguese equity market and the tax year-end is the 31st of December.

Shin (2003)[16] compares monthly prices and equity returns across several countries with and without risk-adjustments to identify the January effect or any other periodic pattern. Shin (2003) uses various statistical methods like correlation, regression,

[15] In 2000 the Lisbon Equity Exchange and the Oporto Derivatives Exchange merged; as a result the BVLG was renamed the PSI Geral (Balbina & Martins, 2002: 5).

[16] Shin's work includes an analysis on developed markets; however there is a definite focus on emerging markets and thus for the purposes of this thesis it is categorized under an emerging market study.

autocorrelation, runs test, variance ratio test, unit root tests, the Johansen cointegration test, ARIMA, VAR, ARCH, ARCH-M, GARCH, spectral analysis and factor analysis. The Johansen co-integration test is used since the data sets used are long and thus long-run relationships may exist between variables used in the models. Shin (2003: 12) takes the January return as the return of a portfolio (January portfolio) and then calculates the twelve-month average return as the market portfolio. Therefore twelve portfolios for each of the equity exchanges are examined. Risk-adjusted returns for each of these portfolios are computed after omitting the risk-free rate.

If the EMH hypothesis holds then the risk-adjusted monthly returns should be randomly distributed and without periodic patterns. Shin (2003) test the hypothesis with monthly data for the various exchanges: Standard & Poor's 500 equities (1971-2002), the Korea Equity Exchange (KOSPI, 1980-2002), the Daiwa Index (for Tokyo, 1984-2002), Shangai Equity Exchange (1991-2002) and the Jakarta Equity Exchange (1989-2002). Shin (2003) first finds the absence of a seasonal pattern from the plot of the monthly equity prices, monthly return series and monthly returns by year. Shin's (2003: 16) regression analysis of the January effect is in accordance with Keim (1983) and Kato & Schallheim's (1985) dummy variable approach.

Shin (2003: 17) states that the regression analysis is consistent with the January effect only for the S&P 500 equities, but the regression model itself is not significant in terms of the F-value. Shin (2003: 19) also provides regression analysis in the form of ARIMA, ARCH, ARCH-M and GARCH models. In addition, Shin (2003: 19) tests the random walk hypothesis for the five equity exchanges through an autoregressive integrated moving average (ARIMA) model. This model is specified as:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ... + \alpha_p y_{t-p} + e_0 - \beta_1 e_{t-1} - \beta_2 e_{t-2} - ... - \beta_{t-q} e_{t-q} \text{........(2.19)}$$

where: $y_{t-i}$ = autoregressive terms

$e_{t-i}$ = white noise error series, and therefore

$y_t$ is a function of lagged dependent variables and the error series.

The ARIMA models were tested for all five equity exchanges suggesting that the ARIMA models are apt and that significant periodic patterns are absent from the residual series. This confirms that all five equity exchanges follow the random walk hypothesis.

Monthly returns are calculated as the first difference in log monthly equity price indices. For the S&P500, S&P500 total return index and NASDAQ equities there are some significant regression coefficients in the variance equations for the ARCH and GARCH models. For the Dow-Jones equities, the variance equation is not significant. For the South Korean and Shanghai equities, there are significant regression coefficients but there are no significant alpha coefficients for the Tokyo and Jakarta markets. It is also found, with the use of the Lagrange multiplier method, that heteroskedasticity is not significant for these eight equity markets.

Shin (2003: 29) further applies ANOVA, Kruskal-Wallis, Chi-square and the runs test to the monthly returns of the five equity exchanges to test for any possible seasonal pattern such as the January effect. The results reveal an absence of the January effect for all five equity exchanges.

Gao & Kling (2005) examine daily and monthly effects on the market index returns for China's main equity exchanges, Shanghai and Shenzhen, for the period 1990-2001. Gao & Kling (2005) also use individual equity returns of all equities listed on both equity exchanges, since relying on index data is insufficient due to deficiencies in the data (Gao & Kling, 2005: 78). As a result more precise estimates for the shift of monthly patterns over time can be obtained. Gao & Kling (2005: 79) first use descriptive statistics to find seasonal patterns; monthly effects are nearly negligible and are neither positive nor negative. Reasons for this may be that the data set is very small and assumptions like serial independence are required for the derivation of confidence intervals. Serial dependence is provided for by the estimation of ARIMA models while the problem of few observations is corrected through the use of individual monthly equity returns of all listed companies.

The hypothesis of WEMH and therefore the randomness of returns are assumed. Hence the logarithmic market index returns follow a geometric random walk. Gao & Kling use the conventional dummy variable model, Equation (2.1), and apply the Huber-White sandwich estimator in order to obtain robust t-values in the presence of heteroskedasticity. When they examine the autocorrelation (ACF) and partial autocorrelation functions (PACF) for both markets they conclude that an AR(1) process for both exchanges is appropriate and identify a calendar effect for the Shanghai Equity Exchange only. This calendar effect is present in the months of February and November when returns are positive and significant. This finding is of interest, since February represents the New Year in China.

The authors also investigate the change in calendar effects over time and in order to do this they expand the data sample to include individual data on equities from 1990-2001. A variant of equation (2.1) is estimated:

$$r_{it} = \alpha_i + \sum_{j=1}^{p} \beta_j m^j + e_{it} \quad \text{......(2.20)}$$

where: $m$ = variable month and takes value of between one and twelve,

$i$ = an individual equity,

$j$ = the dummy variables replaced by a sufficient number of powers of the variable month.

The estimation of the above Equation (2.20) indicates that monthly returns drop from March/April to December, so Gao & Kling (1005: 82) cannot confirm a positive year-end effect for the Shanghai equity exchange when the model is based on individual data. The estimation of model (2.20) has three major advantages compared with working with dummy variables: the degrees of freedom are greater since fewer coefficients are estimated, it is less dependent on extreme observations which might affect a single dummy variable more, and a reference month can be specified at the analyst's discretion. Gao & Kling (2005: 82) therefore continue the analysis based on model (2.20). When interaction terms that allow a shift in the intercepts and slope coefficients in order to quantify changes in the monthly pattern over time are used, positive returns are apparent in the beginning of the year, the Chinese New Year in February, with returns decreasing considerably during the year. The evidence suggests that the monthly time patterns flatten continually; thus the calendar effect disappears from the market. This is evident from the 2001 data, which indicates a negligible calendar effect.

Gao & Kling (2005) find a monthly effect in the Chinese markets similar to the January effect. Average returns during March and April are significantly greater than average returns in other months. Tax-loss selling is obviated as an explanation for this, given that capital gains are exempt from taxation in China. If this is the case, then investors in Chinese equities are amateur speculators who often embezzle business funds for private trading. These speculators must return this money to the business before the year-end. Thus, money is withdrawn near the Chinese year-end. Afterwards, extra money flows into the market. The seasonal pattern observed flattens over time, which indicates that investors exploit this pattern, which is consistent with the WEMH. Surprisingly, this is evidence of the WEMH applying in a socialist state's strictly-controlled equity market.

Chotigeat & Pandey (2005) analyse equity index returns for the emerging equity markets of India and Malaysia for the presence of seasonality. For India, monthly closing equity price data of the Bombay Equity Exchange's Sensitivity Index (SENSEX) during the 1991–2002 period is used, during which time there were significant reforms to India's economy, including deregulation after 1996. India's tax system differs from that of the USA and many other developed and developing countries. The tax year ends in March. Both resident Indian taxpayers and non-resident taxpayers are subject to CGT from the sale of equities. Capital losses can be offset against capital gains. Thus, Chotigeat & Pandey (2005: 4) investigate whether tax-loss selling explains seasonality in Indian equity returns among alternative hypotheses, such as the information hypothesis.

For Malaysia, monthly closing equity price data of the Kuala Lumpur Equity Exchange's EMAS Index during the 1992- 2002 period is used. Of interest in this country is that resident and non-resident equity holders are exempt from CGT. If Berges, et al (1984) and Kato & Schallheim (1985) are correct in asserting that the tax-loss selling hypothesis is irrelevant as an explanation for seasonality, any seasonal pattern found in the Malaysian market would be due to the information hypothesis (Chotigeat & Pandey, 2005).

Chotigeat & Pandey (2005: 2) analyse the returns of these two equity indices expecting that each index is informationally efficient. Equity returns are measured as the continuously compounded monthly percentage change in the equity price index.

Previous studies use OLS regression analysis in testing for seasonality. The problem with this approach is that if the dependent variable/s are non-stationary, the regression analysis will be spurious. Chotigeat & Pandey (2005) examine the index return series for stationarity by examining the ACF and PACF. They also use a formal test of stationarity, the Augmented Dickey-Fuller (ADF) test. The examination of the ACF and PACF indicate that the series are indeed stationary for India and Malaysia, and therefore they proceed in testing for equity return seasonality by using the conventional dummy variable model, Equation (2.1).

If there is no seasonal effect then the coefficients for each month should be statistically equal to zero. As Chotigeat & Pandey (2005: 3) correctly point out, if the residuals from Equation (2.1) are serially dependent then the results will be biased; therefore the authors improve upon Equation (2.1) by constructing an ARIMA model for the residual series of this equation. The ARIMA model is then substituted for the implicit error term in Equation (2.1), hence the augmented model:

$$r_t = \alpha_1 + \alpha_2 D_{2t} + \ldots + \alpha_{12} D_{12t} + \beta_1 R_{t-1} + \ldots + \beta_p R_{t-p} + \delta_1 u_{t-1} + \ldots + \delta_q u_{t-q} \text{ ...........(2.21)}$$

A problem, which could arise from the augmented model is that the residuals may exhibit autoregressive conditional heteroskedasticity (ARCH) effects. Chotigeat & Pandey (2005) mention that this can be controlled by using an ARCH or GARCH specification for the errors.

The Indian case suggests an October seasonal at the five percent level of significance. All the other months are not statistically significantly different from zero; however the $R^2$ and F-statistic suggest a poor model fit and the Durbin-Watson statistic indicates serial dependence in the residuals. To confirm that the residuals are serially dependent, the autocorrelation and partial autocorrelation functions for the residuals are examined. The Ljung-Box Q-statistic is also examined. This analysis reveals that the residuals are not white noise; the residuals are serially dependent.

As mentioned previously, to overcome serial dependence in the residuals Chotigeat & Pandey (2005) estimate an ARIMA model. After substantial experimentation, the ARMA (12, 4) model is selected. Residuals from the augmented model are white noise; hence the estimators are serially independent. The estimates of the coefficients change once serial dependence is incorporated and reveal that the benchmark month, January, is 0.935 percent and, apart from February, returns for all of the other months are lower. The coefficients for March and October are the only statistically significant months, which reveal seasonality in SENSEX monthly returns.

The evidence from India suggests that a seasonal pattern is observed in March that is consistent with tax-loss selling - however, an April seasonal is absent. Since the Indian tax year ends in March this evidence provides weak support for the tax-loss selling hypothesis; therefore the tax-loss selling hypothesis can only be considered as a partial explanation of the observed seasonality in Indian equity returns. The seasonal patterns may exist due to the Indian capital market's inefficiency, which may be caused by non-disclosure, poor disclosure, or the slow processing of disclosed information. Chotigeat & Pandey (2005: 9) like Keim, 1983; and Reinganum, 1983, suggest that the information hypothesis better explains seasonal effects in emerging markets' equity returns like those of India.

The analysis of the Malaysian case, is approached in the same manner as that of India. The initial regression analysis suggests serial dependence in the residuals. Again, Chotigeat & Pandey (2005: 11) examine the Ljung-Box Q-statistic, which again confirms this. The dummy variable model is then combined with an ARIMA (8,0,6) model and reveals that results are white noise. The Ljung-Box Q-statistic also indicates that the residuals are white noise. Chotigeat & Pandey (2005) then test for any ARCH effects in the model with the Lagrange Multiplier (LM) and find the absence of such effects in the residuals. Again, the coefficients' values change once serial dependence is incorporated. During February and December returns are statistically significant at the ten percent level and the average return for the benchmark month, January, is –0.851 percent and it is the least of all months for monthly equity returns in Malaysia.

The evidence from Malaysia therefore reveals seasonality in EMAS returns for the months of February and December. The equity returns during January are not significant and hence an absence of the January effect is found in EMAS monthly equity returns. The year-end for Malaysia is in December, so a year-end effect is apparent, but this is inconsistent with the tax-loss selling hypothesis since in Malaysia capital gains are tax-exempt. Again, Chotigeat & Pandey (2005: 12) suggest the information hypothesis as an explanation. Thus, this study confirms the existence of seasonality in equity returns for both capital markets and the tax-loss selling hypothesis only provides a partial explanation for the seasonality in monthly returns in the case of India. As tax-loss selling is precluded as an explanation of the seasonality observed in Malaysia, the information hypothesis may hold. Analysis reveals that the markets of India and Malaysia are informationally inefficient, so abnormal returns can be obtained if economic agents transact in these markets when it is propitious.

Alagidede & Panagiotidis (2006) examine daily closing prices on the equally-weighted Databank Equity Index of the Ghana Equity Exchange during the 1994-2004 period in order to identify any calendar anomalies. Using the conventional dummy variable regression model, Equation (2.1), in testing for the January effect reveals that mean monthly returns are significant for the months of February, March, April and July. Thus, the above analysis suggests the absence of a January effect for Ghana. This is surprising since the Ghanaian tax year ends in December and CGT is applicable to equity returns. Therefore, Alagidede & Panagiotidis's (2006) study reveals that the tax-loss selling hypothesis cannot be solely responsible for observed January effects in various other developed and emerging markets of the world.

#### 2.3.3.3 Evidence from South Africa

Few studies of seasonality and specifically the January effect have been done on the world's emerging capital markets. The scarce extant literature on the January effect and TY seasonal in relation to the South African equity market begins with Bradfield (1990).

Equity returns on the Johannesburg Stock Exchange during the 1974-984 period are examined by Bradfield (1990) for evidence of the January effect. Several equally-weighted indices are considered: the mining equity index, an industrial equity index and an all equity index.[17] This data set includes weekly returns for each respective index, which in turn is subsequently partitioned and averaged within each index for each month of the year. Bradfield (1990) tests monthly returns according to the paired t-test and finds the absence of the January effect for all three indices. However, a statistically significant December effect is found for all three indices. A July effect is also present for the mining index.

Bradfield (1990: 8) suggests that the July effect is a consequence of the particular sample period. However, explaining away the December effect is more difficult. It is suggested that thin and lacklustre trading on the JSE during December, a well known characteristic (Bradfield, 1990: 8), may be responsible. Since thin trading leads to non-synchronous prices being recorded, the variances of returns are underestimated. Thus, the return series has considerably less variance than the true series. Bradfield (1990) therefore suggests that the observed December effect may be the result of less volatility rather than substantial returns in December.

Hattingh & Smit (1993) investigate six seasonal patterns among these six the January effect is included. In testing for these seasonal patterns Hattingh & Smit (1993) compare seasonal patterns in daily price movements of the Post Office, Escom 168 and RSA bonds with the equally-weighted gold, industrial and overall indices of the JSE (Hattingh & Smit, 1993: 143). The bond market data covers the 1984-1992 period while the equity indices cover the 1978-1992 period. Hattingh & Smit (1993) use the Kruskal-Wallis test in order to test for differences in equity returns across months of the year. Their analysis reveals the absence of the January effect, confirming the analysis conducted by Bradfield (1990).

[17] This comprises 112 equities for the mining index, 357 industrial equities and thus 469 equities for the all equity index.

Coutts & Sheikh (2000) investigate the January effect and monthly seasonality in the All Gold Index on the Johannesburg Equity Exchange (JSE) for the period1987-1997. In testing for the January effect the conventional dummy variable regression model is used with daily continuously compounded rates of return. It is found that the mean January equity return is negative; however, not statistically significant. This suggests an absence of the January effect and indeed the absence of any monthly seasonality in South African All Gold Index equity returns, which is consistent with Bradfield (1990) and Hattingh & Smit (1993). However, Bradfield (1990) does identify a December effect for equity returns on the JSE.

More evidence of the absence of seasonal patterns in equity prices and returns in South Africa is provided by le Roux & Smit (2001). With daily closing prices of four of the JSE's equity indices they determine whether there are various equity market anomalies during the periods 1987-1989 and 1990-1998. These indices include the erstwhile All Equity Index, All Gold Index, Industrial Index and the Financial Index. Le Roux & Smit (2001) only use ANOVA F-tests and Kruskal-Wallis tests to detect seasonalities in equity index returns. Le Roux & Smit (2001) test for anomalies including day-of-the-week, week-of-the-month, turn-of-the-month and month-of-the-year effects. The month-of-the-year analysis is of interest and reveals an absence of a significant monthly effect in equity index returns during both periods.

## 2.4 SUMMARY AND CONCLUSION

Many financial economists are fascinated by the January effect and TY seasonal, given the absence of conclusive evidence of these effects across time and space. It is only natural that many studies have been done in this area and explanations of these effects are sought, where evidence of these effects is observed. Prominent among these explanations are the small-firm effect and the tax-loss selling effect. The foregoing studies consist of the detection of these seasonals. Methods of detection range from the simple to the more advanced. The latter are the consequence of the application of new econometric and statistical approaches in empirical finance. Regressions containing dummy variables are traditionally favoured for detection in these studies, but advances in econometric theory have ensured that ARIMA and GARCH specifications are required for valid inferences. Chapter three thus, consolidates the various methods used in the empirical literature to test for the January and TY effect in South African equity returns. Furthermore, a method is developed in order to analyse seasonality in South African risk premia.

# CHAPTER THREE
# METHODOLOGY

## 3.1 INTRODUCTION

This chapter contains a description of the method used in the analysis, which is guided by the approaches described in the previous chapter. This method is then applied to FTSE/JSE All Share Index monthly and daily return data during the 1995-2006 period. The results from this chapter provide evidence as to the seasonality of equity returns for the South African equity market. The chapter consists of four broad sections. A description of the data and where it is obtained is presented in Section 3.2. The literature on the January / Turn-of-the-Year (TY) effect and seasonality are consolidated in Section 3.3 to develop a model that allows for the testing of these equity market anomalies. The chapter is finally concluded in Section 3.4.

## 3.2 DATA

The data used consists of the daily closing prices of the FTSE/JSE All Share Index[19], a free float value or market capitalisation weighted index, excluding dividends, representing ninety-nine percent of the full market capital value of all ordinary equities listed on the JSE's Main Board (FTSE, 2006: 12 and STRATE, 2006: 1). There is a significant deficiency in using intra-day or daily data for equity prices and indices at least, which relates to confounding microstructure influences such as the bid-ask bounce and non-synchronous trading (Moskowitz, 2003). This data covers the period 1995-2005 and will form the basis from which the TY effect will be analysed.

Monthly values of the FTSE/JSE All Share Index, adjusted for dividends or the total return index during the 1995-2006 period, are used in the analysis of the January effect. A deficiency of monthly values is that each month of the year varies in length, distorting

[19] The FTSE/JSE All Share Index incorporates corporate actions such as equity splits and consolidations of the constituents. The Index was rebased according to the old index closing value on the 21st of June 2002.

returns, especially if day-of-the-week effects are present. Monthly returns should be avoided, but these depart less from normality than daily returns.

Equity returns are computed according to the log first difference of the FTSE/JSE All Share Index values between consecutive observations, which may correspond to daily, weekly, monthly or annual frequencies. This is known as the log or continuously compounded return. Reasons for calculating log or continuously compounded index returns are that the index can never be zero, the transformation of data measured in levels with logarithms dampens the exponential pattern of the indices observed in empirical finance and the index is assumed log-normally distributed, thus the logarithmic first difference is normally distributed. This assumption is necessary for the use of OLS in estimation of the seasonal model.

General changes in the price level are subject to seasonal patterns, which may significantly impact equity index values. Therefore, following Campbell & Shiller (1988) South Africa's headline Producer Price Index (PPI) for the period January 1995 – July 2006 deflates the FTSE/JSE All Share Index.[20] This mitigates relevant monthly seasonal price fluctuations that may distort the equity index's value (Shiller, 2005: 2). The seasonally unadjusted PPI is measured on a monthly basis by Statistics South Africa (SSA)[21], with a base year of 2000=100.[22] The PPI is considered a better deflator than headline or core consumer price indices since numerous constituents of the FSTE/JSE All Share Index may be more sensitive to the PPI.

[20] It is recognised that there are leap years during the period under investigation which may distort equity returns.
[21] The PPI is subject to measurement error (Statistics South Africa, 2006).
[22] A sample of products is drawn from the 1996 Manufacturing Census and 1995 / 1996 import and export information from the South African Revenue Service (SARS). This sample of products is revised every five years along with weights assigned to each group. On average 20,000 price quotations are collected from approximately 5,500 outlets every month from which the index is calculated. Price relatives are then calculated for each product, per respondent by dividing the current prices by the previously quoted price. A geometric mean of the price relatives is then calculated; this price relative is then applied to the product index for the previous month in order to obtain a product index for the relevant month. These product indices are then weighted according to each group's weighting structure using the Laspeyres index formula.

The deflated FTSE/JSE All Share Index monthly values are computed according to:

$$Index_{d,t} = (Index_t / PPI_t) \times 100 \qquad (3.1)$$

where $Index_{d,t}$ is the value of the deflated FTSE/JSE All Share Index for month $t$, $Index_t$ is the index value for month $t$ and $PPI_t$ is the PPI value for month $t$. From this a deflated series of values for the FTSE/JSE All Share Index is obtained. Continuously compounded returns are then computed from this deflated series, rendering the return data as continuously compounded real returns. Four different measures of return are analysed for comparison purposes. These include log (continuously compounded) returns, log real returns, log realised returns and log realised real returns.[23]

In deflating the FTSE/JSE All Share Index it is possible to deflate according to the nominal bilateral exchange rate between the rand and, for instance, the American dollar, since studies on exchange rate seasonality suggest significant seasonal patterns. Thus, seasonality in exchange rates may distort equity price and return (Ballie & Bollerslev, 1989). It would then be necessary to analyse the degree to which the market is influenced by exchange rate seasonality and to deflate accordingly. This is beyond the scope of this analysis; however it is noted that seasonality in exchange rates may impact equity market returns and thus deserves further investigation in future research of this nature.

## 3.3 MODEL SPECIFICATION

In this section models in testing for the January and TY effect are developed in accordance with the literature and adapted to the available data. In testing for the January and TY effect the few preceding studies of seasonality in the South African context are extended. In addition, the more recent literature is also considered.

[23] Log returns are calculated from the unadjusted FTSE/JSE Index values, whilst log real returns are log returns deflated with the PPI. Log realised returns are calculated using the dividend adjusted FTSE/JSE Index values, whilst log realised real returns are log realised returns deflated with the PPI.

### 3.3.1 The January effect

The general approach in analysing the January effect, in recent studies, is to broadly analyse the properties of the sample data used in testing for seasonal patterns before advancing to more formal techniques, such as ANOVA and regression analysis. In this study, the data's descriptive statistics will be investigated first. This approach reveals the characteristics of the data and whether it is amenable to inference about seasonal patterns.

The first four moments of the distribution are considered. The mean or arithmetic average reveals the months of the year during which prices or returns are greater or lower, whilst the standard deviation indicates the volatility of these prices or returns. Skewness is a measure of asymmetry and kurtosis a measure of tallness or flatness; thus from these two measures one can derive the shape of the probability distribution function (PDF). A negatively skewed PDF indicates that the probability of earning negative returns is greater than the equal probability of high and low returns represented by the familiar bell shaped PDF of the normal distribution, and vice versa for positively skewed PDFs. A tall or leptokurtic PDF, a stylised fact of equity return / price data, implies relatively large and frequent changes in return for the period under consideration in comparison to the normal PDF, and vice versa.

The analysis of the descriptive statistics will indicate if the return data is normally distributed. If the return data is normally distributed then analysis of variance (ANOVA) will be used in testing for differences in mean return, otherwise the distribution-free Kruskal-Wallis test will be used. In addition to this the paired t-test is used to further test for differences in mean returns.

#### 3.3.1.1 Testing for differences in returns

If it is assumed that equity returns are randomly distributed, then the estimates should be randomly distributed as well, therefore equity returns should be absent of any seasonal pattern. ANOVA can be used to test the hypothesis that mean returns are equal across months, i.e. no seasonal pattern. If the ANOVA F-statistic is statistically significant then the null hypothesis is rejected and therefore concluded that mean returns across months are unequal, i.e. seasonality is present. Shin (2003: 13) states, however that ANOVA is based on two assumptions: the distribution of returns is assumed to be normally distributed and the population variances of return are all equal. Thus, if these assumptions do not hold, the results from ANOVA are invalid. This indicates that it is necessary to further investigate the normal distribution of equity return.

If the returns are non-normally distributed, normality is violated; the seasonality of monthly equity returns can be ascertained by the distribution-free Kruskal-Wallis test. The Kruskal-Wallis test is equivalent to ANOVA in terms of the use of rank numbers (Shin, 2003: 14). In order to run the Kruskal-Wallis test, the returns are ranked in ascending order. The least return is then assigned a rank of 1 and the greatest return gets a rank of N; where N is the total number of all values. The null hypothesis is that the medians across months are equal for returns. Thus, if the computed Kruskal-Wallis H statistics are significant, which is indicated by a small *p*-value, then the rule is not to accept the null hypothesis and conclude that there is seasonality in equity returns.

To determine if the observed seasonal effects are statistically significant, the paired t-test is then used. The paired t-test determines if mean monthly return for a particular month of the year is significantly different from the twelve month population mean return, thus indicating a statistically significant seasonal effect. The null hypothesis is that a particular month's mean return is equal to the population mean return. Thus, this allows for the identification of a monthly seasonal pattern and the significance of these observed seasonal effects relative to the population mean. However, it omits the identification of a seasonal effect relative to each month of the year simultaneously. For this reason, regression analysis, specifically dummy variable regression analysis, is essential.

#### 3.3.1.2 The Dummy Variable Approach

In identifying monthly seasonal patterns in equity returns the following model is specified following Keim (1983) and Brown et al. (1983):

$$R_t = \alpha_1 M_{1t} + \alpha_2 M_{2t} + \alpha_3 M_{3t} +,...,+ \alpha_{11} M_{11t} + \alpha_{12} M_{12t} + e_t \text{ ...............................(3.2)}$$

where $R_t$ is, for the purposes of this analysis, either the monthly log return (continuously compounded rate of return), log real return, log realised return or log realised real return for month $t$. The coefficients $\alpha_1,...,\alpha_{12}$ are the average monthly equity returns for a particular month with $M_{1t}$ as a seasonal dummy variable which takes the value of one if the monthly return is observed in January and zero otherwise, $M_{2t}$ is a seasonal dummy variable which takes the value of one if the monthly return is observed in February and zero otherwise, and so on. The term $e_t$ is the stochastic, white noise, error term. From equation (3.2) a test for seasonal effects can be done. The null hypothesis is that monthly returns across months of the year are not significantly different from one another.

The alternative hypothesis is that all $\alpha$ are unequal. Thus, if the null is rejected, there is a monthly seasonal pattern in equity returns. A statistically significant $\alpha_1$ coefficient is consistent with the January effect.

Tinic & West (1984), Tinic & West (1986) and Corhay et al. (1987) examine the risk-return relationship for evidence of seasonality. The risk premium is the amount by which the investor has to be compensated for investing in a risk asset. Thus, if equation (3.2) suggests a positive January seasonal effect in equity return, it is expected that a positive market risk premium for January exists. Theory dictates that to earn higher returns an investor has to take on higher levels of risk. Tinic & West (1984) and Corhay et al. (1987) have found that this risk-return relationship only holds for January and is contrary to this basic risk-return relationship central to finance theory. The dummy variable approach is used to detect seasonal patterns in the market risk premium for South Africa.

However, it is necessary first to understand how risk premium values are calculated before advancing to model specification. Risk premium is calculated according to the Fama-MacBeth procedure, which is discussed now.

*The Fama-MacBeth Procedure*

Monthly equity return data on 255 equities during the period 1997-2005 is used to investigate the behaviour of the Fama-MacBeth estimates of the two-parameter Capital-Asset Pricing Model (CAPM) (Tinic & West, 1984):

$$R_{pt} = \gamma_{0t} + \gamma_{1t}\beta_{p,t-1} + u_{pt} \quad \text{.........(3.3)}$$

where:
- $R_{pt}$ = return for portfolio, $p$, for each month, $t$.
- $\gamma_{0t}$ = intercept representing return on a standard minimum variance zero- beta portfolio.
- $\gamma_{1t}$ = risk premium based on systematic risk (beta).
- $\beta_{p,t-1}$ = systematic risk of a portfolio, $p$, in time period $t$-1.
- $u_{pt}$ = error term.

To estimate the values of $\gamma_{0t}$ and $\gamma_{1t}$ the first year of monthly continuously compounded equity return data is used to calculate the betas for each equity:

$$\beta_i = \frac{\text{cov}(R_i, R_m)}{\text{var}(R_m)} \quad \text{.........(3.4)}$$

where:
- $\beta_i$ = beta for equity $i$
- $R_i$ = mean monthly return for equity $i$.
- $R_m$ = mean monthly market index return.

The equities are then ranked according to these beta values. Equities are then assigned to twenty equally-weighted portfolios according to this ranking, with portfolio one consisting of equities with the highest risk. Then all the equity betas are recalculated using the second year of data. The arithmetic mean of these betas is then calculated for each portfolio; representing the portfolio's beta. Banz (1981: 5) mentions that this grouping of equities reduces the errors-in-variables problem, which is introduced by the use of estimated betas from equation (3.4). The third year of data is then used to calculate the monthly returns for each portfolio over the twelve-month period. These twenty portfolio returns, for each month, are then cross-sectionally regressed on estimated betas according to equation (3.3). Thus, from the twelve cross-sectional regressions, twelve estimates of $\gamma_{0t}$ and $\gamma_{1t}$ are obtained corresponding to each month of the year.

This process is then repeated using the second year of data to estimate and assign equities to groups (construct portfolios), the third year to calculate portfolio betas and then the fourth year to estimate the monthly relationship between return and risk premia. Continuing in this fashion, one year is dropped and another added, until the year 2005.

Following Tinic & West (1984) and Corhay et al. (1987) the dummy variable model is estimated to test for seasonal effects in risk premia:

$$\gamma_t = \alpha_1 M_{1t} + \alpha_2 M_{2t} + \alpha_3 M_{3t} +,...,+ \alpha_{11} M_{11t} + \alpha_{12} M_{12t} + e_t \qquad (3.5)$$

where $\gamma_t$ is the monthly risk premium for month $t$ calculated according to the Fama-MacBeth (1973) procedure as discussed above, $\alpha_1,...,\alpha_{12}$ are the average monthly risk premium values corresponding to a particular month, $M_{1t}$,..., $M_{12t}$ are seasonal dummy variables, with $M_{1t}$ equal to one where the monthly risk premium is observed in January and zero otherwise. $M_{2t}$ equals one where the monthly risk premium is observed in February, zero otherwise, and so on. The null hypothesis is that risk premia across months are not significantly different. The alternative hypothesis is that all $\alpha$ are unequal and therefore a monthly seasonality in risk premia exists. Thus, if the coefficient, $\alpha_1$, in equation (3.5) is statistically significantly different from zero it will be concluded that a January effect is present in South African equity risk premia.

It is necessary to run diagnostic checks on residuals from equation (3.2) and equation (3.5) in order to verify the validity of these results. Diagnostic checks include testing the residuals from equation (3.2) and equation (3.5) for normality, serial dependence and autoregressive conditional heteroskedasticity (ARCH) effects.

Normality of the residuals from equation (3.2) and equation (3.5) is examined using graphical techniques as well as formal tests of normality, such as the Anderson-Darling and Liffiefors tests. It is expected that the residual normality analysis will reveal non-normally distributed residuals from equation (3.2) and equation (3.5), since it is a stylised fact of empirical finance that equity return data is leptokurtic and non-normally distributed. In addition to this, OLS test procedures are invalid in the presence of residual serial dependence. For this reason the Breush-Godfrey LM test and the Ljung-Box Q-statistics are used to detect serial dependence in the residuals of equation (3.2) and equation (3.5). To detect ARCH effects in the residuals of equation (3.2) and equation (3.5) the ARCH LM test is used. If ARCH effects are present in the residuals then the model is re-specified as a GARCH model.

#### 3.3.1.3 The GARCH approach

There is increasing evidence that equity returns are associated with volatility clustering and leptokurtosis (Fama, 1965; Mandelbrot, 1963 in Alagidede & Panagiotidis, 2006). Linear models such as equation (3.2), often omit these features. Estimation models which capture the time dependence of variability in the return series is thus more appropriate than traditional OLS models (Kamath et al., 1998: 99). To capture these characteristics Bollerslev's (1986) Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model is a very useful approach (Kamath et al., 1998: 99).

Testing the residuals from equation (3.2) for ARCH effects would further indicate the need for a GARCH model in analysing the seasonality of equity returns. Including an ARCH or GARCH specification for the errors will correct for ARCH effects. Thus, a more reliable model of monthly seasonal effects for South African equity returns is provided.

To test the null hypothesis that there are no ARCH effects up to order q in the residuals, the following model is estimated:

$$e_t^2 = \beta_0 + \left( \sum_{s=1}^{q} \beta_s e_{t-s}^2 \right) + v_t \quad \text{.......(3.6)}$$

Equation (3.6) is a regression of the squared residuals on a constant and lagged square residuals up to order q. Thus, from equation (3.6), if the coefficient of the lagged squared residual is not significant then the null hypothesis is accepted; therefore ARCH effects are absent in the residuals (Murray, 2006). However, if the coefficient of the lagged squared residual is significant, a GARCH model may be appropriate in incorporating the effect of autoregressive conditional heteroskedasticity.

Brooks (2002: 452) states that the GARCH model allows the conditional variance to depend upon its previous own lags, so that the conditional variance equation is:

$$\sigma_t^2 = h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad \text{.......(3.7)}$$

The variable $\sigma_t^2$ is the conditional variance since it is a one-period ahead estimate for the variance. The GARCH model is a more parsimonious model,[24], avoids over-fitting and is less likely to breach non-negativity constraints (Brooks, 2002: 453) when compared to the standard ARCH framework. Thus, the GARCH model is preferred to the ARCH model.

[24] Refer to Brooks (2002: 453-455) for an illustration as to why the model is parsimonious.

The GARCH model is non-linear and therefore it is inappropriate to employ OLS in GARCH estimation. Brooks (2002: 455) mentions that there are numerous reasons for OLS being inappropriate, the most fundamental being that OLS minimises the residual sum of squares. The problem with this is that the residual sum of squares depends only on the parameters in the conditional mean equation rather than on the conditional variance. Thus the residual sum of squares minimisation is no longer desired (Brooks, 2002: 455). Therefore, the maximum likelihood procedure must be used. In essence the maximum likelihood procedure finds the most likely values of the parameters, given the data set[25].

Following Connolly (1989), Kamath et al. (1998), Shin (2003) and Alagidede & Panagiotidis (2006), who estimate a GARCH model in their analysis of calendar effects, the following model is utilised in analysing South African return for the January effect:

$$R_t = \alpha_1 M_{1t} + \alpha_2 M_{2t} + \alpha_3 M_{3t} +,...,+ \alpha_{11} M_{11t} + \alpha_{12} M_{12t} + \beta R_{t-1} + e_t \text{.....................(3.8)}$$

where: $e_t \sim N(0, h_t)$

$$h_t = \sigma^2 = \beta_0 + \beta_1 e_{t-1}^2 + \delta\sigma_{t-1}^2$$

It is evident from the mean equation (3.8) that the GARCH model has an autoregressive component. If the residuals of equation (3.2) are serially dependent then this transformation in equation (3.8) provides a serially independent series of standardised residuals (Kamath et al., 1998: 100). Thus, the above model incorporates the effects of serial correlation, heteroskedasticity and volatility. Therefore, GARCH estimates the $\alpha$ coefficients more accurately, which consequently allows the size of an observed seasonal effect and the significance of such a seasonal to be interpreted more accurately. ARCH effects are then tested for again, to verify that all ARCH effects have been captured by the model.

[25] For an in-depth discussion on the maximum likelihood procedure refer to Brooks (2002: 456-457).

### 3.3.2 The turn of the year (TY) effect

The TY effect refers to an anomaly where abnormal returns accrue to equities on the last trading day of December and the first four trading days of January (Keim, 1983; Roll, 1983 and Al-Rjoub, 2005). This definition clearly indicates the difference between the January effect, which is a monthly seasonal effect, and the TY effect, a daily seasonal effect. However, numerous authors use the two terms interchangeably. In a similar approach to Pearce (1995) the following dummy variable model is employed in testing for the TY effect:

$$R_t = \alpha_1 + \alpha_2 TY_t + e_t \qquad (3.9)$$

where $R_t$ is the daily continuously compounded log rate of change for month $t$ on the FTSE/JSE All Share Index, $TY_t$ is a dummy variable, which takes on the value of one if the daily return falls on either the last trading day of December or the first four trading days of January; zero otherwise. For the TY effect to exist it is expected that the coefficient $\alpha_2$ in equation (3.9) will be statistically significantly different from zero, otherwise there is an absence of the TY effect in South African daily equity returns. To test for the TY effect in risk premia it would be necessary to calculate the risk premium for daily observations. However, no extant literature suggests that implementing the Fama-MacBeth procedure is appropriate in calculating daily risk premium values. Thus, the analysis of the TY effect is restricted to South African daily equity returns.

Diagnostic checks on the residuals from equation (3.9) will be done in a similar fashion to the manner prescribed in Section 3.3.1.3 and if necessary the analysis will be extended to include a GARCH model.

## 3.4 CONCLUSION

This chapter sets out the method used in analysing FTSE/JSE All Share Index daily and monthly returns for the TY and January effect respectively. Based on international and domestic literature as well as data availability, a dummy variable model is specified to test for these effects. In addition to this, a GARCH model is specified that incorporates ARCH effects and serial dependence. A model in testing for the January effect in risk premium is specified as well; thus from these models seasonal effects in monthly returns and risk premium can be identified. These techniques are now applied in Chapter four, to achieve the study's objectives.

CHAPTER FOUR
# RESULTS

## 4.1 INTRODUCTION

The various techniques discussed in chapter three are applied in this chapter, which consists of three sections. The empirical results are presented in section 4.2 whilst concluding remarks with regard to these findings are presented in section 4.3.

## 4.2 EMPIRICAL FINDINGS

A preliminary examination of the monthly return data used in analysing the January effect is presented in Section 4.2.1. Regression analysis results and diagnostic checks on monthly returns are presented in section 4.2.2. Section 4.2.3 contains a preliminary examination on the Fama-MacBeth estimates used in analysing seasonal effects for risk premium and section 4.2.4 consists of the regression analysis on these estimates. Section 4.2.5 presents a preliminary examination on the daily return data used in testing for the TY effect with Section 4.2.6 reporting results from the regression analysis.

### 4.2.1 PRELIMINARY EXAMINATION OF FTSE/JSE MONTHLY RETURN DATA AND FINDINGS

The greatest average monthly equity return is obtained during January and December for the log and log realised real returns (Table 4.1). For the log real returns, the greatest average monthly equity return is obtained during September and December. April and December are months in which log realised returns are the greatest. December is consistently the month during which average monthly equity returns are the greatest across all four return measures. In addition to this, the mean return during January is greater than any other month except December in log and log realised returns; thus a January and December effect may apply to South African equity returns.

**Table 4.1: Descriptive statistics: FTSE/JSE All Share Index return measures (1995-2006)**

| Return measure | Category | Metric | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Log | Mean | Percent | 2.118 | 0.948 | 0.282 | 2.054 | 0.289 | 0.082 | -0.336 | -0.347 | 0.159 | 1.910 | 1.393 | 3.480 | 0.991 |
| | Standard deviation | Units | 7.263 | 4.611 | 5.538 | 5.929 | 6.311 | 5.599 | 5.882 | 12.145 | 5.309 | 5.995 | 5.032 | 5.535 | 6.345 |
| | Skewness | Units | -1.001 | -0.101 | -0.482 | 0.053 | 0.582 | -0.422 | -1.105 | -2.356 | -0.266 | 0.258 | 0.404 | 0.154 | -1.415 |
| | Kurtosis | Units | 3.454 | 1.762 | 2.488 | 1.884 | 2.865 | 2.959 | 3.706 | 7.484 | 2.869 | 2.713 | 1.953 | 1.683 | 9.430 |
| | Sample size | Number | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 11 | 11 | 11 | 11 | 11 | 139 |
| Log real | Mean | Percent | 1.201 | 0.466 | 0.014 | 1.061 | -0.215 | -0.836 | -1.032 | -0.868 | 1.369 | 0.164 | 0.893 | 3.287 | 0.440 |
| | Standard deviation | Units | 8.538 | 4.578 | 5.508 | 6.056 | 6.786 | 5.547 | 6.029 | 12.222 | 6.007 | 8.729 | 4.992 | 5.335 | 6.783 |
| | Skewness | Units | -1.278 | 0.020 | -0.437 | 0.042 | 0.724 | -0.183 | -1.166 | -2.371 | -0.320 | -1.150 | 0.271 | 0.153 | -1.463 |
| | Kurtosis | Units | 4.196 | 1.949 | 2.491 | 2.025 | 3.149 | 2.809 | 3.758 | 7.532 | 2.638 | 4.773 | 1.867 | 1.639 | 8.689 |
| | Sample size | Number | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 11 | 11 | 11 | 11 | 11 | 139 |
| Log realised | Mean | Percent | 2.087 | 1.175 | 0.525 | 2.117 | 0.568 | 0.372 | -0.582 | 0.886 | -0.590 | 2.042 | 1.618 | 3.696 | 1.146 |
| | Standard deviation | Units | 7.056 | 4.563 | 5.550 | 5.501 | 6.194 | 5.670 | 5.751 | 8.853 | 5.546 | 5.611 | 4.690 | 5.558 | 5.844 |
| | Skewness | Units | -1.052 | 0.039 | -0.409 | -0.009 | 0.592 | -0.367 | -1.013 | -2.058 | 0.092 | 0.256 | 0.394 | 0.077 | -0.675 |
| | Kurtosis | Units | 3.641 | 1.780 | 2.532 | 1.899 | 2.827 | 3.170 | 3.656 | 6.536 | 2.562 | 2.561 | 2.081 | 1.684 | 4.637 |
| | Sample size | Number | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 11 | 11 | 11 | 11 | 11 | 139 |
| Log realised real | Mean | Percent | 1.477 | 0.693 | 0.258 | 1.125 | 0.065 | -0.545 | -1.278 | 0.365 | 0.620 | 0.296 | 1.118 | 3.504 | 0.622 |
| | Standard deviation | Units | 7.524 | 4.545 | 5.520 | 5.609 | 6.675 | 5.620 | 5.911 | 8.941 | 6.503 | 8.343 | 4.656 | 5.343 | 6.224 |
| | Skewness | Units | -1.026 | 0.191 | -0.377 | -0.033 | 0.723 | -0.134 | -1.064 | -2.066 | -0.033 | -1.186 | 0.259 | 0.088 | -0.801 |
| | Kurtosis | Units | 3.491 | 2.007 | 2.531 | 2.053 | 3.134 | 3.018 | 3.677 | 6.577 | 2.141 | 4.789 | 1.988 | 1.634 | 4.902 |
| | Sample size | Number | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 11 | 11 | 11 | 11 | 11 | 139 |

**Table 4.2: Descriptive statistics: FTSE/JSE All Share Index return measures for selected periods (1995-2006)**

| Return measure | Category | Metric | All | All (excluding Dec) |
|---|---|---|---|---|
| Log | Mean | Percent | 0.991 | 0.777 |
| | Standard deviation | Units | 6.345 | 6.384 |
| | Skewness | Units | -1.415 | -1.491 |
| | Kurtosis | Units | 9.430 | 9.663 |
| | Sample size | Number | 139 | 127 |
| Log real | Mean | Percent | 0.440 | 0.196 |
| | Standard deviation | Units | 6.783 | 6.855 |
| | Skewness | Units | -1.463 | -1.504 |
| | Kurtosis | Units | 8.689 | 8.728 |
| | Sample size | Number | 139 | 127 |
| Log realised | Mean | Percent | 1.146 | 0.927 |
| | Standard deviation | Units | 5.844 | 5.837 |
| | Skewness | Units | -0.675 | -0.730 |
| | Kurtosis | Units | 4.637 | 4.754 |
| | Sample size | Number | 139 | 127 |
| Log realised real | Mean | Percent | 0.622 | 0.374 |
| | Standard deviation | Units | 6.224 | 6.285 |
| | Skewness | Units | -0.801 | -0.684 |
| | Kurtosis | Units | 4.902 | 4.720 |
| | Sample size | Number | 139 | 127 |

For all four return measures, in Table 4.2, mean return during December has a relatively large impact on the population's mean return. Thus, monthly returns obtained during December may have a significant effect on returns for the entire period. To test the significance of these results the t-test of differences in mean returns is discussed later.

The data is negatively skewed, since skewness values for each return measure is less than zero. Kurtosis is greater than three across return measures, so the distribution of returns is leptokurtic, which is a stylised fact of empirical finance. Thus, for this data set, the probability of negative returns is greater than the equal probability of high and low returns represented by the familiar bell shaped probability density function of the normal distribution.

### 4.2.1.1 Graphical investigating of normality

An investigation of the return data's probability distribution is essential. A visual inspection of Figure 4.1 through Figure 4.4 for log and log real returns reveals that returns are non-normally distributed. In addition to this, the figures confirm that returns are leptokurtic and negatively skewed.

**Figure 4.1: Histogram of residuals: Log returns**

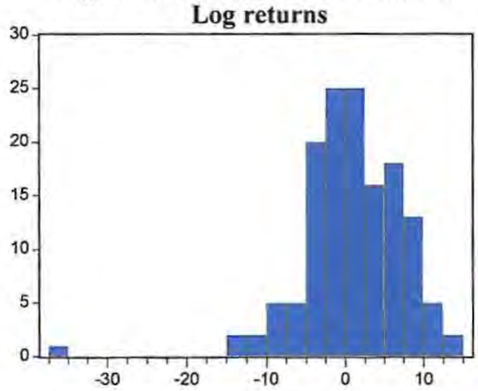



**Figure 4.2: Normal probability plot: Log returns**

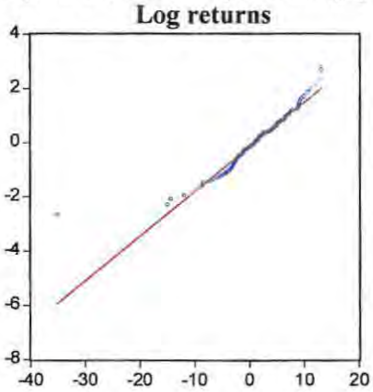



**Figure 4.3: Histogram of residuals: Log real returns**

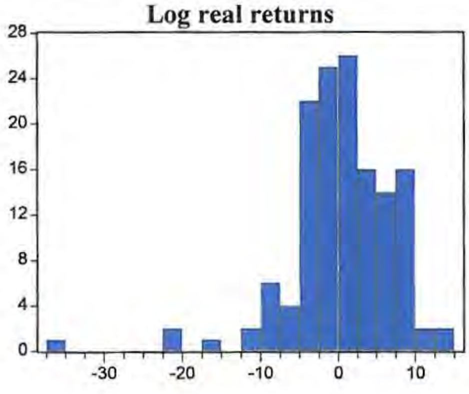
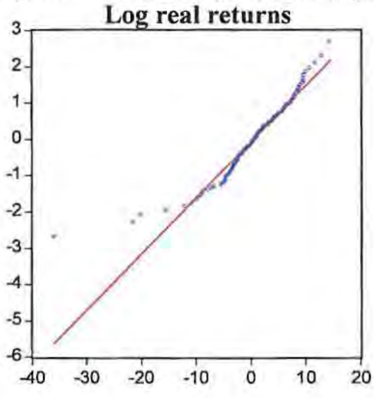



**Figure 4.4: Normal probability plot: Log real returns**



Visual inspections of Figure 4.5 through Figure 4.8, below reveal that log realised and log realised real returns are non-normally distributed. The histogram of residuals is negatively skewed and leptokurtic whilst the normal probability plots deviate from the theoretical normal distribution.

**Figure 4.5: Histogram of residuals: Log realised returns**

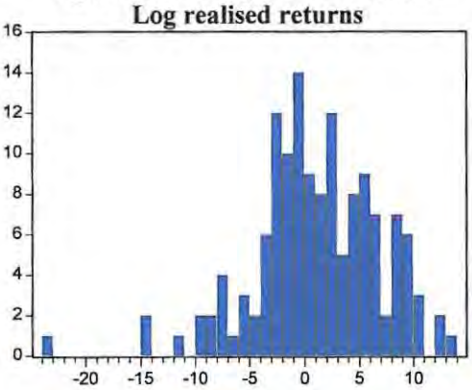



**Figure 4.6: Normal probability plot: Log realised returns**

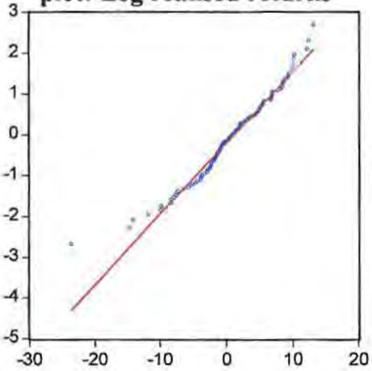



**Figure 4.7: Histogram of residuals: Log realised real returns**

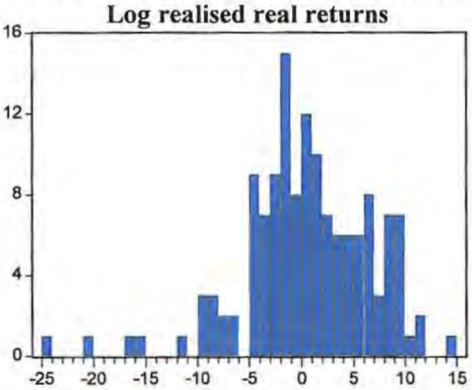
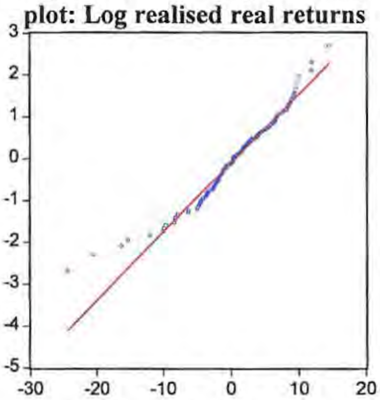



**Figure 4.8: Normal probability plot: Log realised real returns**




In spite of *prima facie* evidence of non-normal returns, formal tests of normality are necessary for the sake of rigour.

### 4.2.1.2 Formal tests of normality

The simultaneous use of the Anderson-Darling (AD), and Lilliefors tests for normality in this analysis admits comparison between test results. *A priori*, the data is non-normally distributed and this will be assumed when using these tests.

The AD test is a Goodness of Fit test, specifically a distance test since it uses a cumulative distribution function (CDF) approach. Romeu (2005: 1) mentions that the AD test is among the best distance tests for small samples and can be used for large samples as well. Romeu (2005: 1) states that there is a well-defined series of steps to follow when using a distance test like the AD test. First, the data is assumed to be normally distributed. The distribution parameters are then estimated from the data. This in turn comprises the null hypothesis ($H_0$), with several parts that must be jointly true (Romeu, 2005: 2). If the AD test statistic is significantly greater than the critical value the null is rejected and thus the return data is non-normally distributed.

The Lilliefors test compares the cumulative distribution of data to the expected cumulative normal distribution (Öztuna, et al., 2006: 3) and is a variant of the Kolmogorov-Smirnov (KS) test. The null hypothesis is that the data is normally distributed, with a significant value for the Lilliefors test indicating that the data is non-normally distributed.

The AD and Lilliefors test are conducted on the sample data. For log and log real returns the Lilliefors and AD test both suggest that the data is non-normally distributed. However, in testing log realised and log realised real returns the Lilliefors test suggest that the data is normally distributed whilst the AD test suggests non-normally distributed returns. The results from the graphical analysis, in addition to these test results, lead to the conclusion that the data is non-normally distributed, despite the contradictory results yielded by the two formal tests for log realised returns. Thus, the aptness of the method of OLS in analysing seasonal effects on South African equity returns is impugned since the OLS estimators may be biased due to the size of the sample under investigation and violation of the assumption of normality. In addition, the *t* statistics may not follow the *t* distribution which is related to the normal distribution (Gujarati, 2003: 338).

#### 4.2.1.3 Testing for differences in returns

The descriptive statistics for the return data sets suggest the presence of a December seasonal effect across all four return measures. From Table 4.1 it is evident that the mean return for the month of December is consistently higher than any other month of the year. In addition to this, the mean return for the entire period, excluding December, is relatively smaller than returns for the entire period. Therefore it is necessary to investigate the seasonality of returns and the statistical significance of the observed seasonal patterns in Table 4.1.

The Kruskal-Wallis test results on all four return measures suggest that the median return across months is equal and thus that no seasonal pattern exists in equity returns.[26] This is surprising since the return pattern in Table 4.1 and Table 4.2 indicate a December seasonal pattern. To further test for possible seasonal patterns in return the paired t-test is used.

**Table 4.3: Paired t-test: Across return measures**

| Return Measure | Category | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Log | Mean | 2.118 | 0.948 | 0.282 | 2.054 | 0.289 | 0.082 | -0.336 | -0.347 | 0.159 | 1.910 | 1.393 | 3.48* |
| | t-statistic | -0.521 | 0.03 | 0.42 | -0.592 | 0.369 | 0.534 | 0.745 | 0.362 | 0.493 | -0.487 | -0.249 | -1.419 |
| Log real | Mean | 1.201 | 0.466 | 0.014 | 1.061 | -0.215 | -0.836 | -1.032 | -0.868 | 1.369 | 0.164 | 0.893 | 3.287* |
| | t-statistic | -0.3 | -0.018 | 0.252 | -0.337 | 0.321 | 0.75 | 0.803 | 0.351 | -0.489 | 0.103 | -0.281 | -1.666 |
| Log realised | Mean | 2.087 | 1.175 | 0.525 | 2.117 | 0.568 | 0.372 | -0.582 | 0.886 | -0.590 | 2.042 | 1.618 | 3.696* |
| | t-statistic | -0.449 | -0.02 | 0.37 | -0.583 | 0.312 | 0.452 | 0.998 | 0.096 | 0.995 | -0.508 | -0.315 | -1.459 |
| Log realised real | Mean | 1.477 | 0.693 | 0.258 | 1.125 | 0.065 | -0.545 | -1.278 | 0.365 | 0.620 | 0.296 | 1.118 | 3.504* |
| | t-statistic | -0.382 | -0.05 | 0.217 | -0.295 | 0.279 | 0.684 | 1.064 | 0.093 | 0.001 | 0.127 | -0.331 | -1.699 |

Note: The t-statistic 10% critical value = 1.289, thus * denotes the rejection of the hypothesis that the mean return for a particular month is equal to the population mean return. $t = \mu_p - \mu_m / se(\mu_p - \mu_m)$, where $\mu_p$ is the population mean and $\mu_m$ is mean monthly return for the month under consideration.

Table 4.3 suggests that the December mean monthly equity return across all return measures is significantly different from the population mean. Accordingly, the paired t-test reveals that there is a slightly significant difference in returns for the FTSE/JSE All Share Index for the month of December only. However, the paired t-test only allows for the comparison of returns between two groups and thus cannot identify a seasonal effect relative to each month of the year simultaneously. It is for this reason that regression analysis is employed.

### 4.2.2 Regression analysis on monthly returns

The descriptive statistics in Table 4.1 and Table 4.2 suggest a December effect in equity returns, thus it is expected that the coefficient $\alpha_{12}$ will be statistically

[26] Results from the ANOVA are not reported, due to these results being invalid under non-normality. However, the results from the ANOVA analysis are in agreement with those of the Kruskal-Wallis test.

significant. Estimation of the dummy variable model for all four return measures yields the following:

**Table 4.4: Dummy variable regression results: monthly return**

| Return measure | Category | Regression coefficients | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\alpha_4$ | $\alpha_5$ | $\alpha_6$ | $\alpha_7$ | $\alpha_8$ | $\alpha_9$ | $\alpha_{10}$ | $\alpha_{11}$ | $\alpha_{12}$ |
| Log | Mean | 2.118 | 0.947 | 0.282 | 2.054 | 0.289 | 0.082 | -0.336 | -0.347 | 0.159 | 1.91 | 1.393 | 3.48* |
| | t-statistic | 1.128 | 0.504 | 0.15 | 1.09 | 0.154 | 0.044 | -0.179 | -0.177 | 0.081 | 0.973 | 0.71 | 1.774 |
| | p-value | 0.261 | 0.615 | 0.881 | 0.276 | 0.878 | 0.965 | 0.858 | 0.86 | 0.936 | 0.332 | 0.479 | 0.079 |
| Log real | Mean | 1.201 | 0.466 | 0.014 | 1.061 | -0.215 | -0.836 | -1.032 | -0.868 | 1.369 | 0.164 | 0.893 | 3.287 |
| | t-statistic | 0.597 | 0.232 | 0.007 | 0.528 | -0.107 | -0.416 | -0.513 | -0.413 | 0.652 | 0.078 | 0.425 | 1.565 |
| | p-value | 0.551 | 0.817 | 0.994 | 0.599 | 0.915 | 0.678 | 0.609 | 0.68 | 0.516 | 0.938 | 0.672 | 0.12 |
| Log realised | Mean | 2.087 | 1.175 | 0.525 | 2.117 | 0.568 | 0.372 | -0.582 | 0.886 | -0.59 | 2.042 | 1.618 | 3.696** |
| | t-statistic | 1.211 | 0.682 | 0.305 | 1.229 | 0.33 | 0.216 | -0.338 | 0.192 | -0.328 | 1.135 | 0.899 | 2.054 |
| | p-value | 0.228 | 0.497 | 0.761 | 0.221 | 0.742 | 0.829 | 0.736 | 0.623 | 0.744 | 0.259 | 0.37 | 0.042 |
| Log realised real | Mean | 1.477 | 0.693 | 0.258 | 1.125 | 0.065 | -0.545 | -1.278 | 0.365 | 0.62 | 0.296 | 1.118 | 3.504* |
| | t-statistic | 0.802 | 0.76 | 0.14 | 0.61 | 0.05 | -0.296 | -0.694 | 0.19 | 0.22 | 0.154 | 0.581 | 1.821 |
| | p-value | 0.424 | 0.708 | 0.889 | 0.543 | 0.972 | 0.768 | 0.489 | 0.849 | 0.748 | 0.878 | 0.562 | 0.071 |

Note: * denotes significance at the ten percent level, whilst ** denotes significance at the five percent level of significance.

The $p$-values in Table 4.4 indicate the probability of observing a difference in mean returns for each month of the year from the null hypothesis. Thus, evidence of a December effect in returns for three of the four return measures is provided in table 4.4. The coefficient $\alpha_{12}$ suggests that log and log realised real returns during December are statistically significantly different from zero at the ten percent level of significance. Furthermore, the coefficient $\alpha_{12}$ is statistically significant at the five percent level for log realised returns. Deflating the return series renders the December effect less significant. Thus, seasonality of the PPI may influence seasonality in equity markets.

From this analysis a slight December effect is found in FTSE/JSE All Share Index returns. All other coefficients corresponding to the remaining months of the year are not statistically significant. Thus, these results reveal that investing in December will on average yield greater returns to an investor. However, diagnostic checks on the regression model should be done in order to verify the validity of the results. These diagnostic checks include testing the residuals for normality, serial dependence and autoregressive conditional heteroskedasticity (ARCH) effects.

#### 4.2.2.1 Normality

The preliminary examination of the data in Section 4.2.1 reveals that the FTSE/JSE All Share Index returns are not normally distributed. Specifically the analysis identifies leptokurtic and slightly negatively skewed returns. Thus, it is expected that the residuals from monthly return dummy variable regression model should be non-normally distributed and therefore the results may be biased. To formally test these residuals the Jarque-Bera (JB) test for normality is used.

The JB test is an asymptotic, large sample test based on OLS residuals and tests the joint hypothesis that skewness and kurtosis are zero and three respectively (Gujarati, 2003: 148). Thus, the JB statistic is expected to equal zero. If the computed $p$ value of the JB statistic is sufficiently low, then the JB statistic is significantly different from zero and hence the hypothesis is rejected. It should be noted, however that the sample under consideration only has 139 observations for each return measure, which may influence the validity of the JB test. The JB test results reveal that the residuals are non-normally distributed for all four return measures. Thus, inferences made from the estimation results in Table 4.5 may be invalid.

#### 4.2.2.2 Serial dependence

Due to OLS being inefficient and standard OLS-based test procedures being invalid in the presence of serial dependence, it is necessary to test the hypothesis of serially independent disturbances before relying on OLS and the standard test procedures (Murray, 2006: 446). Thus, it is necessary to use formal tests for serial dependence. The tests used are the Breush-Godfrey (LM) and the Ljung-Box Q-statistic tests.

*The Breusch-Godfrey Test*

The Breusch-Godfrey Lagrange multiplier (LM) test can be used to test for high-order serial dependence in the seasonal models as specified (Worthington, 2005 and Standton & Wallace, 1995). The Breush-Godfrey test is based on a regression in which the residuals appear. This regression includes a dependent variable, the OLS residual, and the independent variables from the equation of interest and a number of lagged residuals (Murray, 2006: 452). The null hypothesis of serially independent disturbances is rejected if the lagged residuals explain enough of the variation of the current residual. The Breusch-Godfrey test first comprises estimation of the equation of interest by OLS. The residuals are then regressed against the explanatory variables in the equation of interest and some number, $L$, of the residuals' lagged values:

$$e_t = a_0 + a_1 X_{1t} + ... + a_k X_{kt} + a_{k+1} e_{t-1} + ... + a_{k+L} e_{t-L} + v_t \text{ ..............................} (4.1)$$

If $TR^2$ from Equation (4.1) exceeds the critical value for a Chi-square statistic with $L$ degrees of freedom for a chosen level of significance then the null hypothesis is rejected. Thus, the residuals would be serially dependent.

The benefit of using the Breusch-Godfrey test is that, unlike the Durbin-Watson test, it is sensitive to correlations between non-consecutive disturbances as well as being sensitive to correlations between adjacent disturbances. However, the Breusch-Godfrey test often suffers from distorted sizes in small samples. This can be corrected by modifying the Breusch-Godfrey test by replacing the Chi-square test with an F-test of the hypothesis that the lagged residuals in Equation (4.1) all have zero coefficients (Murray, 2006: 452).

The Breusch-Godfrey test returns an F-statistic that is not statistically significant for all four return measures, thus the residuals from the monthly return dummy variable regression model are serially independent.

*The Ljung-Box Q-statistic test*

The Ljung-Box Q-statistic tests for serial dependence by examining the residuals of a particular model. If serial dependence is absent the Q-statistics should be insignificant and have large $p$-values. Thus, if the residuals of the dummy variable regression model are serially dependent, the $p$-values of the Q-statistics will all be statistically significant.

The Ljung-Box Q-statistics are not significant, indicated by large $p$-values, thus the residuals from the dummy variable regression model are serially independent, further confirming the results from the Breusch-Godfrey test.

#### 4.2.2.3 Autoregressive conditional heteroskedasticity

Volatility clustering and leptokurtosis is apparent in the FTSE/JSE All Share Index return data. Linear models such as the monthly return dummy variable regression model are incapable of explaining these features thus Bollerslev's (1986) Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model (Kamath, et al., 1998: 99) is used.

If the residuals from the dummy variable model reveal ARCH effects then a GARCH model must be used to incorporate these effects. When the residuals from this model are tested for ARCH effects, the F-statistics for all four return measures are not statistically significant. Thus, ARCH effects are absent in these residuals. Employing GARCH analysis on the FTSE/JSE All Share Index return data may thus be inappropriate.

From the above diagnostic checks the OLS regression analysis on the monthly return dummy variable model is based on non-normally distributed data; however, serial correlation and ARCH effects are absent in the residuals from the dummy variable model. It is an empirical regularity that financial data is leptokurtic with data distributions that are non-normal. Thus, although returns are non-normally distributed, this analysis still provides some valuable insight into the seasonality of FTSE/JSE All Share Index monthly equity returns.

The next matter to address is if a seasonal effect exists in risk premia and whether these seasonal patterns follow that of the above analysis. A central assumption in finance is that greater returns are earned on riskier assets. Thus, risk premia should demonstrate a positive seasonal pattern for the month of December. Otherwise the traditional risk-return trade-off does not hold for the FTSE/JSE All Share Index monthly equity returns.

### 4.2.3 Preliminary examination of Fama-Macbeth risk estimates and findings

This section follows the broad steps as conducted in Section 4.2.2.1; however, in order to analyse the seasonality of the risk premia, risk premia are first computed.[27] These values are calculated according to the Fama-MacBeth procedure which is discussed in chapter three. Using the Fama-MacBeth procedure, there are seven monthly estimates of the risk-premium for each month of the year, with a total of eighty-four observations for the period January 1999 – December 2005. Again, the descriptive statistics are analysed before advancing to the dummy variable regression analysis.

**Table 4.5: Descriptive statistics: Fama-MacBeth based risk premium estimates on FTSE/JSE All Share Index**

| Category | Metric | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | Percent | 2.643 | -1.445 | -5.039 | -2.544 | 0.831 | -1.947 | -4.911 | -0.744 | -5.407 | -1.147 | -1.487 | -0.603 | -1.817 |
| Standard deviation | Units | 6.369 | 2.726 | 5.22 | 6.204 | 7.07 | 4.523 | 4.919 | 5.218 | 7.625 | 9.99 | 6.207 | 5.755 | 6.244 |
| Skewness | Units | -0.562 | 0.017 | 0.695 | 0.277 | -0.764 | 0.354 | -1.29 | 0.857 | -0.846 | 0.424 | 0.463 | -0.274 | 0.027 |
| Kurtosis | Units | 0.741 | -0.804 | -1.341 | -1.047 | -1.223 | -1.128 | 1.541 | 1.432 | 0.035 | 0.03 | -1.153 | 1.005 | 3.034 |
| Sample size | Number | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 84 |

It is important to note from Table 4.5 that there are relatively few observations of risk premia. This deficiency is due to data constraints. From Table 4.5 three months of the year are conspicuous by their risk premia. The mean monthly risk premium during March, July and September is greater than four. Thus, a March, July and September seasonal may be present in risk premia. In addition to this, the measures of skewness and kurtosis for all observations suggest that the data is slightly positively skewed and mesokurtic. Therefore, it is expected that formal tests of normality will reveal that the data is normally distributed.

#### 4.2.3.1 Investigating normality

The distribution of the Fama-MacBeth estimates of risk premia closely approximates the normal distribution's bell-shaped curve (as shown in Figure 4.9 and Figure 4.10). In addition, the normal probability plot appears in Figure 4.10 and reveals normally distributed risk premia since all observations lie extremely close to the theoretical

[27] This section analyses risk premia in relation to log returns.

normal distribution line. Thus, risk premium estimates are normally distributed. To verify this, formal normality tests are used.

**Figure 4.9: Histogram of residuals: Fama-MacBeth estimates of monthly risk premium**

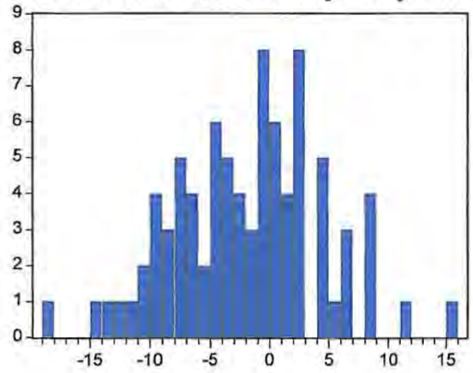
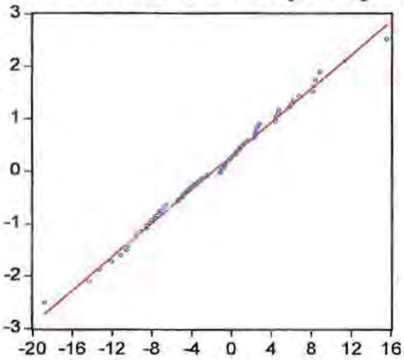



**Figure 4.10: Normal probability plot: Fama-MacBeth estimates of monthly risk premium**




The Lilliefors and AD tests confirm the conclusions reached from the descriptive statistics and graphical analysis – risk premia are normally distributed. The distribution of the Fama-MacBeth risk premium estimates is therefore normally distributed. A possible deficiency, as mentioned before, is that the data set is fairly small which may bias the results from OLS regression.

### 4.2.3.2 Testing for differences in risk premium

The descriptive statistic analysis in Section 4.2.1 suggests that there is a March, July and September seasonal in risk premia. To determine whether a seasonal effect is present, ANOVA analysis is used. The ANOVA test indicates that mean risk premia are equal across months and thus seasonality is absent. Again, this is surprising since monthly seasonal patterns in risk premia are apparent in Table 4.5. To further test for these possible seasonal patterns in risk premia, the paired t-test is used.

**Table 4.6: Paired t-test: Fama-MacBeth risk premium estimates**

| Category | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 2.643** | -1.445 | -5.039* | -2.544 | 0.831 | -1.947 | -4.911* | -0.744 | -5.407 | -1.147 | -1.487 | -0.603 |
| t-statistic | -1.782 | -0.301 | 1.544 | 0.298 | -0.960 | 0.071 | 1.563 | -0.514 | 1.212 | -0.174 | -0.135 | -0.533 |

Note: The t-statistic 10% critical value = 1.282, 5% critical value = 1.658, thus * denotes the rejection of the hypothesis at the 10% level and * denotes the rejection at the 5% level that risk premium for a particular month is equal to the population mean risk premium.

These results suggest that the risk premium in January is significantly different from the population mean. Furthermore, results from Table 4.6 confirm that a statistical difference exists for the risk premium during March and July. To analyse the significance of the difference in risk premia from zero for all months of the year simultaneously, dummy variable regression analysis is used.

### 4.2.4 Regression analysis on Fama Macbeth risk premium estimates

For the risk-return trade off to hold, there should be a positive risk premium seasonality during December, since a December effect in returns has already been documented. However, the descriptive statistics in Table 4.5 suggest that the risk premia during March, July and September should be significantly different. Furthermore, results from Table 4.6 reveal that risk premia during January, March and July should be significant.

**Table 4.7: Dummy variable regression analysis: risk premium**

| Category | Regression coefficients | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\alpha_4$ | $\alpha_5$ | $\alpha_6$ | $\alpha_7$ | $\alpha_8$ | $\alpha_9$ | $\alpha_{10}$ | $\alpha_{11}$ | $\alpha_{12}$ |
| Mean | 2.643 | -1.445 | -5.039** | -2.544 | 0.831 | -1.947 | -4.911** | -0.744 | -5.407** | -1.147 | -1.487 | -0.603 |
| t-statistic | 1.123 | -0.614 | -2.141 | -1.081 | 0.353 | -0.827 | -2.087 | -0.316 | -2.297 | -0.488 | -0.632 | -0.256 |
| p-value | 0.265 | 0.541 | 0.036 | 0.283 | 0.725 | 0.411 | 0.04 | 0.753 | 0.025 | 0.627 | 0.529 | 0.799 |

Note: ** denotes significance at the five percent level of significance.

A negative seasonal effect in risk premia during March, July and September, with *p*-values of less than 0.05 indicating statistical significance at the five percent level is observed in Table 4.7. In addition, the December risk premium is not statistically significantly different from zero. It must be noted that due to data constraints the two periods under consideration are slightly different. In Section 4.2.2 a slightly significant seasonal effect is found to exist in FTSE/JSE All Share Index returns during December. *A priori*, it is then expected that risk premium would be significantly large during December, since higher returns are earned on riskier assets. The opposite of this, however, holds true, as is evident from Table 4.7. Investors are penalised for investing in risky assets during March, July and September and no risk premium seasonal effect is observed during the month of December; however, higher than normal returns are earned during December. Thus, the traditional risk-return trade-off does not hold. To ensure the validity of these results diagnostic checks are run on the residuals of the regression model.

#### 4.2.4.1 Normality

The preliminary examination of the Fama-MacBeth risk estimates suggest that the data is normally distributed. It is expected then that the residuals from the regression model are normally distributed and thus valid inferences from the regression estimates can be made. To formally test these residuals the JB test for normality is used. The JB test returns a statistic of 0.0358 with a corresponding $p$-value of 0.9822. Thus, these residuals are normally distributed.

#### 4.2.4.2 Serial dependence

The two formal tests that are used to test for serial dependence in the residuals of the regression model are the Breusch-Godfrey and Ljung-Box Q-statistic tests.

The Breusch-Godfrey test returns an F-statistic of 0.3839 with an associated $p$-value of 0.6826. Thus, the Breusch-Godfrey test suggests that the residuals are serially independent. The Ljung-Box Q-statistics are all relatively small with $p$-values greater than 0.57, which confirms that the residuals from the regression model are serially independent.

#### 4.2.4.3 Autoregressive conditional heteroskedasticity

If the ARCH effect affects the residuals from the OLS regression model, the model must be expanded to a GARCH model since linear models such as OLS omit these effects. The ARCH LM test returns an F-statistic of 2.212 and an associated probability of 0.141. Thus, ARCH effects are absent in the regression model residuals. The data is normally distributed and ARCH effects are absent; therefore it would be superfluous to include GARCH analysis for the Fama-MacBeth monthly estimates of risk. From these diagnostic checks it is concluded that the results from the risk premium regression analysis are valid, although the small sample size may have introduced some bias to the results presented in Table 4.7.

### 4.2.5 Preliminary examination of FTSE/JSE daily return data for the TY effect

Before a regression can be estimated for the detection of the TY effect, the FTSE/JSE All Share Index daily return data must be analysed to detect seasonal patterns which may require more investigation.

**Table 4.8: Descriptive statistics: FTSE/JSE All Share Index daily returns (1995-2005)**

| Category | Metric | TY | All excluding TY | All |
|---|---|---|---|---|
| Mean | Percent | 0.319 | 0.049 | 0.054 |
| Standard deviation | Units | 1.22 | 1.178 | 1.179 |
| Skewness | Units | 1.549 | -0.851 | -0.795 |
| Kurtosis | Units | 3.964 | 9.212 | 9.107 |
| Sample size | Number | 55 | 2640 | 2695 |

There is substantial difference between average daily return for days corresponding to the turn-of-the-year when compared to the average daily return for the remaining days of the year, with returns equal to 0.319 percent as compared to 0.049 percent (Table 4.8). This suggests that a TY effect is present in FTSE/JSE All Share Index daily returns for the period under consideration. Once returns corresponding to the TY effect are removed, the average daily return for the entire period drops from 0.054 percent to 0.049 percent. Thus, average returns during the last day of the year and the first few days of the subsequent year have a positive impact on average daily returns. Returns are slightly negatively skewed and in addition to this, the measure of kurtosis is larger than three, indicating that returns are highly leptokurtic. Since the data is fat-tailed, an investor may observe relatively large and frequent changes in return during this period.

#### 4.2.5.1 Graphical investigating of normality

Superimposing the normal bell shaped curve on Figure 4.11 indicates that the data is leptokurtic and further verifies the results from Table 4.8. Furthermore, the data is negatively skewed. An S-shaped curve is presented in the normal probability plot (Figure 4.12). This reveals that the return distribution has shorter than normal tails, confirming that the distribution is leptokurtic. The distribution of daily equity returns is therefore non-normally distributed. However, for the sake of rigour formal tests for the normality of returns are then used.

Figure 4.11: Histogram of residuals: FTSE/JSE All Share Index daily return

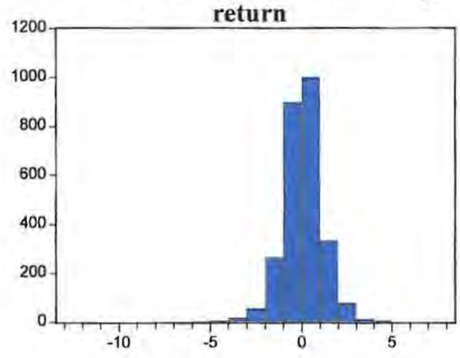
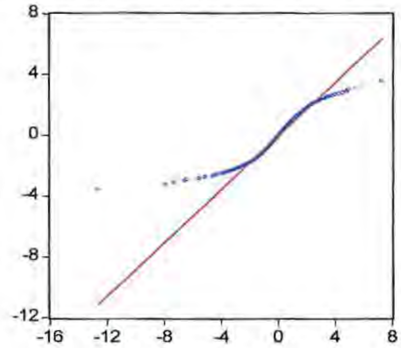



Figure 4.12: Normal probability plot: FTSE/JSE All Share Index daily return




### 4.2.5.2 Formal tests of normality

The AD and Lilliefors test are again used on the sample data before advancing to regression analysis. The Lilliefors and AD test both return a $p$-value of 0.0000, which means that both test statistics are highly significant, indicating that the data is non-normally distributed. This result further verifies the results provided in Table 4.8 as well as the conclusions reached from the graphical analysis. Thus, the method of Ordinary Least Squares regression analysis may lack relevance in the analysis of seasonal effects on South African daily equity returns, since the estimators may be biased.

### 4.2.5.3 Testing for differences in returns

The descriptive statistics for the daily return data reveal that a TY seasonal effect is present in South African equity daily equity returns (Table 4.8).

The Kruskal-Wallis analysis reveals that a significant seasonal effect is absent in FTSE/JSE All Share Index daily returns. This is surprising, since TY returns in table 4.8 are significantly different from the population mean. To further test for possible seasonal patterns in daily returns the paired t-test is used. The paired t-test indicates that the average daily return for days corresponding to the turn-of-the-year is significantly different to the average daily return of the sample. Thus, the paired t-test reveals that a slightly significant TY effect exists for FTSE/JSE All Share Index daily equity returns.

### 4.2.6 Regression analysis to identify a TY effect

The dummy variable analysis reveals that the average daily return for days at the turn-of-the-year is statistically significantly different from the average daily return for the remaining days of the year. This difference is approximately 0.271 percent at the ten percent level of significance. Thus, there is a weakly significant TY effect in FTSE/JSE All Share Index daily returns. Diagnostic checks on the TY regression analysis are done to verify the validity of this finding.

#### 4.2.6.1 Normality

The preliminary examination of the data in Section 4.2.5.1 reveals that the return data is non-normally distributed. Specifically, the preliminary examination identifies that the data is negatively skewed and highly leptokurtic. Therefore, it is expected that the residuals from the TY regression analysis are non-normally distributed.

The JB test returns a test statistic that is highly significant at the one percent level of significance. Thus, the residuals from the TY regression are non-normally distributed and therefore inferences made from the regression analysis may not be entirely accurate.

#### 4.2.6.2 Serial dependence

The Breusch-Godfrey test returns an F-statistic of 18.679 with an associated *p*-value of 0.0000. Thus, the residuals are serially dependent. The Ljung-Box Q-statistics are all statistically significant at the one percent level, confirming the Breusch-Godfrey test result.

#### 4.2.6.3 Autoregressive conditional heteroskedasticity

The ARCH LM test will determine if ARCH effects exist in the residuals of the TY regression model. The ARCH LM test returns an F-statistic that is highly significant at the one percent level. Therefore, ARCH effects are present in these residuals. Thus, the GARCH methodology is used to incorporate these ARCH effects.

#### 4.2.6.4 GARCH analysis

The results reveal that the average daily return for days excluding days at the turn-of-the-year are highly significantly different from zero. Furthermore, the average daily return for days at the turn-of-year is highly statistically significantly different from average daily return for the rest of the year. Thus, on average, daily returns at the turn-of-the-year are 0.462 percent higher than the average daily return for the rest of the year at the one percent level of significance. Therefore, a highly significant TY effect is present in FTSE/JSE All Share Index daily returns.

To ensure that the results from the GARCH model are accurate and that all ARCH effects have been captured, the residuals are examined for serial dependence and ARCH effects. The ARCH LM test returns an F-statistic of 0.003 with an associated $p$-value of 0.956, which suggests that all ARCH effects have been captured. Furthermore, the Ljung-Box Q-statistics are examined for evidence of serial dependence and reveal that the residuals are serially independent. Thus, the GARCH model is appropriate in testing for the TY effect in FTSE/JSE All Share Index daily returns. An investor is therefore likely to earn greater returns during days at the turn-of-the-year than during any other days of the year.

## 4.3 CONCLUSION

South African equity returns are analysed for the presence of a TY and January effect during the period 1995-2005 and 1995-2006 respectively. Descriptive statistics, tests for differences in mean returns and regression analysis are used in the analysis. The January effect is analysed with regard to four different monthly return measures: log, log real, log realised and log realised real returns on the FTSE/JSE All Share Index. Furthermore, daily log returns on the FTSE/JSE All Share Index are used to detect a TY effect.

The dummy variable analysis on monthly returns finds the absence of a January effect; however, a slightly significant December effect is found for South African equity returns. Furthermore, the effect is less significant in log real returns, thus seasonality in equity returns may be significantly influenced by seasonal patterns in inflation. These findings suggest that abnormal returns can be earned by buying equities before December and selling these same equities during December. GARCH regression analysis on daily returns reveals that days at the turn-of-the-year have a highly significantly greater average mean daily return compared to the remaining days of the year. Thus, investors earn greater than normal returns during days at the turn-of-the-year.

In addition to the return data analysis, evidence of seasonality in the Fama-MacBeth risk premium estimates for the South African data is documented. This analysis reveals that investors are penalised during the months of March, July and September; i.e. a statistical significant negative seasonal effect in risk premia is identified for South Africa during March, July and September. Thus, the risk-return trade-off central to modern finance may be invalid. This risk premium analysis serves as exploratory work which authors may augment in the future with better data sets.

These findings are consistent with empirical literature on the South African market; however the evidence of a December effect is only consistent with Bradfield's (1990) study.

# CHAPTER FIVE
# CONCLUSION

## 5.1 SUMMARY OF THE STUDY AND CONCLUSIONS

The study analyses monthly and daily returns from the FTSE/JSE All Share Index for evidence of the January and Turn-of-the-Year (TY) respectively. In addition, analysis is done on the monthly Fama-MacBeth risk premium estimates to detect seasonality. Monthly equity returns are analysed during the 1995-2006 period, daily equity returns during the 1995-2005 period and risk premia during the 1997-2005 period. The monthly return data analysed for the January effect consists of four different return measures. These return measures include log, log real, log realised and log realised real returns. Realised returns are calculated from the FTSE/JSE All Share Total Return Index, whilst real returns are deflated with the South African PPI.

Based on the review of the empirical literature, descriptive statistics, tests for differences in mean returns and regression analysis are used in the analysis of South African equity returns. The results reveal an absence of the January effect in FTSE/JSE All Share Index monthly equity returns; however a slightly significant December effect is identified. This December effect is less significant for log real and log realised real returns when compared to log and log realised returns. This suggests that seasonal patterns in inflation may influence seasonal patterns observed in equity markets. The presence of a December effect means that investors can earn abnormal returns by selling equities during December. The risk premia analysis on monthly equity returns reveals a statistically significant negative seasonal pattern during March, July and September. Thus, investors are penalised for investing in equities during these months. In addition to this, it is found that the December effect is absent in risk premia. Thus the basic risk-return trade-off central to modern finance may be invalid.

GARCH regression analysis on FTSE/JSE All Share Index daily equity returns reveals that days at the turn-of-the-year have a highly statistically significant greater mean daily return than remaining days of the year. Thus, a TY effect is present in FTSE/JSE All Share Index daily equity returns. Therefore, investors earn greater mean daily returns during days at the turn-of-the-year than if they were to invest in equities on any other day of the year.

## 5.2 LIMITATIONS OF THE STUDY

Due to data limitations the analysis of the January effect is based on few observations. The seasonal analysis on the Fama-MacBeth risk premia estimates is deficient in this aspect as well. Thus, the results from this analysis may be biased. Expanding the data set to prior 1995 does not solve this problem, since the data would be structurally unstable due to the change in political climate prior to 1995. The best possible solution would then be to conduct this same analysis in a few years' time, once the data set is more substantial. In addition to this, analysis on the size-effect is prevented due to discontinuities in the available market capitalisation data. Once all discontinuities are incorporated, the number of equities available for portfolio formation is inadequate. Thus, the analysis does not test for size-effects.

With regard to the tax-loss selling hypothesis, it is difficult to ascertain whether the observed December effect in South equity returns can be ascribed to this hypothesis, since the tax year-end for firms in South Africa is discretionary. Thus, the analysis is unable to prove or refute the tax-loss selling hypothesis.

## 5.3 AREAS FOR FUTURE RESEARCH

The areas for future research that emerge from the study include the analysis of inflation seasonality and the degree to which it may affect seasonality in equity markets. Other issues concern the appropriateness of inflation indices in deflating equity market indices. Research into this area will reveal whether it is necessary to deflate equity market indices, and which inflation measure may be better to use. Additionally, future studies could incorporate exchange rate seasonality, which may significantly impact the significance of equity market seasonalities.

Significant seasonal affects are found in this study; however only the January and TY effect are analysed. Thus, future research on the South African equity market should include an analysis of the various other documented seasonal patterns in the anomalies literature, such as the day-of-the-week effect. In addition, future research on a larger data set may better indicate the significance of the December effect as identified in this study.

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# 7. APPENDICES

Appendix 1: Panel 1 (1942-1976)

| Author | Country | Financial year ends (1=31 Jan., 2=31 Mar., 3=5 Apr.,4=31 May, 5=30 Jun., 6=31 Dec., 7= discretionary) | Tax regime(1 if taxes on capital gains apply, 0 otherwise) | Period | Equity | | | | Anomaly sought | Method (1 if parametric, 2 if semi-parametric, 3 if non-parametric) | 1 if Anomaly is detected, 0 otherwise |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Price | Price Index (2 if price weighted, 1 if equally weighted, 0 if value / market capitalisation weighted) | Portfolio (1 if equally weighted, 0 if value/market capitalisation weighted) | Other | | | |
| Wachtel (1942) | USA | 6 | 1 | 1927-1942 | | Dow Jones Industrial Average (2) | | | January effect | 3 | 1 |
| Granger & Morgenstern (1963) | USA | 6 | 1 | 1875-1926 | | Standard & Poor's (1), Securities and Exchange Commission's (1), Dow-Jones Industrial Average (2) | | | Seasonal patterns | 3 | 0 |
| Granger & Morgenstern (1970) | USA | 6 | 1 | 1875-1926 | | Standard & Poor's (1), Securities and Exchange Commission's (1), Dow-Jones Industrial Average (2) | | | Seasonal patterns | 3 | 0 |
| Bonin & Moses (1974) | USA | 6 | 1 | 1962-1971 | 30 Industrial Equities listed on Dow Jones | | | | Seasonal patterns | 3 | 1(Weak evidence) |
| Officer (1975) | Australia | 5 | 1 | 1958-1970 | 651 Equities listed on Melbourne Equity Exchange | | | | | 1 | 1 |
| Rozeff & Kinney (1976) | USA | 6 | 1 | 1904-1909 | | Cowles Commission Equity Price (1) | | | Seasonal patterns | 2 | 1(January effect) |
| | | | | 1910-1925 | | Standard & Poor's (1) | | | | | |
| | | | | 1926-1974 | | All common equities listed on NYSE (1) | | | | | |

Panel 2 (1981-1983)

| Author | Country | Financial year ends (1=31 Jan., 2=31 Mar., 3=5 Apr.,4=31 May, 5=30 Jun., 6=31 Dec., 7= discretionary) | Tax regime(1 if taxes on capital gains apply, 0 otherwise) | Period | Equity | | | | Anomaly sought | Method (1 if parametric, 2 if semi-parametric, 3 if non-parametric) | 1 if Anomaly is detected, 0 otherwise |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Price | Price Index (2 if price weighted, 1 if equally weighted, 0 if value/market capitalisation weighted) | Portfolio (1 if equally weighted, 0 if value/market capitalisation weighted) | Other | | | |
| Banz (1981) | USA | 6 | 1 | 1926-1975 | | 1. CRSP index (1) 2.CRSP index (0) 3.CRSP return data on corporate and government bonds (1) | | | Size-effect in explaning January effect | 1 | 1 |
| Keim (1983) | USA | 6 | 1 | 1963-1979 | CRSP daily equity price files | | 0 | | January effect in relation to size-effect and tax-loss selling | 1 | 1 |
| Reinganum (1983) | USA | 6 | 1 | 1962-1979 | CRSP daily price files | | 0 | | January effect in relation to size-effect and tax-loss selling | 1 | 1 |
| Brown et al. (1983) | Australia | 5 | 1 | 1958-1981 | Merged File | 1 | 1 | | Seasonal patterns | 1 | 1(December, January, July and August effects) |
| Gultekin & Gultekin (1983) | Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK and the USA | Australia (5), Austria (6), Belgium (6), Canada (6), Denmark (6), France (6), West Germany(1), Italy (6), Japan (7), Netherlands (6), Norway (6), Singapore (6), Spain (6), Sweden (6), Switzerland (6), UK (3) and the USA (6) | Australia (1), Austria (1), Belgium (1), Canada (0, 1after 1972), Denmark (1), France (1), West Germany (0), Italy (1), Japan (0), Netherlands (1, but not on long-term), Norway (1), Singapore (0), Spain (1), Sweden (1), Switzerland (0), UK (1) and the US | 1959-1979 | | Capital International Perspective (CIP) indices (0), NYSE (1) | | | January effect | 2 | 1 |

Panel 3 (1984-1990)

| Author | Country | Financial year ends (1=31 Jan., 2=31 Mar., 3=5 Apr.,4=31 May, 5=30 Jun., 6=31 Dec., 7= discretionary) | Tax regime(1 if taxes on capital gains apply, 0 otherwise) | Period | Equity | | | | Anomaly sought | Method (1 if parametric, 2 if semi-parametric, 3 if non-parametric) | 1 if Anomaly is detected, 0 otherwise |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Price | Price Index (2 if price weighted, 1 if equally weighted, 0 if value/market capitalisation weighted) | Portfolio (1 if Equally weighted, 0 if Value/Market Capitalisation weighted) | Other | | | |
| Berges et al. (1984) | Canada | 6 | 0 | 1951-1972 | 391 Companies listed on Toronto Stock Exchange | | 0 | | January effect | 3 | 1 |
| | | 6 | 1 | 1973-1980 | | | | | | | |
| Tinic & West (1984) | USA | 6 | 1 | 1935-1982 | | 1 | | | January effect | 1 | 1 |
| Jaffe & Westerfield (1985) | Japan | 7 | 0 | 1970-1983 | | Nikkei-Dow (2), Tokyo Equity Exchange (0) and Standard & Poor's Composite 500 (0) | | | Day-of-the-week effect & January effect | 1 | 1 |
| Kato & Schallheim (1985) | Japan | 7 | 0 | 1964-1981 | Nissho Monthly Equity Price and Returns files & Nikkei Needs Financial Data files | Nissho Monthly Stock file index (0) and an index computed from return data (1). | 0 | | January effect in relation to size-effect and tax-loss selling | 1 | 1 and 0 (tax-loss selling) |
| Tinic et al. (1987) | Canada | 6 | 1 (after 1972) | 1956-1981 | 317 Canadian equities | Toronto Stock Exchange 300 (0) | 1 | | Seasonal patterns | 1 | 1 (January effect) |
| Corhay et al. (1987) | USA, UK, France and Belgium | USA (6), UK (3), France (6) and Belgium (6) | 1 | 1969-1983 | | CRSP Index (1, USA) & Domestic equity average indices (1, Belgium, France & UK) | 1 | | January effect | 1 | 1 (USA & Belgium), 1 (April effect, UK) & 0 (France) |
| Ritter (1988) | USA | 6 | 1 | 1971-1985 | CRSP daily returns file | | 0 | Buy / sell ratios of cash account holders (Merrill Lynch) & Sales volumes on the NYSE (Merril Lynch's Market Analysis Department) | Turn-of-the-year in relation to parking-the-proceeds hypothesis | 1 | 1 |
| Barone (1990) | Italy | 6 | 1 | 1975-1989 | | MIB Storico Index (0) | | | Seasonal patterns | 1 | 1 |
| Bradfield (1990) | South Africa | 7 | 0 | 1974-1984 | | Mining (1), Industrial (1) & All-share (1) | | | January effect | 3 | 0 |

Panel 4 (1992-1999)

| Author | Country | Financial year ends (1=31 Jan., 2=31 Mar., 3=5 Apr.,4=31 May, 5=30 Jun., 6=31 Dec., 7= discretionary) | Tax regime(1 if taxes on capital gains apply, 0 otherwise) | Period | Equity | | | | Anomaly sought | Method (1 if parametric, 2 if semi-parametric, 3 if non-parametric) | 1 if Anomaly is detected, 0 otherwise |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Price | Price Index (2 if price weighted, 1 if equally weighted, 0 if value/market capitalisation weighted) | Portfolio (1 if equally weighted, 0 if value/market capitalisation weighted) | Other | | | |
| Lee (1992) | China (Hong Kong), Japan, South Korea, Singapore and Taiwan. | China (1), Japan (7), South Korea (4), Singapore (6) and Taiwan (6). | 0 | 1970-1989 (China, Taiwan and Singapore), 1975-1989 (South Korea and Japan). | | Hang Seng (0), Nikkei-Dow (2), South Korea Composite Equity Price (0), Straits Times Industrial (1) & Taiwan Equity Exchange (0) | | | January effect | 1 | 1& 0 (South Korea) |
| Hattingh & Smit (1993) | South Africa | 7 | 0 | 1978-1992 (Equity indices) 1984-1992 (Bond) | Post Office, Eskom 168 & RSA bonds | Gold Index (1), Industrial Index (1) & Overall Index (1) | | | Seasonal patterns | | 0 (January effect) |
| Seyhun (1993) | USA | 6 | 1 | 1926-1991 | CRSP daily and monthly files | | 1 | | January effect and the ommitted risk factor hypothesis | 1 | 1and 0 (ommitted risk factor hypothesis |
| Griffiths & White (1993) | USA and Canada | 6 | 1 | 1977-1989 (Canada), 1984-1989 (USA) | WESTERN database (Canada), CRSP files (America) | | 1 | Intraday data on equity listed on the Toronto Equity Exchange (Canada), Intraday data on NYSE and AMEX equities (America) | Turn-of-the-year effect in relation to parking-the-proceeds hypothesis. | 1 | 1 |
| Raj & Thurston (1994) | New Zealand | 4 | 1 | 1983-1993 | New Zealand Herald | New Zealand Stock Exchange 40 (0), Computed small-stock (1) | | | January or April effect | 1 | 0 |
| Pearce (1995) | USA | 6 | 1 | 1974-1991 | CRSP files | | 0 & 1 | | January, weekend, turn-of-the-month, and pre-holiday effects | 1 | 1 |
| Tan & Tat (1998) | Singapore | 6 | 0 | 1975-1994 | | All-Singapore (0) | | | Seasonal patterns | 1 | 1 |
| Ayadi et al. (1998) | Ghana, Nigeria and Zimbabwe | 6 | 1 | 1991-1996 (Ghana) 1984-1995 (Nigeria) 1987-1995 (Zimbabwe) | | IFC Indices (0) | | | January effect | 1 | 1(weak evidence for Ghana) & 0 (Nigeria and Zimbabwe) |
| Cheung & Coutts (1999) | China (Hong Kong) | 1 | 0 | 1985-1997 | | Hang Seng (0) | | | Seasonal patterns | 1 | 0 |

Panel 5 (2000-2005)

| Author | Country | Financial year ends (1=31 Jan., 2=31 Mar., 3=5 Apr.,4=31 May, 5=30 Jun., 6=31 Dec., 7= discretionary) | Tax regime(1 if taxes on capital gains apply, 0 otherwise) | Period | Equity | | | | Anomaly sought | Method (1 if parametric, 2 if semi-parametric, 3 if non-parametric) | 1 if Anomaly is detected, 0 otherwise |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Price | Price Index (2 if price weighted, 1 if equally weighted, 0 if value/market capitalisation weighted) | Portfolio (1 if equally weighted, 0 if value/market capitalisation weighted) | Other | | | |
| Coutts & Sheikh (2000) | South Africa | 7 | 0 | 1987-1997 | | Gold Index (1) | | | January effect | 1 | 0 |
| Le Roux & Smit (2001) | South Africa | 7 | 0 | 1978-1989<br>1990-1998 | | All Equity Index (1), All Gold Index (1), Industrial Index (1) & Financial Index (1) | | | Seasonal patterns | 2 | 0 (January effect) |
| Fountas & Segredakis (2002) | Argentina, Chile, Colombia, Greece, India, Jordan, South Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela and Zimbabwe | Argentina (6), Chile (6), Colombia (6), Greece (6), India (2), Jordan (7), South Korea (4), Malaysia (6), Mexico (6), Nigeria (6), Pakistan (5), Philippines (6), Portugal (6), Taiwan (6), Thailand (6), Turkey (6), Venezuela (6) and Zimbabwe (6). | Argentina (1), Chile (1), Colombia (1), Greece (0), India (1), Jordan (1), South Korea (0), Malaysia (0), Mexico (1), Nigeria (1), Pakistan (1), Philippines (1), Portugal (1), Taiwan (1), Thailand (1), Turkey (1), Venezuela (1) and Zimbabwe (1). | 1987-1995 (monthly) 1989-1996 (weekly) | | IFC Indices (0) | | | January effect in relation to tax-loss selling | 1 | 0, except for Chile |
| Balbina & Martins (2002) | Portugal | 6 | 1 | 1988-2001 | | BVL Geral (0) | | | Seasonal patterns | 1 | 0 (January effect) & 1(Others) |
| Shin (2003) | South Korea, Japan, Indonesia, China and the USA | South Korea (4), Japan (7), Indonesia (?), China (1) and the USA (6) | South Korea (0), Japan (0), Indonesia (?), China (0) and the USA (1). | 1971(USA), 1980-2002 (South Korea), 1984-2002 (Japan), 1991-2002 (China), 1989-2002 (Indonesia) | | Standard & Poor's 500 (0), South Korea Equity Exchange (0), Daiwa Index (0) Shanghai Equity Exchange (0) & Jakarta Equity Exchange (0) | | | Seasonal patterns | 1 | 0 (January effect) & 1(Monthly effects) |
| Gao & Kling (2005) | China | 1 | 0 | 1990-2001 | All equities listed on both the Shanghai and Shenzhen markets | Shanghai (0) and Shenzhen (0) | | | Calendar effects | 1 | 1 |

Panel 6 (2005-2006)

| Author | Country | Financial year ends (1=31 Jan., 2=31 Mar., 3=5 Apr.,4=31 May, 5=30 Jun., 6=31 Dec., 7= discretionary) | Tax regime(1 if taxes on capital gains apply, 0 otherwise) | Period | Equity | | | | Anomaly sought | Method (1 if parametric, 2 if semi-parametric, 3 if non-parametric) | 1 if Anomaly is detected, 0 otherwise |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Price | Price Index (2 if price weighted, 1 if equally weighted, 0 if value/market capitalisation weighted) | Portfolio (1 if equally weighted, 0 if value/market capitalisation weighted) | Other | | | |
| Bentzen & Hansson (2005) | USA | 6 | 1 | 1966-2002 | | NYSE Composite (0), Industrial (0), Transportation (0), Utility and Finance (0) Indices | 1 | | January effect | 1 | 1 |
| | | | | 1993-2004 | | | | | Size-effect | | |
| Chotigeat & Pandey (2005) | India and Malaysia | India (2) and Malaysia (?) | India (1) and Malaysia (0) | 1991-2002 (India) 1992-2002 (Malaysia) | | Bombay Equity Exchange Sensitivity Index (0), Kuala Lumpur Equity Exchange EMAS (0) | | | Seasonal patterns | 1 | 1 |
| Alagidede & Panagiotidis (2006) | Ghana | 6 | 1 | 1994-2004 | | Databank Equity Index (1) | | | January effect | 1 | 0 |

Appendix 2: FTSE/JSE All Share Index data used in the study