OVERREACTION, SIZE EFFECTS AND SEASONALITY IN MALAYSIAN AND FAR-EASTERN MARKETS

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ABSTRACT

This study investigates stock market anomalies in the Kuala Lumpur Stock Exchange (KLSE), Malaysia, with some comparisons with three other Far-Eastern markets, namely the Stock Exchange of Singapore (SES), the Stock Exchange of Thailand (SET) and the Stock Exchange of Hong Kong (SEHK). The main anomaly investigated is overreaction in the KLSE. Seasonality and firm size effects, which are usually associated with the overreaction effect, are also examined individually, and in the context of the overreaction effect. The impact of time-varying risk on overreaction is also investigated. First, stock market seasonality across four markets - KLSE, SES, SET and SEHK- is examined. The evidence suggests the existence of December and January effects in Singapore and Hong Kong respectively. A Chinese New Year effect is observed in all countries except Thailand. Next, stock market overreaction in the KLSE is investigated. Two portfolios of extreme stocks (based on their past 3-year excess returns) are formed, and their performance is measured in the next three years for evidence of overreaction. The initial results are consistent with overreaction; winner (loser) portfolios, which outperform (underperform) the market in the prior period, underperform (outperform) the market in the next period. The reversal in performance is more dramatic for losers. Further analyses show that risk and size factors cannot explain fully the observed phenomenon. A seasonal pattern is revealed in the excess returns of winners and losers; there is a pronounced February effect in both. Moreover, the February effect is observed to be greater for smaller firms. Lastly, a post-script chapter is included whereby the effect of the recent Asian economic turmoil on the markets, and on KLSE overreaction, is looked at. It is found that several months into the crisis, both winners and losers underperform the market.

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CHAPTER 1

INTRODUCTION

1.1: Preamble

Something is termed as an anomaly when it deviates from the rule. A finding is anomalous, according to Thaler (1987), "if it is difficult to 'rationalize', or if implausible assumptions are necessary to explain it within the paradigm" (p. 169). In the stock market literature, a very well known and widely accepted proposition - the Efficient Market Hypothesis (EMH) - has been unable to explain the existence of many anomalies. A great deal of evidence has been discovered that future share prices are predictable, contrary to the argument of the hypothesis which claims that the movement of a change in share price is best characterised by a random walk.

For example, the hypothesis has been unable to explain why some variables could determine future share returns. Evidence suggests that size, price-earning ratio, and dividend yields of companies may determine returns. Many studies also find that returns can be determined according to the days of the week or months of the year. In addition, contrary to the hypothesis that past returns as an information set cannot determine future returns, more recent studies discover that future prices can be determined by stocks' past performance; stocks doing very well in a period are likely to underperform the market in the next period, and vice versa for stocks doing very poorly. In other words, share price tends to mean-revert, i.e., there is an apparent overreaction in the market.

Such irregularities have been a popular subject with academics in the field of financial economics and have been exploited to some extent by investors in the market place. Research has blossomed in the past two or so decades documenting the predictability of share prices, and it is likely that this line of research will continue. For investors, such findings provide opportunities to devise better investment strategies to maximise returns.

The globalisation of world markets has also benefited investors by creating an opportunity for diversification. However, an understanding of world markets is a prerequisite for such a strategy to be successful. The need for market studies, therefore, is paramount. A lot of studies have been done to better understand the markets. However, the majority of these studies have concentrated on the US and UK markets. Until recently, the emerging markets in the Far East have been relatively neglected areas of research, despite the rapidly growing interests of major international investors in this region of the world. For example, most fund management houses offer investment funds constructed from securities of emerging markets like the Philippine, South Korea, Taiwan, Singapore, Hong Kong, Thailand and Malaysia. An understanding and knowledge of these markets, therefore, is essential for international investors.

It is due to these reasons that this study is undertaken. Research using data from the Malaysian and other Far Eastern markets is still comparatively small despite the huge potential of the region. Moreover, especially true for Malaysia, the conclusion from previous studies may no longer be valid not only because the market has grown tremendously in the last decade, but also because the KLSE itself has undergone many structural changes in the late eighties and early nineties. The results of this study, thus, reflect the current situation of the market.

1.2: Objectives of the Study

The general objective of this study is to investigate the presence of some anomalies in the Kuala Lumpur Stock Exchange, Malaysia (KLSE). Specifically, three anomalies will be looked at, namely stock market seasonality, firm size effect and overreaction effect. Related investigations will first be carried out to examine stock market seasonality in four Far Eastern markets. The main work, however, will centre around the examination of the overreaction effect in the KLSE; this includes how the other anomalies relate to the overreaction effect. Therefore, as roughly outlined in the table of contents, the specific objectives of this study are;

(i) to examine stock market seasonality in 4 Far-Eastern markets, namely Malaysia, Singapore, Thailand and Hong Kong,

(ii) to detect the presence of overreaction in the KLSE,

(iii) to examine the influence of time-varying risk on overreaction,

(iv) to detect the presence of size effects, and explain the relationship between size effects and overreaction in the KLSE, and

(v) to investigate seasonal patterns in the mean-reversions of loser and winner portfolios of the KLSE stocks.

1.3: Importance and Background of the Malaysian and Other Markets

Recently, there has been a rising interest by institutional investors in investing in the Far Eastern markets, also referred to as Asian Emerging Markets (AEMs), due to the huge growth potential of the region. International fund management houses launch various investment funds that invest in the region. Apart from sharing economic growth, the reason is also for diversifying away risk inherent in the developed western markets. Therefore, it is important that this study describes the background and characteristics of these markets. The description of the KLSE will first be given in detail, followed by the other markets.

1.3.1: Background of the KLSE

a. Introduction

The Kuala Lumpur Stock Exchange (KLSE), as known today, was established in 1973. Like other stock exchanges, this public company limited by guarantee offers a central market-place for both local and foreign buyers and sellers to transact in such securities as ordinary and preferred shares, bonds, loan stocks, loan notes, property trust units, warrants, transferable subscription rights, and call warrants. Over the last several years, the KLSE has developed rapidly. The number of companies grew from 262 in 1973 to

565 at the end of June 1996, with a market capitalisation of RM705.8 billions[1]. Comparatively, as of December 1995, it is the second biggest in Asia after Hong Kong (excluding Japan) with a value of US$222 billion (IFC, 1996). Yearly trading volume was 0.5 billion units in 1973 and reached the all-time high of 107.7 billion units in 1993. Trading pace slackened from then on, and stood at 36 billion shares for the first half of 1996, representing a daily average of 302.3 million shares. Background information on the number of companies listed, average daily volume and value traded, and market valuation of the KLSE is given in Tables 1-1, 1-2, and 1-3 respectively.

Companies are listed on either of two boards, i.e., the Main Board and the Second Board. The first comprises large companies, while the latter consists of smaller firms whose paid-up capital do not exceed RM20 millions. There are several indices in the KLSE. The most-followed ones are the KLSE Composite Price Index, comprising 100 blue-chip companies, and the EMAS index, the all-share index for the main board. The others are mostly sectoral indices, i.e., industrial products, consumer products, construction, trading /services, finance, property, mining, plantation, and the second board indices. All of the above are value-weighted indices. Another index is the New Straits Times industrials index, which is just a simple average of daily closing prices of 30 KLSE stocks.

[1] RM refers to Ringgit Malaysia, i.e., the Malaysian currency. On average, in 1996, the exchange rate is about RM2.7 to a dollar.

Table 1-1: Number of company listed on KLSE by country of incorporation

Year	Main Board				Second Board	Grand Total	New Listings		
	M'sian	S'pore	Others	Total			Main Board	Secon d Board	Total
1973	155	69	38	262	-	262	-	-	-
1974	163	67	34	264	-	264	8	-	8
1975	167	67	34	268	-	268	4	-	4
1976	173	64	27	264	-	264	6	-	6
1977	177	59	20	256	-	256	4	-	4
1978	180	57	16	253	-	253	3	-	3
1979	185	56	12	253	-	253	5	-	5
1980	182	56	12	250	-	250	-	-	-
1981	187	55	11	253	-	253	5	-	5
1982	194	56	11	261	-	261	8	-	8
1983	204	56	11	271	-	271	10	-	10
1984	218	56	8	282	-	282	14	-	14
1985	222	56	6	284	-	284	4	-	4
1986	227	55	6	288	-	288	5	-	5
1987	232	54	5	291	-	291	5	-	5
1988	238	53	4	195	-	295	6	-	6
1989	249	53	3	305	2	307	11	2	13
1990	268	-	3	271	14	285	19	12	31
1991	289	-	3	292	32	324	21	18	39
1992	314	-	3	317	52	369	25	20	45
1993	326	-	3	329	84	413	12	32	44
1994	344	-	3	347	131	478	19	47	66
1995	366	-	3	369	160	529	18	33	51
As at 28/6/96	379	-	3	382	183	565	9	27	36

Note:
M'sian = Malaysian
S'pore = Singaporean

Source: KLSE (1996) *Investing in the Stock Market in Malaysia*

Table 1-2: Daily volume and value traded in the KLSE, 1973-1996

Year	Daily Average Volume (million units)				Daily Average Value (RM million)			
	Main Board	Second Board	Call Warrants	Total	Main Board	Second Board	Call Warrants	Total
1973	3.1	-	-	3.1	12.2	-	-	12.2
1974	1.6	-	-	1.6	2.9	-	-	2.9
1975	2.5	-	-	2.5	5.3	-	-	5.3
1976	1.7	-	-	1.7	4.0	-	-	4.0
1977	2.4	-	-	2.4	4.2	-	-	4.2
1978	4.6	-	-	4.6	10.4	-	-	10.4
1979	2.6	-	-	2.6	6.7	-	-	6.7
1980	6.0	-	-	6.0	22.6	-	-	22.6
1981	6.7	-	-	6.7	32.8	-	-	32.8
1982	4.4	-	-	4.4	13.3	-	-	13.3
1983	9.2	-	-	9.2	32.0	-	-	32.0
1984	7.6	-	-	7.6	23.3	-	-	23.3
1985	11.9	-	-	11.9	25.7	-	-	25.7
1986	9.2	-	-	9.2	13.6	-	-	13.6
1987	21.4	-	-	21.4	40.8	-	-	40.8
1988	16.3	-	-	16.3	27.6	-	-	27.6
1989	41.5	0.1	-	41.6	75.7	0.3	-	76.0
1990	53.3	0.3	-	53.6	119.6	0.9	-	120.5
1991	48.5	1.1	-	49.6	117.5	3.4	-	120.9
1992	74.8	2.9	-	77.7	198.3	9.2	-	207.5
1993	421.7	11.0	-	432.7	1,496.5	58.8	-	1,555.3
1994	236.9	5.6	-	242.5	1,283.3	39.5	-	1,322.8
1995	127.0	12.7	0.163	139.8	649.8	85.9	0.305	736.0
Up to 28/6/96	232.2	69.8	0.203	302.3	1,288.3	606.4	0.273	1,894.9

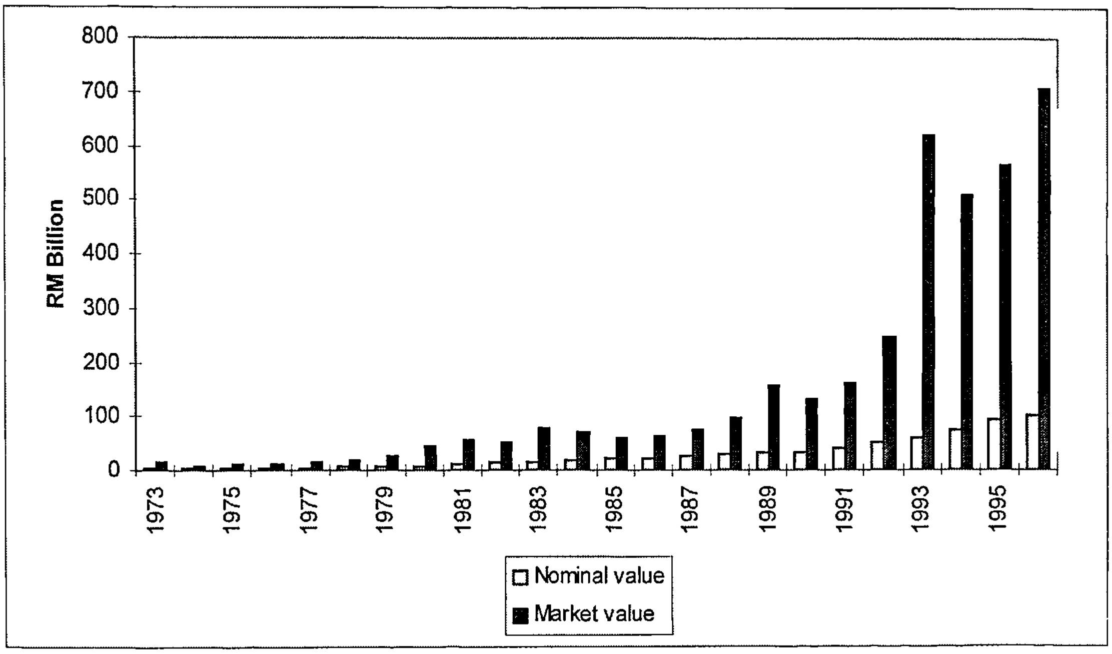
Source: KLSE (1996) *Investing in the Stock Market in Malaysia*

Table 1-3: KLSE nominal value and market valuation: 1973-1996

As at year	Nominal value (RM billion)				Market valuation (RM billion)			
	Main Board	Second Board	Call Warrants	Total	Main Board	Second Board	Call Warrants	Total
1973	3.8	-	-	3.8	13.3	-	-	13.3
1974	4.3	-	-	4.3	8.1	-	-	8.1
1975	4.8	-	-	4.8	11.7	-	-	11.7
1976	5.0	-	-	5.0	12.7	-	-	12.7
1977	5.2	-	-	5.2	13.7	-	-	13.7
1978	5.9	-	-	5.9	18.3	-	-	18.3
1979	6.5	-	-	6.5	24.6	-	-	24.6
1980	7.9	-	-	7.9	43.1	-	-	43.1
1981	10.7	-	-	10.7	55.4	-	-	55.4
1982	13.6	-	-	13.6	52.9	-	-	52.9
1983	16.3	-	-	16.3	80.3	-	-	80.3
1984	20.4	-	-	20.4	69.3	-	-	69.3
1985	22.6	-	-	22.6	58.3	-	-	58.3
1986	23.5	-	-	23.5	64.5	-	-	64.5
1987	26.6	-	-	26.6	73.9	-	-	73.9
1988	29.4	-	-	29.4	98.7	-	-	98.7
1989	34.3	0.03	-	34.3	156.0	0.1	-	156.1
1990	35.1	0.2	-	35.3	131.1	0.6	-	131.7
1991	41.2	0.5	-	41.7	159.9	1.5	-	161.4
1992	52.3	0.9	-	53.2	242.9	2.9	-	245.8
1993	60.0	1.6	-	61.6	606.1	13.5	-	619.6
1994	73.0	2.9	-	75.9	493.0	15.9	-	508.9
1995	88.4	3.9	0.07	92.4	542.8	22.7	0.12	565.6
28/6/96	97.4	4.7	0.07	102.2	665.7	39.9	0.11	705.8

Source: KLSE (1996) *Investing in the Stock Market in Malaysia*

Figure 1-1: KLSE nominal value and market valuation: 1973-1996



Source: KLSE (1996) *Investing in the Stock Market in Malaysia*

b. History

The first formal organisation in the securities business in Malaysia started when the Singapore Stockbrokers' Association was formed in 1930. It was re-registered as the Malayan Stockbrokers' Association in 1937. However, public trading of shares in Malaysia only began on 9 May, 1960 when the Malayan Stock Exchange was formed. In 1961, the board system was introduced with two trading rooms, in Singapore and Kuala Lumpur, that were linked by direct telephone lines into a single market with the same stocks listed at a single set of prices on both boards.

With the secession of Singapore from Malaysia in 1965, the common stock exchange continued to function but as the Stock Exchange of Malaysia and Singapore (SEMS). In 1973, currency interchangeability between Malaysia and Singapore was terminated and SEMS was separated into The Kuala Lumpur Stock Exchange Berhad (KLSEB) and The Stock Exchange of Singapore (SES). During this time, Malaysian companies continued to be listed on SES and vice versa. The Kuala Lumpur Stock Exchange (KLSE), as it is known today, was established in 1973 and took over operations from KLSEB as the stock exchange in Malaysia. In 1990, Singapore incorporated companies were delisted from KLSE and vice-versa. In 1994, the Exchange became known simply as Kuala Lumpur Stock Exchange, without 'The' as a prefix.

c. Equity distribution of listed companies

A survey by the KLSE in 1995 revealed that as at 31st December 1994, small shareholders holding 500 - 5,000 shares represent the largest group of investors, accounting for 76.4

percent of total investors in the KLSE. However, in terms of equity held, shareholders holding more than 10,000 shares control the largest portion of total equity, i.e., 89.7 percent, even though they account for only 7.8 percent of total investors. Individuals are the largest type of investors accounting for 95.3 percent, while the institutions only make up 2.3 percent of the shareholders. These institution, however hold 42.9 percent of the equity, compared with only 16.7 percent and 38.6 percent for individuals and nominees respectively. Bumiputera investors[2] represent 17.3 percent of the total investors, while the non-Bumiputeras and foreigners make up 69.7 and 13.0 percent respectively. These non-Bumiputera, who are predominantly Chinese, control 49.1 percent of the equity of the listed companies, while the Bumiputeras only 31.8 percent.

Foreign ownership of companies is generally restricted to 30 percent. However, this does not apply to specific projects approved by the government. In July 1988, however, this limit was increased to 49 percent.

d. Regulatory structure

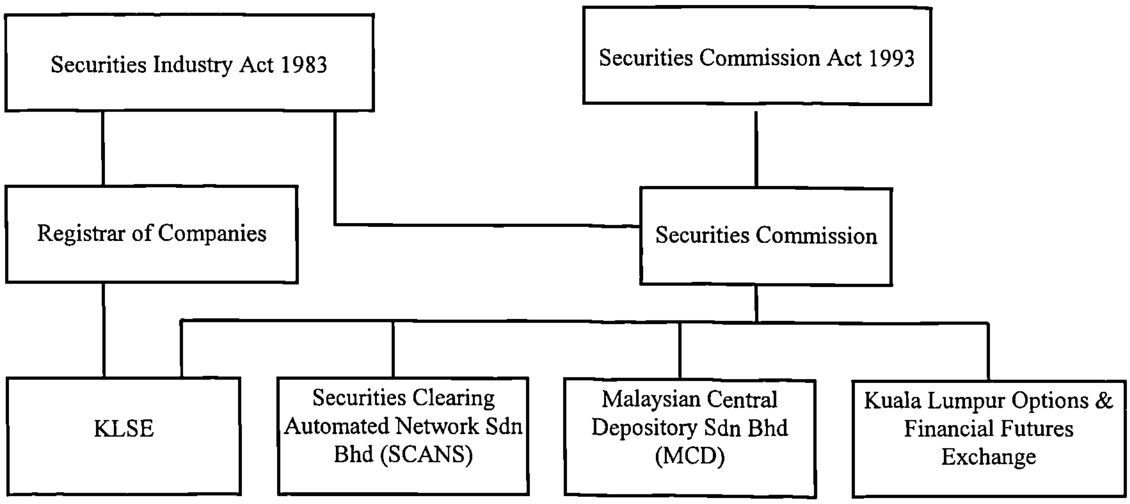
A specific law for the Malaysian securities industry was first promulgated by Parliament in 1973 in the form of the Securities Industry Act (SIA), which came into force in 1976. This ACT enables the present KLSE to be established as a stock exchange. SIA provides the regulatory framework of the securities industry in Malaysia, and is responsible to the Ministry of Finance. It also requires a stockbroker to hold a dealer's licence issued by the Registrar of Companies (ROC). The ROC is the body responsible for the registration and

[2] Bumiputera refers to the indigenous people of Malaysia, i.e., the Malays.

incorporation of companies. It is the custodian of Companies Act 1965, and also the SIA 1973. In 1983, the Securities Industry Act 1983 totally replaced SIA 1973. The SIA 1983 gave formal recognition to the Capital Issues Committee (CIC) with the primary functions of advising the Minister of Finance (MOF) on matters relating to the securities industry and approving the listing and quotation of securities on the KLSE.

In 1991, the Securities Industries (Central Depository) Act (SICDA) which allows for the establishment, maintenance and operation of a central depository system, was promulgated. The ROC was again appointed as the custodian of this Act. An important milestone in the KLSE was seen in 1993 when the Securities Commission Act (SCA) was passed. Under this Act, the Securities Commission (SC) was established. It took over the functions of CIC and Panel of Takeover and Mergers. The SCA, SICDA and SIA were later amended in 1996, which saw more power shifted to the SC in regulating securities industry in Malaysia. Figure 1-2 illustrates the regulatory structure of securities and financial future industry in Malaysia.

Figure 1-2: Regulatory structure of securities and financial futures industry in Malaysia (supervisory and monitoring)



Source: KLSE (1996) *Investing in the Stock Market in Malaysia*

e. Investment advisory services

As of June 1996, there are 60 brokerage houses throughout the country, which provide investment advisory services, in addition to their core business. The services are also provided by corporations that have been specifically issued with the relevant license by the Securities Commission (SC) under the SIA 1983. There are 28 such companies; most of them are affiliated with established foreign investment advisory services companies, such as Baring Research, Credit Lyonnaise, BZW, Nomura and SG Warburg. The services are also provided to some extent by commercial banks, Islamic banks, insurance companies/societies, trust companies, and also by local newspapers and business magazines.

Another type of company is the Asset Management Company (AMC). This is a company incorporated under Companies Act 1965 to provide portfolio management services for institutional, trust, pension, insurance, employees' provident and private individual funds. There are 42 AMCs as of June 1996 in the country. The approving authority to set up an AMC is the Ministry of Finance, and the licence is issued by the SC.

f. Trading on KLSE

Trading normally takes place 5 days a week (Monday - Friday) with two trading sessions. The morning session runs from 9.30 a.m. to 12.30 p.m., while the afternoon session runs from 2.30 p.m. to 5.00 p.m. Trading is done under the Exchange's trading system called SCORE (System on Computerised Order Routing and Execution) which was launched in 1989 to replace the open outcry system. Initially, SCORE was on a semi-automated basis, whereby orders were computerised but matchings were not. Orders were keyed into the SCORE terminal at the stockbroking company and relayed to KLSE. Once in the system, they were routed to the Exchange's matching room and matched by KLSE staff manually. By the end of November 1992, it was converted into a fully automated trading system without any human intervention in the matching process. In February, 1995, a broker front-end system called WinSCORE was implemented. It allows order entry, trade routing, credit control management, confirmation of trades and price, and news monitoring via a single terminal. Prior to this, the order-entry function and real-time stock price information were under two separate systems.

Clearing services for stockbroking are provided by Securities Clearing Automated Network Services Sdn. Bhd. (SCANS), a wholly subsidiary of KLSE established in 1983. To facilitate clearing and settlement, the KLSE has established a Fixed Delivery and Settlement System (FDSS) in February, 1990. The KLSE adopts the system based on a T+5 rolling settlement, where 'T' is defined as the day of trade, and '5' represents five working days. Sellers will get paid by brokers on T+6, and buyers shall pay brokers no later than T+7. More recently, the Central Depository System (CDS) has done away with delivery and collection of physical scrips beginning in 1993. Under the system, delivery of shares is through book-entry. The FDSS will continue, except that delivery will now be replaced by book-entry. Shares are normally traded in board lots of 1000 units. However, in a move to enable highly priced and, as such, thinly traded securities to be more affordable to a larger section of the investing public, the KLSE has now allowed trading of board lots of 200 units of certain companies.

The minimum bids for securities range from 0.5 sen for securities whose price is below RM1.00, to 50 sen for those whose price is more than RM100[3]. Transaction costs also vary depending on the value of transaction. For transaction values of up to RM500,000, a brokerage fee of 1.00% is charged. For transaction values of RM500,000 - RM2 million, the fee is 0.75%, while a fee of 0.50% is charged for transactions exceeding RM2 million. In addition, an investor also needs to pay a clearing fee and stamp duty of 0.05% and 0.10% of transaction value respectively.

Cash transactions and margin transactions are two types of transaction allowed in the KLSE. Moreover, in order to facilitate trade and arbitrage activities in the market, the KLSE recently allowed the practice of short-selling. Contra transaction facilities are also accorded to certain clients by the brokerage companies. In Malaysia, there is no tax on capital gains arising from securities transaction.

1.3.2: Background of the other markets

The growing market in the Far-Eastern economies are generally referred to as the Asian Emerging Markets (AEMs). This includes South Korea, Hong Kong, Taiwan, Thailand, the Philippines, Singapore, Indonesia and Malaysia[4]. As the Gross Domestic Product (GDP) of these countries increases, so do their securities market variables, such as the number of companies listed, market capitalisation and trading volume (Sedaghat, *et al.* 1994). Some backgrounds of these markets are described below. Though only four

[3] 1 sen is equal to RM 0.01

[4] An emerging market can be defined in different ways. For example, it can refers to a market which is growing in size and sophistication, or to a market in a developing country (IFC, 1996). The IFC does not

countries are investigated in this study, the other markets are also reviewed since many international investors look at the Asian markets as a single market.

To start with, some statistics of the AEMs, together with those for the US and UK as comparisons, are presented in Table 1-4. As can be seen, some of these markets are among the top 15 in the world in terms of market value. Hong Kong, for example, is in ninth place. With regard to the value traded, Taiwan and Korea are in sixth and ninth positions respectively at the end of 1995. However, the rankings of AEMs by the number of companies listed are not impressive, as only Korea is able to place itself in the top ten. Table 1-4 also gives a general idea of how concentrated the markets are. Two measures of market concentration, i.e., the percentage of market capitalisation held by the 10 largest companies, and the percentage of value traded held by the 10 most active stocks are given in columns 8 and 9 respectively. Though the percentages of both measures are quite high, they have generally been decreasing as more and more companies are listed, and the markets become bigger. For example, a study by Divecha *et al.* (1992) finds that using the percentage market capitalisation of top 10 companies as a measure of market concentration, the Philippines has the highest percentage, i.e., 65.2%, followed by Singapore (54.5), Indonesia (53.4) and Hong Kong (45.2), whilst market concentration in some others like Malaysia (25.0), and Korea (28.9) are more or less like that of the UK (25.5).

categorise Hong Kong and Singapore as emerging markets. However, they are included here mainly for the purpose of comparison.

Table 1-4: Some summary statistics of AEMs, December 1995

Market	Market capitalisation (US$ mil)	World ranking	Value traded (US$ mil)	World ranking	Number of companies	World ranking	% of MV held by the 10 largest companies	% of value traded held by the 10 most active stocks
Hong Kong	303,750	9	106,888	11	518	16	n.a.	n.a.
Indonesia	66,585	25	14,403	30	238	27	41.3	36.0
Korea	181,955	16	185,197	9	721	10	34.8	17.5
Malaysia	222,729	12	76,822	16	529	15	29.4	17.1
Philippines	58,859	26	14,727	29	205	35	39.1	34.0
Taiwan	187,206	15	383,099	6	347	22	29.9	19.9
Thailand	141,507	20	57,000	19	416	18	35.9	27.7
Singapore	148,004	18	60,461	17	212	33	n.a.	n.a.
US	6,857,622	1	5,108,591	1	7,671	2	n.a.	n.a.
UK	1,407,737	3	1,020,262	4	2,078	4	n.a.	n.a.

Notes:

n.a. - not available

Source: *IFC's Emerging Stock Market Factbook 1996*

Among the stock markets in the emerging Asian economies, it is well known that Hong Kong is the least regulated , while Singapore is the most regulated. Together with the non-existence of price stabilisation mechanisms, these are the two major reasons contributing to the high volatility of the Hong Kong Stock Exchange (Ko, *et al.*, 1991). Another market sharing the status of the most volatile market in the Pacific Rim is Taiwan. According to a report[5], this is also one of the most speculative markets. It has one of the highest turnover rates in the world, with trading levels at times reaching approximately $3.8 billion a day.

Taiwan is also known as one of the most closed markets in Asia. It was only opened to foreigners, with some share purchase restrictions, in early 1991. Actual foreign holdings amount to less than 3 percent of the market in the early 1994[6]. The absence of foreign investors may be one of the reasons for its low correlation with the other world markets. Another country with many restrictions to foreign investors is Korea, which only opened its stock market to foreigners in January 1992. Any one foreign investor can own no more than 3 percent of a company, and the total foreign ownership generally may not exceed 10 percent of a company[7]. Like Taiwan, the Korean Stock Exchange (KSE) also has a very low correlation with the other world stock markets probably due to the lack of internationalisation of the market. With its huge potential for economic growth, Korea is expected to take second place (after Japan) as a financial centre in the region. However, corruption charges and scandals by politicians and Securities and Exchange Commission officials have reduced

[5] East Asian Executive Report (1991), v. 13, no. 1, January 15, pp.22-25
[6] See Institutional Investors (1994), v. 28, February, pp.23-24
[7] See The Economist, v. 232, January 4, 1992, p. 72

investors' confidence in late 1995 and 1996. Not surprisingly, since October 1995, the KSE has been one of the worst performers in Asia[8].

Stock markets in the ASEAN[9] countries are comparatively more open. Singapore, for example, generally allows 100 percent foreign investment ceilings for listed companies, Indonesia sets the ceiling at 49 percent, the Philippines at 30-40 percent, and Thailand at 10-49 percent (IFC, 1996). In Malaysia, the ceiling is 49 percent. In terms of market regulation, Singapore is regarded as having the most regulated market in Asia. According to Clark (1994), Singapore's market receives the region's highest rating from investors for enforcement of investors protection, insider trading, and share manipulation regulations. The country also has a higher standard of investment analysis than many of the other Asian markets (Bauman, 1997). Thailand, on the other hand, is voted to be among the most susceptible to insider trading and corruption[10].

Like Hong Kong, the Singapore Stock Exchange also does not have a price stabilisation mechanism - there is no limit to the price change during a trading session. In the other ASEAN stock exchanges, however, the authorities set up a price change limit in order to control volatility and therefore stabilise the price. In Thailand, daily price movements cannot decrease or increase by more than 10 percent from the previous close. The Manila Stock Exchange specifies that a security shall be frozen if its price moves 50 percent up or 40 percent down on a particular day from the last closing price or the last posted bid price, whichever is higher. In Malaysia, the limit is 30 percent of the closing price of the previous trading session. Therefore, when

[8] See The Banker, v. 146, July 1996, pp. 68-70
[9] ASEAN stands for Association of South East Asian Nations, which includes Brunei, Indonesia, Malaysia, Philippines, Singapore and Thailand. Only Brunei does not have a stock market.

trading is halted in Malaysia due to shares reaching the price change limit, trading in those Malaysian shares listed in Singapore may switch to the CLOB, the Singapore's over-the-counter market (Clark, 1994).

1.4: Organisation of the Study

This study is organised as follows. Chapter 2 will review related literature on market efficiency and market anomalies, and summarises the evidence from both the US and developed markets, and the Malaysian and other Far-Eastern markets. In Chapter 3, I begin my empirical analysis. Stock market seasonalities are investigated in four markets, namely Malaysia, Singapore, Thailand and Hong Kong. Specifically, two analyses will be carried out - the analyses of the January effect, and the Chinese New Year effect. The next four chapters will focus on the Malaysian market. Chapter 4 will look at the initial evidence of mean reversions in returns which is claimed as a manifestation of overreaction in stock markets. The influence of time-varying risk on returns and the effect of firm size on mean reversions are investigated in Chapter 5. Chapter 6 examines the seasonal variations in the mean reversion of KLSE stocks. The next chapter (Chapter 7) is a post-script chapter. It looks at the recent Asian economic turmoil, and its impact on the main results in the previous chapters. A summary of the main findings and the conclusion of the study are given in Chapter 8.

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[10] See Euromoney, December 1993, pp. 68-70

CHAPTER 2

REVIEW OF LITERATURE

2.1: Introduction

One of the major areas of research on stock markets focuses on testing for the validity of the Efficient Market Hypothesis (EMH), i.e., testing whether the price of a security fully and rapidly reflects the available information about the security. Earlier works relating to testing for the validity of the EMH start with studies examining the behaviour of speculative assets prices, such as those of stocks and commodites. The main objective is to determine whether price movements are predictable, so that they exhibit any recognisable pattern. As surveyed in Fama (1970), the evidence of such patterns is generally weak. The movements of these assets are best described by a random walk. The EMH is therefore hailed as the most consistent proposition in financial economics, and is often taken for granted in research as the working paradigm.

However, more recent evidence casts doubt on the EMH. Benefiting from the progress in research techniques, i.e., larger data bases which cover more securities and longer time periods, improved statistical techniques, and lower computational costs, researchers were able to detect recognisable patterns in assets prices and hence their returns. Recent studies have done damage to the EMH in two ways. First, instead of examining the predictability of daily, weekly and monthly returns typical of the earlier works, these studies also look at the predictability of returns for longer horizons, such as yearly. Secondly, recent studies also consider the forecasting powers of variables like price-earning ratios (P/E), dividend yields (D/P), and market value of firms, in contrast to the pre-1970 works which only concentrate on forecasting returns from past series of returns. In both ways, evidence of successful forecasting techniques is found.

2.2: Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) has been a subject of interest for many years now. However, the discussion and debate among the academics on the subject is still intense, especially in the past decade or so. Moreover, even though the knowledge of the EMH has become widespread, it still has not been generally accepted as a basis for making investment decisions. Therefore, questions pertaining to the hypothesis are still relevant today as they were many years ago. This section will not give an extensive review of the hypothesis, but will only give a brief overview of it. For a more detailed discussion and debate of the EMH, a reference to papers like Fama (1970, 1991), Beaver (1981) and Ball (1989) would be more appropriate.

2.2.1: What is market efficiency?

In the context of securities markets, the term 'efficient market' is first used in Fama, Fisher, Jensen and Roll (1969), who study the relationship between returns and stock splits. They define an efficient market as "a market that adjusts rapidly to new information" (p. 1). However, no explicit development of the efficient market theory is provided in the paper. It is a year later that the theory is formalised in Fama's (1970) classic article. According to Fama, an efficient market is a market in which "prices always 'fully reflect' available information" (p. 383). Plainly speaking, it means that an investor cannot use information about a stock which is available in the market to make above-normal profits since the price of the stock has already incorporated that information. The hypothesis is that stock prices instantaneously and unbiasedly adjust to new information, which is seen as an implication of rational, utility-maximising investor behaviour in competitive markets. Some conditions, however, are in order. Fama states that for a market to be efficient, "(1) there are no transaction costs in trading securities, (2) all available information is costlessly available to all market participants, and (3) all agree on the implications of current information for the current price and distributions of future prices of each security" (p.387). Expectation of future price is thus simplified by assuming that investors have homogeneous beliefs. Furthermore, since the future price is unobservable, an equilibrium asset pricing model is needed. Therefore, market efficiency must be tested jointly with an asset pricing model, such as the Capital Asset Pricing Model (CAPM), Market Model, etc.

Fama (1970) further classifies market efficiency into three types, depending on the information set that is fully reflected in security price - (i) weak-form, where the information set is the historical prices of the security, (ii) semistrong-form, where the information set is the publicly available information, and (iii) strong-form, where the information set is all information, including inside information[1]. A weakly efficient market is defined as a market where past prices provide no information that would allow an investor to earn a return above what could be attained with a naive buy-and-hold strategy. The semi-strong efficient market hypothesis requires that all public information be fully reflected in security prices. The strong-form efficient markets hypothesis suggests that all information, public or not, is fully reflected in security prices.

The evidence in most of the pre-1970 works on weak-form market efficiency seems unexpectedly consistent with Fama's definition of an efficient market. Studies by Working (1934), Kendall (1953), Roberts (1959), Osborne (1959), Alexander (1961), Cootner (1962) and Fama (1965), among others, produce evidence which suggest that successive price changes are independent of each other, and that the behaviour of common stocks and other speculative prices could be well approximated by a random walk. In other words, future share returns are not predictable.

2.2.2: Critiques and extensions of Fama's definition

Fama's (1970) definition serves as a good or clean benchmark that allows him to lay out the early evidence on the adjustment of prices to various kind of information. However, as he himself admits (Fama, 1991, p. 1575), the strong version of EMH definition is surely false in the real world. In reality, there are a lot of imperfections in the market. First, a market is normally characterised by non-instantaneous availability and incomplete dissemination of information to all participants. This may prevent the price from impounding the information fully and instantaneously. Secondly, there are positive information and trading costs and other institutional constraints in the market. This has led Jensen (1978) to define an efficient market as follows;

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[1] In his sequel paper on EMH, Fama (1991) changes the categories to (i) test for return predictability,

> "A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t. By economic profit, we mean the risk-adjusted returns net of all costs" (p.96).

The idea is that if some set of information, such as a corporate earnings announcement, is widely known to participants in a stock market, competition drives prices in that market to be such that on average, investors can only earn the market risk-adjusted rate of return from trading on that information. Investors, thus, can only earn a normal profit from their investments. Underlying the EMH is competition for information.

Thirdly, the market is characterised by the existence of heterogeneous belief arising partly from differential information interpretation across participants and the timing of the information. With respect to this, Beaver (1981) makes a further refinement to the definition of market efficiency. Defining efficiency based on the information distribution, he states that a market is efficient with respect to a specific information set if the price that exists is the same as the price that would exist if everyone had that information set. He states that "market efficiency with respect to an information item means that prices act as if everyone knows that information" (p.28). Beaver's definition of market efficiency therefore implies that efficiency can exist in a market with heterogeneous beliefs. Individual investors need not perceive the market as efficient for efficiency to exist. Another implication is that market efficiency can be defined with respect to separate information sets.

(ii) event studies, and (iii) test for private information, respectively.

Another critique to the EMH claims that in a market with mixtures of agents, there are some who behave less than fully rationally, dismissing the assumption of investors' rationality in a competitive securities market. Though economists acknowledge that many market participants, such as individual investors, brokers, chartists, and portfolio managers sometimes are far from rational, this is not thought to matter to market efficiency as rational arbitrageurs will eliminate them. However, recent works investigating 'noise' traders (Black, 1986; De Long, Summers, Shleifer and Waldman, 1990), fashions and fads (Shiller, 1984), and excessive stock price volatility (Shiller, 1981, Cutler, Poterba and Summers, 1989) provide evidence which defies rational economic explanations. There is also evidence from studies on stock market anomalies and mean reverting-behaviour of returns which questions the notion that stock prices reflect news about fundamentals, since they are difficult to be attributable to news about fundamentals. More importantly, this evidence suggests that future share prices are predictable, challenging the earlier notion that prices follow a random walk. Some popular tests for a random walk are reviewed below.

2.2.3: Random Walk Tests

There are several tests used to determine whether a time series of economic variables, such as stock returns, follows a random walk. Traditionally, the two most popular and widely used tests are the serial correlation test, and the runs test. Later studies have also employed unit root tests. These tests are briefly described below.

a. Serial correlation test

Serial correlation measures the association between two elements in a time series separated by a constant number of time periods. The number of time periods that separates the two elements is known as the order of the serial correlation. For example, the *j*th-order serial correlation coefficient measures the extent to which Y_t and Y_{t+j} move together. If a higher (lower) than average observation tends to be followed by a higher (lower) than average observation *j* period later, then Y_t and Y_{t+j} are said to be positively serially correlated. If a higher (lower) than average observation tends to be followed by a lower (higher) than average observation, then Y_t and Y_{t+j} are negatively serially correlated. The *j*th-order serial correlation for a sample of time series is defined as[2];

$$r_j = \frac{\sum_{t=1}^{N-j}(y_t - \bar{y})(y_{t+j} - \bar{y})}{\sum_{t=1}^{N}(y_t - \bar{y})^2} \tag{2-1}$$

where; r_j = sample serial correlation at lag j

y_t = return of security at time t

y_{t+j} = return of security at time $t + j$

N = number of observations

The range of r_j is between -1 and +1. A theoretical property of the first-differenced series[3] of a random walk model is $r_j = 0$ for all $j = 1$ to n, where n is the number of serial correlation that can be computed with the series. Testing whether a series behaves as a random walk involves estimating the r_j's for the actual series and comparing them with the theoretical prediction of the random walk model. The

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[2] See Pindyck & Rubinfeld (1991, p.447)

[3] A first-differenced series refer to the changes in consecutive observations, for example, $(X_{t+1} - X_t)$, $(X_{t+2} - X_{t+1})$, ... $(X_{t+n} - X_{t+n-1})$.

sample serial correlations are therefore used to test the hypothesis the population correlation coefficient at lag j is zero. The sample standard error is computed in order to determine the statistical significance of r_j, and is given by;

$$S(r_j) = (1/\sqrt{N-j}) \tag{2-2}$$

where; r_j , N and j are defined as above. The null hypothesis, H_0 : $\rho_j = 0$ is tested using the formula;

$$t_{observed} = \frac{r_j}{S(r_j)} \tag{2-3}$$

H_0 is accepted at the 0.05 level of significance if $t_{observed}$ is within -1.96 and +1.96.

To test the joint hypothesis that all the serial correlation coefficients are simultaneously equal to zero, the Box-Pierce Q-statistics is used. Under the null hypothesis that all serial correlations equal to zero (i.e., $H_0 : \rho_1 = \rho_2 = \dots\dots = \rho_j = 0$) ;

$$Q = N\sum_{j=1}^{k} r_j^2 \tag{2-4}$$

where N is the number of observations, and r_j is the serial correlation at lag j. Q-statistics is approximately distributed as a chi-square distribution with k degrees of freedom. The null hypothesis is rejected if Q is greater than χ^2 with k degrees of freedom at the corresponding 0.05 level of significance.

b. Runs test

Another popular test of Random Walk is the run test. A run is defined as unbroken sequence of like elements. For example, +++-----00 constitutes three runs. The question is: Are the 3 runs observed in the example consisting of 9 observations too many or too few as compared with the number of runs expected in a strictly random sequence of 9 observations? If there are too many runs, it would mean that in the example, the observations change frequently, thus indicating negative serial correlation. Similarly, if there are too few runs, they may suggest positive serial correlation. Therefore, testing whether a series behaves as a random walk involves comparing the actual run for the series and the expected number of run for the series. When H_0, i.e., the null hypothesis of randomness, is true, the number of runs, R, has a sampling distribution that is approximately normal with mean, u_R[4] ;

$$u_R = \frac{\left[N(N+1) - (n_1^2 + n_2^2 + n_3^2)\right]}{N} \tag{2-5}$$

and sample standard deviation, s_R;

$$s_R = \sqrt{\frac{(n_1^2 + n_2^2 + n_3^2)(n_1^2 + n_2^2 + n_3^2 - N(N+1) - 2N(n_1^2 + n_2^2 + n_3^2) - N^3}{N(N-1)}} \tag{2-6}$$

where; n_1 = number of positive return

n_2 = number of negative return

n_3 = number of zero return (i.e., no change in return)

N = Total number of observations (i.e., $n_1 + n_2 + n_3$)

[4] See Wallis & Roberts, 1957, p. 571

The null hypothesis is tested using the formula;

$$z_{observed} = \frac{R - u_R}{s_R} \tag{2-7}$$

The null hypothesis of randomness will be accepted if $z_{observed}$ falls within + or -1.96 at 0.05 significance level.

c. Unit Root Test

A relatively new test for the random walk is the unit root test, introduced by Dickey and Fuller (1979, 1981). A distinct difference between this test and other traditional tests is that it can incorporate drift (cyclicality) and time trend in the time series of the variables in question. The easiest way to introduce this test is to consider the following regression model:

$$Y_t = \rho Y_{t-1} + u_t \tag{2-8}$$

where u_t is the stochastic error term with zero mean, constant variance σ^2, and is nonautocorrelated. If $\rho = 1$ from the regression, the stochastic variable Y_t above is said to have a unit root. A time series that has a unit root is known as a random walk.

As works based on time series data assume that the underlying series is stationary, the series need to be differenced (in the order of 1) so that it becomes stationary.

Therefore, ΔY_t in the regression above will be looked at. For theoretical and practical reasons, the unit root test applied to regressions runs in the following forms;[5]

$$\Delta Y_t = (\rho - 1)Y_{t-1} + u_t \tag{2-9}$$

$$\Delta Y_t = \alpha + (\rho - 1)Y_{t-1} + u_t \tag{2-10}$$

$$\Delta Y_t = \alpha + \beta t + (\rho - 1)Y_{t-1} + u_t \tag{2-11}$$

The differences between (9), (10) and (11) are the inclusion of α, i.e., the positive drift term and t, the trend term. In equations (10) and (11) we assume that Y_t has been growing because it follows a random walk with a positive drift (i.e., $\alpha > 0$, $\beta = 0$, and $\rho = 1$). The standard F ratio is then calculated to test whether $\beta = 0$ and $\rho = 1$ hold. If they do, then the hypothesis of random walk in the time series is concluded. However, instead of using the standard F distribution, the distribution tabulated by Dickey and Fuller (1981) to determine the significance of the F ratio is used[6].

It should be noted that though the unit root test is widely used, its power is limited. It only allows us to reject (or fail to reject) the hypothesis that a variable is not a random walk. A failure to reject (especially at a high significance level) is only weak evidence in favour of the random walk hypothesis.

[5] See Gujarati (1995)

[6] The critical values for Dickey and Fuller's distribution are larger than those for the standard F distribution. For example, for a sample size of 250 observations, the critical value at 0.05 level is 6.34, compared with that of the standard F distribution of 3.00

2.3: Stock Market Anomalies - Size and Seasonal Effects

Numerous anomalies have already been detected in the capital markets, and the list keeps growing[7]. There are, for example, studies which suggest that prices under-react to information, while others suggest otherwise, i.e., over-react to such information. Other evidence suggests that price varies according to day-of-the-week, month-of-the-year, market value of firms, dividend-yield, P/E ratios, and other variables which are difficult to be rationalised economically. While not directly related to the manner in which prices respond to information (and therefore on the implication of market efficiency), most of this evidence has seemingly defied rational economic explanation. A review of all these anomalies will not be done here. Instead, only those directly related to this study will be looked at. These are the firm size effect and the seasonal effects.

2.3.1: Size Effect: Explanation and evidence

Standard asset-pricing models such as CAPM, predict a positive relation between an asset's risk and its expected returns. However, evidence supporting this relation is inconclusive (see Fama and MacBeth, 1973; Fama and French, 1992, for examples). It is this possible missepecification of CAPM that leads other researchers to search for other factors which better explain returns, such as size. Consequently, there has been a growth in papers documenting the size effect, offering some possible explanations, such as the misassessment of risk due to infrequent trading, changing risk premium, and transaction costs bias.

[7] See Francis (1993, pp. 565-575) for a long list of anomalies.

The size effect refers to the tendency for smaller capitalisation stocks to yield abnormally higher returns than the larger capitalisation stocks. Among the first to observe this phenomenon is Banz (1981). He reports that smaller firms on the NYSE in the period 1926 - 75, on average, have higher returns than the larger firms. This size effect, however, is more pronounced for the smallest firms; returns of large firms are not much different from those of the average-size firms. Banz's paper actually relies on earlier work by Reinganum (1981), who suggests that the CAPM is misspecified. He observes that portfolios based on firm size and price-earnings ratio experience average returns systematically different from those predicted by CAPM. Subsequent studies by Givoly and Ovadia (1983) and Keim (1983) among others, confirm the existence of a firm-size effect. Keim (1983), for example, claims that the size premium was 30.3 percent annually.

One of the explanations for the size effect is that smaller firms are perceived to be more risky, and hence have higher risk, as measured by beta (β). Since they have higher risk, the capital asset pricing model (CAPM) predicts that they should yield higher returns. However, some studies reveal that even after adjusting for the firms' betas, smaller firms still yield higher returns (Reinganum, 1983; Banz, 1981). Some researchers argue that the apparent abnormal returns might be attributed to the misspecification in the model to estimate the firms' betas (Roll, 1981; Brown and Barry, 1984). According to Roll, the misassessment of betas is due to infrequent trading of smaller firms. Especially true for short-term (such as daily) data, infrequent trading induces positive serial correlation. This results in downward biased measures of portfolio risk and corresponding overestimates of risk-adjusted returns. In response to Roll's (1981) conjecture, Reinganum (1982) estimates betas according to methods designed to account for infrequent trading problems proposed by Williams and Scholes (1977) and Dimson (1979). He finds that the magnitude of the size effect is not very sensitive to the use of these estimates.

Another critique of the firm size effect based on risk mismeasurement comes from Chan and Chen (1988). They argue that the size effect is observed in Banz (1981) because the betas used in the study are measured imprecisely, which allow firm size to serve as a proxy for the true beta. However, Jegadeesh (1992) shows that, using test portfolios constructed so that the cross-sectional correlations between beta and the size proxy are small, the betas explain virtually none of the cross-sectional differences in portfolio returns. Fama and French (1992) also use test portfolios sorted on both size and beta. They find that the size effect is not explained by beta.

Basu (1983) finds that the size effect virtually disappears when returns are controlled for differences in price-earning (P/E) ratios. According to Basu, small firms have higher returns because they have low P/E ratios. After controlling for differences in P/E ratios, he discovers that the size effect disappears. This finding is inconsistent with earlier evidence in Reinganum (1981). He maintains that even after controlling for P/E effect, the size effect is still present. When holding size constant, no clear relationship between P/E ratio and return is observed.

Stoll and Whaley (1983) suggest large transaction costs may be responsible for the size effect. The excess returns on small stocks are the result of higher proportional bid-ask spreads in low-priced stocks. Because of this higher proportional bid-ask spread, investors demand a higher rate of returns from these stocks. After adjustment is made for transaction costs and market risk, they find that for holding periods from 3 months to one year, there is no significant positive excess return for smaller firms. In fact, for holding periods of 2 months or less, small firms earn lower returns than large firms. They therefore conclude that using after-transaction cost returns, CAPM cannot be rejected. Shultz (1983), duplicating Stoll and Whaley's test by using portfolios of smaller firms that were costlier to trade, finds that the portfolios do earn excess returns after transaction costs for holding periods as short as one month, if the holding period includes the month of January. He then points out that the transaction costs in January should be higher than in the other months to explain the January seasonal in abnormal returns (see next section), but finds no evidence of seasonally varying transaction costs. He therefore concludes that transaction costs cannot explain the anomalous behaviour of small firm returns.

Chan and Chen (1991) claim that small firms tend to be 'marginal firms', i.e., firms which are not doing very well. They lost market value due to dividend cutting, cash flow problems, and relying on external fundings. Heavy financial leverage, therefore, affects the risk of these companies. Moreover, the authors also postulate that the earning prospects of firms are associated with a risk factor in returns. Firms that the market judges to have poor prospects, signalled by low stock prices , have higher expected returns (i.e., they are penalised with higher cost of capital), than strong-prospects firms. The characteristics of small firms put them under poor prospects category.

Besides the evidence in the US studies above, the firm size effect is also documented in UK studies by Reinganum and Shapiro (1987), Levis (1989) and Corhay, Hawawini and Michel (1988). A recent study by Baker and Limmack (1998), however, reveals that the firm size effect is not persistent over time. Examining UK returns data from 1956 to 1991, they observed that there is a reversals in the size effect in the later period of their study (i.e., 1980-1991). Specifically, they find that there is a decreasing mean return over portfolios 1 - 5 (smaller companies) as expected in the presence of firm size effect, but an increasing mean return over portfolios 6 - 10 (larger companies), so that a reverse *J*-shape distribution of returns across the size portfolios is observed[8]. This indicates that, if attention is focused on the larger companies, such as the top 1000 companies, according to the authors, the reversals of firm size effect would be observed.

Further evidence of a firm-size effect comes from studies on the January effect. Many studies find that returns are higher for smaller than bigger firms in January (Reinganum, 1983; Keim, 1983; Roll, 1983; Berges et al., 1984). These studies reveal that most smaller firms' abnormally high returns are due to their abnormally high returns in January. Roll (1983) in fact, finds that the small-firm effect is significant in the first four trading days in January, and then becomes much less marked in subsequent trading days in January. More evidence and explanation on the January effect are presented below.

[8] In the study, portfolio 1 consists of the smallest companies, while portfolio 10 consists of the largest

2.3.2: Seasonal Anomalies: The January effect and its explanation

The January effect refers to the tendency of stock prices to decline slightly in the last few trading days of December and then move up in January[9]. Much of the year's price appreciation occurs in the month of January. One of the earliest studies is Rozeff and Kinney (1976). The authors find seasonal patterns in an equal-weighted index of NYSE over the period 1904-74. Specifically, the average return in January is about 3.5%, while other months average about 0.5%. Over one-third of the annual return occurs in January alone. Tax-related transactions, biases arising from bid-ask spread and time variation in risk premia are among the reasons frequently advanced in subsequent studies. Some studies, however, suggest a behavioural approach to explain the January effect.

The most popular explanation for this effect is tax-related transaction. It is hypothesised that tax laws encouraged investors to sell securities which have experienced recent price declines, so that (short-term) capital losses can be offset against taxable income. This will press the price further down. After the tax year-end, i.e. January, investors will buy the stocks again, and this buying pressure will increase the price, providing abnormally high returns in January. This is known as the tax-loss selling hypothesis. Importantly, the hypothesis relies on the assumption that investors will wait until the tax year-end to sell their common stock 'loser'. Additionally, it is believed that small firm stocks are likely candidates of tax-loss selling since they typically have higher variances of price changes, and therefore a larger probability of large price declines. That is why the January effect is often analysed in relation to the size effect.

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companies.

Dyl (1977) is among the first to observe this phenomenon and proposes the tax year trading hypothesis. Based on a random sample of 100 stocks traded on the NYSE between 1948 through 1970, he observes that there is a significant trading volume in December in common stocks which had undergone a substantial price change during the preceding year. Specifically, the data reveal abnormally low volume for stocks that have appreciated during the year, presumably reflecting the year-end capital gain tax lock-in effect, and abnormally high volume for stocks that have declined in price during the year, presumably reflecting year-end tax loss selling.

Keim (1983) analyses the January effect in relation to the size effect. Using a set of data from the NYSE and AMEX for the periods 1963 to 1979, he finds that daily abnormal returns are higher in January than in the other months, and that the relation between abnormal return and size is always negative and more pronounced in January. For example, the average size premium is 30.3% annually, but is only 15.4% if the premium in January is excluded. Furthermore, more than 50 percent of the January premium is attributable to large abnormal returns during the first week of trading in the year, particularly on the first day. A similar observation is reported in Reinganum (1983). He finds that abnormally high returns are yielded by small firms in January, and concludes that this January effect is consistent with the tax-loss selling hypothesis. However, tax-loss selling cannot explain the entire January effect since the small firms least likely to be sold for tax reasons (prior year's winners) also exhibit large average January returns. Lakonishok and Smidt (1984) look at the trading characteristics of listed companies by size and year-end behaviour for the period 1970 through 1981. They notice a tendency across all size deciles for price to rise on the last

[9] This is also referred to as the turn-of-the year effect.

trading day of the year. Additionally, small firms exhibit abnormally high returns for the 5 turn-of-the-year days.

Keim (1989) demonstrates that the occurrence of systematic trading patterns introduces bias into returns computed with closing transaction price (i.e., bid or ask). He observes that at the turn-of-the year, there is a distinct shift in investor buying and selling behaviour - the abrupt end of tax-loss selling at the end of the year. Specifically, there is a marked tendency for end-of-day prices in December to be recorded at the bid, and end-of-day prices in early January to be recorded at the ask prices. This can result in large portfolio returns on the last trading day in December and the first trading day in January; even if the 'true' price is unchanged, returns measured with transaction prices tend to be biased upward. Since the bid-ask spread, as a percentage of the price, is larger for lower-priced stocks, this trading pattern bias is larger for such stocks. Keim's finding is supported by the evidence in Griffiths and White (1993), who find that before the tax-year end, transactions are initiated more by sellers (at bid prices) and after the tax-year end, transactions are initiated more by buyers (at ask prices). Bhardwaj and Brooks (1992) also report similar results.

In addition, Bhardwaj and Brooks (1992) argue that the January effect is primarily a low-share price effect and less so a size effect. To prove this, they divide their samples into five groups based on size, and then further divide this size-based group into another five groups based on price. They discover that within each size group, January returns exhibit an inverse relationship with stock price. However, within each price group, there is little relation between January returns and firm size.

The trading patterns of individuals and institutional investors at the turn of the year studied in Sias and Stark (1997) also support the tax-loss selling hypothesis and give little credence to the alternative hypothesis of 'window-dressing'[10]. Consistent with the first hypothesis that individual investors sell stocks that have declined in value (losers) in order to realise tax losses, stocks with more individual investors interest underperform those with more institutional investors interest in late December, but outperform them in early January. The authors find that the trading behaviour of individual investors is more important than trading behaviour of institutional investors at the turn of the year, and is more responsible for the turn-of-the year and the January effect.

The validity of the tax-loss selling hypothesis, however, is refuted in a number of studies. Constantinides (1984) demonstrates on both theoretical and empirical grounds that there are strong economic reasons for taxable investors to take into consideration the holding period status (i.e., long-term or short-term) of their stocks and the time relative to the end of their tax year in deciding on the realisation of their capital gains or losses. Jones, Pearce and Wilson (1987), using data extended as far back as 1871, document that the January effect existed long before income taxes had an effective impact, and that no significant change occurs in the January effect after income taxes are imposed in the US.

Another popular explanation for the January effect is the time-variation in risk premia (for examples, Tinic and West, 1984; Ritter and Chopra, 1989). It is believed that

[10] The 'window-dressing' hypothesis suggests that the turn-of-the year effect and the resultant January effect is due to the year-end portfolio rebalancing of institutional investors. Since the success of fund managers is evaluated in relation to their peers, it is argued that these managers buy winners and sell

systematic risk varies across the year. Tinic and West (1984) for example, report that when the two-parameter test of CAPM is analysed for seasonality, the relationship between returns and systematic risk is consistently positive only in January. They show that the estimated slope coefficient (risk premium) of the relationship between average returns and systematic risk on the NYSE is significantly positive only in January. When the risk-returns analysis excludes January, the estimated risk premia are not significantly different between months. This suggests that returns are higher in January because risk is high during that month. This is supported by Rogalski and Tinic (1984). They reported that betas of small firms tend to be 30 to 60 percent larger in January than in the other months.

There are also evidence of January effect in the non-US markets. Gultekin and Gultekin (1983) examine the association between stock market seasonality and the tax-loss selling hypothesis in major industrialised countries[11]. Their results indicate a prevalent association between the large mean returns and the turn of the tax year as predicted by the tax-loss selling hypothesis. These findings, like those in the US, do not rule out a tax induced January effect in most of the countries except Australia, and also a tax induced April effect in the UK[12].

Brown, Keim, Kleidon and Marsh (1983) analyse the returns to Australian stocks using monthly data from 1958 to 1981. They find that average returns to most Australian stocks are substantially larger in January and July than in the other

losers in order to present respectable year-end portfolio holdings, and justify to clients as prudent investments.

[11] These are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK and US.

[12] The beginning of tax year of all these countries is January 1, except Australia (July 1) and the UK (April 1 for corporations, and April 6 for individuals).

months[13]. Moreover, the small-size decile shows fairly constant premium across months. Therefore, the size effect does not appear to be seasonal. They conclude that tax-loss selling hypothesis does not explain the January or turn-of-the-year effect.

Berges, McConnell and Schlarbaum (1984) document the same phenomenon in Canada using 391 companies listed on the Toronto and Montreal stock exchanges from the period 1950 to 1980. Their results reveal that returns in January are significantly higher compared to the other months even though Canada does not have capital gain tax until 1973. This implies that the tax-loss selling hypothesis cannot explain the January effect there.

A very recent study by Baker and Limmack (1998) discover that the January and April effects exist in the UK, but they are not solely due to tax-related trading. Besides, the persistence of the calendar seasonalities is not always observed. During the period 1956-1991, it was observed that April returns have become less 'dominant' in the later years than January, even though both months still generate higher returns than the other months. Another interesting result in this study is that the small firm effect is not observed in January or April, but is more prevalent in the other months. This is therefore inconsistent with the findings in many US studies, which find that returns of small firms are mostly earned in January.

In the absence of a US style tax regime, the explanation for this end-of -year effect may be behavioural. Shefrin and Statman (1985) (reproduced in Thaler, 1993) propose a theory of investor behaviour which employs prospect theory based on an 'S'-shaped

[13] The fiscal year-end for tax purposes in Australia is June 30.

utility function, mental accounting, regret aversion and self-control. When an investor purchases a stock, he opens what may be termed a *mental account* for that particular security. The reference point for this account is the purchase price of the stock. It is suggested that many investors are reluctant to sell a losing stock - even when this would appear to be the rational option - because they do not want to close this mental account at a loss, relative to their reference point. Shefrin and Statman link this behavioural characteristic with December, the year end, which they suggest is a focal point for US investors' mental accounting;

> "Financial service firms frequently remind investors about the importance of not leaving tax planning decisions until December. We conjecture that tax planning in general, and loss realisation in particular, is disagreeable and requires self control. Should this be the case, then it is reasonable to expect that self-motivation is easier in December than other months because of its perceived deadline characteristic. Thus, a concentration of loss realisations in December is consistent with our behavioral framework..."
> (Shefrin and Statman, 1985, reproduced in Thaler, 1993, pp. 516-17)

Although the above quote makes reference to tax planning, which may not be relevant to investors in other countries, the idea that December acts as a focal point for loss realisation is potentially useful.

Nevertheless, though it has been documented for more than 20 years, the puzzle still remains; if January provides abnormally higher returns than the other months, why couldn't arbitrage eliminate it? After so many years since it is first studied rigorously in Rozeff and Kinney (1976), newer studies, such as that of Haugen and Jorion (1996) still document this anomalous findings in the US.

2.4: Mean Reversions and the Overreaction Effect

2.4.1: Introduction

More recently, there is a resurgence of studies on the time-series predictability of stock returns. However, instead of examining serial correlation of short-horizon returns such as daily or weekly common in earlier studies, these studies investigate returns over longer horizons. Evidence suggests that there is a significant negative serial correlation in stock returns over a long period of time. This suggests that future returns can be predicted by using historical prices, another instance which may violate the weakest-form of the EMH. Fama and French (1988) find that the serial correlation of returns becomes negative for 2-year returns, reaches minimum values for 3-5 year returns and then moves back towards zero for longer return horizon. This is supported by the evidence in Poterba and Summers (1988). The argument is that there is a transitory, mean-reverting component of stock price, which is weak for daily or weekly holding periods, but is significant in long-horizon returns, the notion first tested in Shiller's (1984) and Summers' (1986) model incorporating fads or irrational bubbles. While agreeing that this mean-reverting behaviour of returns may be due to irrational behaviour of investors, Fama and French (1988) also emphasise that this observation may be due to rational time-varying expected returns, and thus is still consistent with the EMH.

The mean reversions of stock price over a long period interval has actually been implicitly investigated in overreaction studies like De Bondt and Thaler (1985)[14].

[14] There is another line of study investigating mean reversions in stock returns. Instead of looking at return horizons over one to five years, this study investigate return reversals over a shorter time periods, such as monthly, weekly and even daily . Zarowin (1989) investigated whether contrarian strategy of

They observe that stocks which perform very well (badly) in a period of 3-5 years tend to earn lower (higher) returns in the subsequent 3-5 years period. Instead of discussing this phenomena in terms of the component of stock price, they interprete their findings as a manifestation of investors' irrational behaviour. Investors are argued to overreact to whatever moves the stock price, especially as it relates to earnings. Consequently, De Bondt and Thaler propose the 'Overreaction Hypothesis', i.e., stocks experiencing bad performance in the past period (losers) tend to perform better in the subsequent period, and vice versa for good performing stocks (winners)[15]. In other words, there are mean reversions in stock returns over a certain period of time[16]. This phenomenon is also called the 'winner-loser' effect. The fact that an investor can earn abnormal profit by buying past losers and short-selling past winners, a trading strategy using past prices as the information set, implies that the market is not efficient in its weakest form. A consistent abnormal profit earned by such a contrarian investment strategy that exploits negative serial dependence in asset returns may thus provide another defect to the EMH.

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buying previous month losers and short-selling previous month winners can provide significant returns in the following month. His results indicate that the strategy earn significant abnormal returns of 2.5% per month. Brown and Harlow (1988) examine stocks with residual returns that gain or lose 20 and 65 percent between 1 to 6 months; they found that there is a larger rebound for losers and no decline for winners except in the first month. Rosenberg, Reid and Lanstein (1985) also use a strategy of buying losers and selling short winners in the previous month; this arbitrage strategy earns 1.36% per month with profits mostly generated by prior losers. Howe (1986) and Lehman (1990) form winners and losers based on the previous week returns. For the next 10 weeks, Howe observes that winners earn -13.0%, while losers earn +13.8%. Lehman finds that for $1 long in zero-investment arbitrage portfolio, 39 cents is earned every 6 months, with two-third of the profits generated by losers. Return reversals are also found within days. Dyl and Maxfield (1987) find that in each of 200 trading days selected randomly, the 3 stocks with the largest 1-day gain underperform the market by 1.8%, while the three stocks with the largest loss outperform the market by 3.6% over the next 10 days.

[15] Actually, De Bondt and Thaler (1985) are not the first to observe the reversals of performance of winners and losers. A pioneering work by Graham and Dodd (1934) had actually revealed such phenomenon, and they had shown that investors could employ the contrarian strategy by means of exploiting mean reversions of winners and losers to earn superior profits. De Bondt and Thaler's work serve as the first attempt to systematically examine whether investors stereotype companies based on past share price performance data.

[16] According to Forbes (1996), the literatures on mean reversion and overreaction are often perceived to be separable with relatively few cross-references between them. However, one fact emerges from these two lines of study; they offer a single coherent critique of the EMH.

2.4.2: Overreaction phenomenon in the psychology of individual decision making

De Bondt and Thaler (1985) argue that investors in the financial market systematically overreact. According to their Overreaction Hypothesis, asset prices tend to overrespond to news, particularly as it relates to earnings. De Bondt (1989) further argues that the hypothesis would stand or fall with the evidence on the relative sophistication of humans as intuitive statisticians.

Evidence in cognitive psychology literature reveals that humans are poor Bayesian decision makers, i.e., they fail to take into account prior probabilities and combine them with the information on-hand in revising beliefs or in making decisions or predictions (see for examples, Kahneman & Tversky, 1982; Grether, 1980; Nisbett, *et al.* 1983; Camerer, 1987; Rucai, 1992). From a series of experiments, Kahneman and Tversky (1972, 1973) find that humans appear to give more weight to recent information without much consideration to prior or base-rate data. People tend to make predictions based on judgmental heuristics, which often lead to biased decisions, and sometimes results in systematic errors (Bazerman, 1986). There are three types of heuristics, namely representativeness, availability, and anchoring and adjustment. A representativeness heuristic is an assessment of the degree of correspondence between a sample and a population, an instance and a category, or generally between an outcome and a model. Biases are generated when the frequency of the outcomes is not well correlated with the model. Another heuristic observed is the availability heuristic; people assess the frequency, probability, or likely causes of an event by the degree to which instances or occurances are readily 'available' in memory (Kahneman and Tversky, 1973). Biases are generated when the frequency of the event in question is not perfectly correlated with its ease of recall. Anchoring and adjustment refer to the tendency of people to make assessment by starting from an initial value and adjusting this value to yield a final decision. Regardless of the basis of this initial value (e.g. historical precedent, random information, etc), adjustments from the initial value tend to be insufficient (Tversky and Kahneman, 1974). Thus, different initial values yield different decisions, which are biased toward the initial values.

The degree of emotional involvement and the immediate availability in their memory with regards to the problem lead people to use simple matching rules when making predictions, as noted by Kahneman and Tversky (1982); "the predicted value is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impressions" (p. 416). This use of short-cuts or rule-of-thumbs to simplify the decision making process is an instance of judgmental heuristics, which violate the basic statistical principles, such as the considerations of base rate, sample size, probability distribution and regression towards the mean. Similarly, Grether (1980), in furthering earlier works by Kahneman and Tversky (1972, 1973) on representativeness heuristics, concludes that "individuals tend to give too much weight to the 'evidence' and thus too little weight to their prior beliefs, though priors are not ignored' (p. 553).

One of the reasons why individuals tend to regress insufficiently towards the mean in making a prediction is due to what Andreassen (1987) terms the attributional effects. The expectation that changes will either persist or regress to previous levels depends in large part on whether causal attributions are provided to explain recent changes. If these attributions are provided, then the tendency to make regressive predictions will diminish. Using financial markets as an illustration, Andreassen argues that news media provide such causal attributions when describing price changes. For example, to attribute a recent price rise, the media will search for those good news or facts from the many available which provide a coherent explanation for the rise, while ignoring those which do not. Similarly, bad news will be provided to explain recent price falls. By providing more attributions of greater coherence and extremity, the media increase the likelihood that individuals will expect recent changes to persist with no return to previous levels. This may, in effect, cause prices to remain high after they have risen, and to stay low after they fall. In a later experiment, Andreassen (1990) finds that news reports affect investors' forecasts by increasing the salience of any trend.

In making decisions or predictions, people also often rely on intuition and fail to use statistical inference when extrapolating time series data or events. For example, Eggleton (1982) concludes that "individuals display only limited ability to perceive and intuitively utilise the statistical characteristics of these time series for their extrapolations" (p. 94). Moreover, Eggleton also suggests that even where sophisticated techniques are employed, human intuitive judgement remains as an essential ingredient in their applications.

Another characteristic of human decision making is undue optimistic bias or overconfidence (Schmalansee, 1976; Griffin and Tversky, 1992; Brenner, *et al.*, 1996; Pulford & Colman, 1996). This overconfidence is usually more associated with positive outcomes. Pulford and Colman, for example, examine the relationship between overconfidence and base rate of behaviour, and how this relationship differs from events with positive versus negative outcomes. Using 98 subjects with ages ranging from 18 to 43 years, they observe that significant overconfidence occurs, but it is greater for positive outcome than negative outcome items. Griffin and Tversky suggest that although overconfidence is not universal, it is prevalent, often massive, and difficult to discriminate. It can lead people to focus on the strength or extremeness of the available evidence with insufficient regards for its weight or credence. This overconfidence phenomenon is also important because confidence controls action (Heath and Tversky, 1991). It has also been argued that overconfidence, like optimism, makes people feel good and moves them to do things that they would have not done otherwise.

Another interesting finding on human decision making is that individuals tend to follow others when making a decision. This is called herd behaviour or herding (Scharfstein and Stein, 1990; Banerjee, 1992; Zeckhauser *et al.* 1991). These individuals are noticed to ignored their own beliefs and information in forming decision rules even though the information may posses substantive value. Benerjee shows that the resulting equilibrium of herding is inefficiency. In business, Scharfstein and Stein argues that managers are reluctant to act according to their own beliefs or information for fearing that their contrarian behaviour will damage their reputation as sensible decision makers.

The above evidence, however, does not suggest that humans are not rational all the time. According to a theory in cognitive psychology called Cognitive-Experiential Self Theory (CEST)[17] individuals apprehend reality by two interactive, parallel processing systems. These are the rational system and the experiential system. Decisions made under a rational system rely on analytical, deliberative and extensional judgements, while the experiential system on intuitive, automatic and heuristic judgements. Behaviour is guided by the joint operation of the two systems, with their relative influence determined by the nature of the situation and the degree of emotional involvement. The greater the emotional involvement, the greater the shift in the balance of influence from the rational to the experiential processing system. Denes-Raj and Epstein (1994) observe that when subjects are carefree and happy or confronted with positive outcomes, they are more apt to process information in the experiential mode. However, when they are distressed or preoccupied with avoiding negative outcomes, they are more apt to process information in the mode of rational system. They also study the consequences when the two modes are put into conflict with each other, and find that most subjects, although fully aware that such behaviour is irrational, choose to behave in accordance with the intuitive mode, i.e., experiential system overrides the rational system.

The above evidence comes mostly from lab experiments in which the settings are different from the economic reality. Deficiencies resulting from the use of hypothetical questions and settings, such as the lack of monetary incentives or stakes in the parts of the subjects and no opportunity for learning are usually coined as the reasons behind the seemingly irrational subjects' behaviour. To counter these arguments, Richard Thaler, one of the leading sceptics of economic models incorporating rational expectations, claims that there is evidence showing that even with monetary incentives, the nonrational behaviour persists (see for example, Grether, 1980). Moreover, for learning to be effective, feedback should be immediate and accurate (Thaler, 1994). These conditions are not always met in the real world.

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[17] For an elaborate description and discussion of CEST, see Epstein (1991), Epstein et al. (1992), and

For example, feedback is often delayed, and even when failure is recognised, there may be multiple explanations for it.

If the findings from the psychological studies above can be applied to economics, it can therefore be suggested that economic agents, such as individual investors may not be rational decision makers too. It follows that their tendency to use intuitive judgement and heuristics without much regard to basic statistical rules has in effect deviated from the theory of economics, namely that choice and judgement are made consistent with the expected utility theory and the principle of optimisation. This further suggests that the economic assumption of individual rational expectation, i.e., individuals assign weight to each outcome of their choice, is not valid. In fact, there is a great deal of evidence dismissing the economic assumption that agents are rational optimisers (for examples, Simon, 1986; Zeckhauster *et al.* 1991)

In the financial market context, De Bondt (1989), in his survey article on overreaction, described some evidence which suggested some indications of market overreaction. For example, prices tend to overshoot due to the presence of optimistic traders, who are argued to determine the stock's market value (e.g Miller, 1977), and that the market, due to waves of optimism and pessimism, may temporarily overvalue or undervalue stocks based on their current or future earnings and dividends (see P/E anomaly of Basu, 1978, 1982; Shiller, 1984). If individuals are found to overweigh more recent and perhaps dramatic news events in revising beliefs, then there are reasons to expect market participants to be so in the stock markets.

Denes-Raj and Epstein, 1994)

2.4.3: DeBondt and Thaler's Overreaction Hypothesis and its critiques

Based on the results in experimental psychology studies above, De Bondt and Thaler hypothesise that investors in the stock market overreact (to new information) in the initial period and subsequently correct themselves. Their overreaction hypothesis asserts that stock prices take temporary swings away from their fundamental values due to waves of optimism and pessimism. Investors are argued to make bias decisions persistently. For example, they tend to base their decision on the most recent, most readily available and most striking information instead of revising their belief in the manner prescribed by Bayes' rule. In short, they interpret this evidence as a manifestation of irrational behaviour of the market participants[18].

In their 1985 paper, De Bondt and Thaler examine monthly returns of NYSE firms between 1926 to 1982. Two portfolios, consisting of 35 extremely bad performing stocks (losers) , and 35 extremely good performing stocks (winners) based on the stocks past three years market-adjusted excess returns, are formed. This 3-year period is labeled as the portfolio formation period. The market-adjusted excess returns for each stocks, u_j, are obtained by using the equation;

[18] DeBondt and Thaler's interpretation of winner-loser performance reversals is in fact consistent with the price-earning hypothesis of Basu (1977). The latter finds that low price-earning ratio (P/E) stocks outperform high P/E stocks. His price-earning hypothesis asserts that the P/E ratio may determine the future performance of firms due to exaggerated investors' expectation. Specifically, he conjectures that exaggerated optimism regarding growth in earnings and dividends leads, on average, to high P/E stocks, while exaggerated pessimism leads to low P/E stocks. In other words, high P/E stocks are overvalued, and low P/E stocks are undervalued. Low P/E stocks have been regarded by many as value stocks, while high P/E stocks as growth or glamour stocks. Besides their relatively low price in relation to earnings per share (according to Basu), value stocks are also those whose prices are low in relation to cash-flow per share (Lakonishok *et al.* 1994), book-value per share (Fama and French, 1992), and dividend per share (Blume, 1980; Rozeff, 1984), while growth stocks have relatively high price in relation to those same variables. These empirical studies have revealed that value stocks generally produce higher returns than growth stocks in the US. The same observation is generally true in a 21-countries study by Bauman, Conover and Miller (1998). Higher risk attached to value stocks is one of the explanation (Fama, and French, 1992), but many others believe the difference in performance is the result of systematic suboptimal market behaviour on the part of market participants (see for examples Lakonishok *et al.* 1994, Porta *et al.* 1997), which is consistent with DeBondt and Thaler's Overreaction Hypothesis.

$$u_{jt} = R_{jt} - R_{mt} \tag{2-12}$$

where the market return, R_{mt}, is based on the average returns of an equally weighted CRSP listed firms. The excess returns in the subsequent 3-year period, labeled as the test period, are then calculated for both portfolios. This process is repeated for sixteen non-overlapping 3-year periods, starting January 1933. Using this procedure, they find that losers outperform the market by 19.6 percent and winners underperform the market by 5.0 percent in the test period, so that the excess returns for the former is 24.6 percent higher than the latter. They also find that the excess return in the 3 years test period is asymmetric, i.e., much larger for losers (in absolute term). Most of the winner-loser effects occur during the second and third years of the test period. In addition, they notice that most excess returns are realised in January.

The proposition of the overreaction hypothesis by De Bondt and Thaler (1985) has generated much interest and controversy in subsequent years. Several studies are sceptical about the hypothesis and advance alternative explanations. Chan (1988) rejects the overreaction hypothesis by presenting an argument based on changes in equilibrium-expected returns. Specifically, he argues that stocks with a series of negative abnormal returns will experience an increase in their equity betas, and thus increase their expected returns. This is because equity beta is a function of gearing (i.e., the relative market values of debt and equity). With other factors remaining constant, a reduction in stock price will lead to increased gearing and therefore, increase equity risk. Likewise, the 'winner' stocks which experience a series of positive abnormal returns have their betas decreasing, and thus lower the expected returns. He claims that there is a measurement error in beta estimated from the rank period (RP) as done by De Bondt and Thaler (1985), i.e., since Loser's beta increases during the rank period, the rank period beta underestimates test period beta (TP). Therefore, beta should be estimated directly in the test period using the regression below;

$$R_{it} - R_{ft} = \alpha_{1i}(1-D_t) + \alpha_{2i}D_t + \beta_i(R_{mt}-R_{ft}) + \beta_{iD}(R_{mt}-R_{ft})D_t + \varepsilon_{it} \qquad (2\text{-}13)$$

where t = 1 to 72 months (i.e., the first 36 months for RP and the second 36 months for TP), D_t is a dummy variable which is equal to 0 in RP and 1 in TP, α_i is the Jensen Performance Index which measures abnormal performance of portfolio i, and β_i is the beta which measures the systematic risk of portfolio i. It is found that Loser's beta increased in TP by 0.23, while for the Winner, the beta decreased by 0.22, and for the arbitrage portfolio, the beta increases by 0.453. Overall, he finds that when risk is properly controlled for, the contrarian strategy does not yield significant abnormal returns.

Chan's (1988) contention that the change in the risk contributes to the higher return for loser firms in the test period is supported by the evidence in Ball and Kothari (1989). Constructing a time series of 52 annual returns for each of 20 portfolios where portfolio 1 consists the poorest performers and portfolio 20 of the best performers in the 5-year ranking period, they find that these extreme portfolios do show share price reversions. However, the increase in return of loser stocks (35.6 percent) is accompanied by an increase in beta from 0.91 to 1.62. Likewise, for winner stocks, the decrease in return by 33.4 percent is accompanied by a decrease from 1.51 to 0.86 in their betas. Their result, therefore, prove the importance of time-varying risk as an explanation behind the mean reversion of returns implied by the overreaction hypothesis.

Jones (1993) looks at time-varying risk premia and returns to a contrarian strategy. He suggests that it is possible that the evidence of overreaction reported in studies such as De Bondt and Thaler may be due to the pattern of market movements. Assuming stock returns are described by the market model, it is expected that when the market is rising, the greatest winners (losers) will be those stocks with the largest (smallest) formation period betas. During market declines, the greatest winners (losers) would be expected to be those with the smallest (largest) formation period betas. If, in addition, risk premia are larger (smaller) after the market has declined (risen), there will be a positive (negative) correlation between the risk premium and the formation period beta for the loser (winner) portfolio. Jones calculates correlations between three-year risk premia and betas, for 17 non-overlapping periods starting from the late 1920s. He also calculates three-year autocorrelations for non-overlappings three-year periods, starting at monthly intervals from 1929. He obtains results which, it is claimed, are consistent with the negative three-year autocorrelation in the US stock returns reported in studies like Fama and French (1988). Thus, Jones suggests that the apparent patterns in US stock returns, and the contrarian profits reported in De Bondt and Thaler (1985) are consistent with rational time-varying expected returns.

Zarowin (1990) challenges the overreaction hypothesis on the grounds of market value differentials. Consistent with the hypothesis, he finds that poorest earners outperform best earners over 36 months subsequent to the extreme earnings year. However, he claims that these are smaller firms, i.e., losers tend to be smaller by the end of the ranking periods. When both winner and loser groups are matched by size, all return discrepancies disappear, except in January. He also analyses the periods when losers are smaller than winners, and in periods when winners are smaller than losers. He discovers that when losers are smaller, they outperform the winners. When winners are smaller, they outperform the losers. Therefore, Zarowin concludes that losers' superior performance over winners during the 3-year test periods is due, not to overreaction, but to size discrepancies. In other words, this phenomenon is just another manifestation of the size effect documented by previous studies (for example, Banz,1981, and Reinganum, 1981).

Related to the size effect, another attack on overreaction comes from those who examine the bid-ask spread bias (see for example, Kaul & Nimalendran, 1990; Conrad & Kaul, 1993). Especially true for small, low-priced firms which have proportionally bigger bid-ask spread and high chances of non-trading, bid-ask spread may induce spurious autocorrelation. The used of cumulative abnormal returns (CARs) in De Bondt and Thaler (1985) is also criticised by the above authors. Conrad and Kaul claim that the method may exaggerate the observed mean reversions in stock prices. Furthermore, they also claim that cumulating single-period return over 3-5 years returns would incur the strategy substantial transaction costs. A buy-and-hold return metric should be used instead.

The critiques of Chan (1988), Ball and Kothari (1988), Zarowin (1990), Conrad and Kaul (1993) and the others have not gone unchallenged. In their subsequent paper, De Bondt and Thaler (1987) reject the explanation that the winner-loser effect is explained by changes in risk as measured by CAPM-betas. They argue that though the (zero-investment) arbitrage portfolio has a positive beta of 0.22, this is insufficient to explain its average annual return of 9.2 percent in the test periods. The dismissal of risk-changes as the explanation is also evidenced in Lakonishok, Shleifer and Vishny (1994), who also offer a behavioural-based explanation for the success of the contrarian strategy; investors are argued to make judgement errors and extrapolate past growth into the future for winner stocks. Examining value stocks (associated with losers) and glamour or growth stocks (winners), the authors find that the formers are no riskier than the latters.

Chopra, Lakonishok and Ritter (1992) present an evidence which is consistent with the overreaction hypothesis and dismiss size-based explanations. After adjusting for size when calculating abnormal returns, they observe the presence of an economically-significant overreaction effect. This effect is actually much stronger among small firms, and according to them, this is due to predominant individual investors in small firms who might overreact. Albert and Henderson (1995) also dismiss the notion that overreaction effect is a manifestation of the size effect. The authors claim that there is a bias in the way firms are ranked in the Zarowin's study. Using a different control, they observe an overreaction effect that is distinct from the size effect. Therefore, once again the overreaction hypothesis is restored even though the argument against it continues. Even Fama (1991) recognises that despite fierce challenges, the overreaction hypothesis is still an unresolved issue.

With regards to the bid-ask spread bias raised by Conrad and Kaul (1993), Loughran and Ritter (1996) argue that though monthly CARs on low-priced stocks are affected by bid-ask spread bias, they do not benefit from the advantages of compounding. These two factors, thus, largely offset each other. The use of CARs by De Bondt and Thaler (1985) instead of buy-and-hold returns for measuring both prior and test period returns, therefore, does not affect their findings. In fact, studies using buy-and-hold returns to form portfolios, such as in Ball and Kothari (1989) and Chopra, *et al* (1992), find greater differences in test period returns that studies using CARs to form portfolios. Loughran and Ritter further claim that the buy-and-hold method provides a sharper distinction between portfolios when classifying firms; but once the portfolios are selected, the CARs and buy-and-hold returns will produce similar conclusions.

Despite the inconclusive explanation that investors overreact as implied by the overreaction hypothesis, and other explanations based on changes in risk and firm size, one fact is clearly observed from the studies mentioned above and other studies examining the phenomenon: there is evidence of strong January seasonals in the price reversals, particularly for the loser stocks. De Bondt and Thaler (1985, Figure 3, p. 805) clearly shows that the Cumulative Average Residuals (CARs) for loser portfolio increase substantially in months 13, 25, 37 and 49 (i.e., the Januaries) in the test periods. It is also quite clear from the figure that the cumulative CARs for the loser portfolio decline between October and December. This observation is consistent with the tax-loss selling hypothesis which, arguably, explains the January effect. Other researchers, such as Zarowin (1990), Jegadeesh (1991), Pettengill and Jordan (1990) and Chopra, Lakonishok and Ritter (1992) also report strong January seasonal in the price reversals of common stocks. In fact, when loser and winner portfolios of comparable size are matched, Zarowin (1990) observes that a performance differential is only present in January. This is confirmed in Fant and Peterson (1995). The authors reveal that January returns are inversely related to the holding-period returns of the prior three years, while February through December returns are positively related to prior returns.

2.4.4: Do earnings drive overreaction?

De Bondt and Thaler's overreaction hypothesis claims that investors overreact to new information, and later correct themselves. However, they do not specifically test what information drives overreaction. Their earlier work (1985) on overreaction only examines whether or not stock prices systematically overshoot. It is only in their 1987 paper that they take a stand on what drives overreaction, i.e., earnings. In the paper, they show that winners' and losers' earnings show reversal patterns that are consistent with overreaction. De Bondt and Thaler (1990) further investigate the overreaction phenomenon in the actual market by studying security analysts' earnings forecast. Regression 2-14 below, which regresses actual earnings changes on forecasted changes, will illustrate whether analysts overreact to earnings changes;

$$A_t - A_{t-j} = a + b[F(A_t) - A_{t-j}] + e_t \qquad (2\text{-}14)$$

where A_t = actual earnings-per-share for year t;

A_{t-j} = actual earnings-per-share for year $t-j$;

$F(A_t)$ = forecast of earnings-per-share for year t;

a = intercept term;

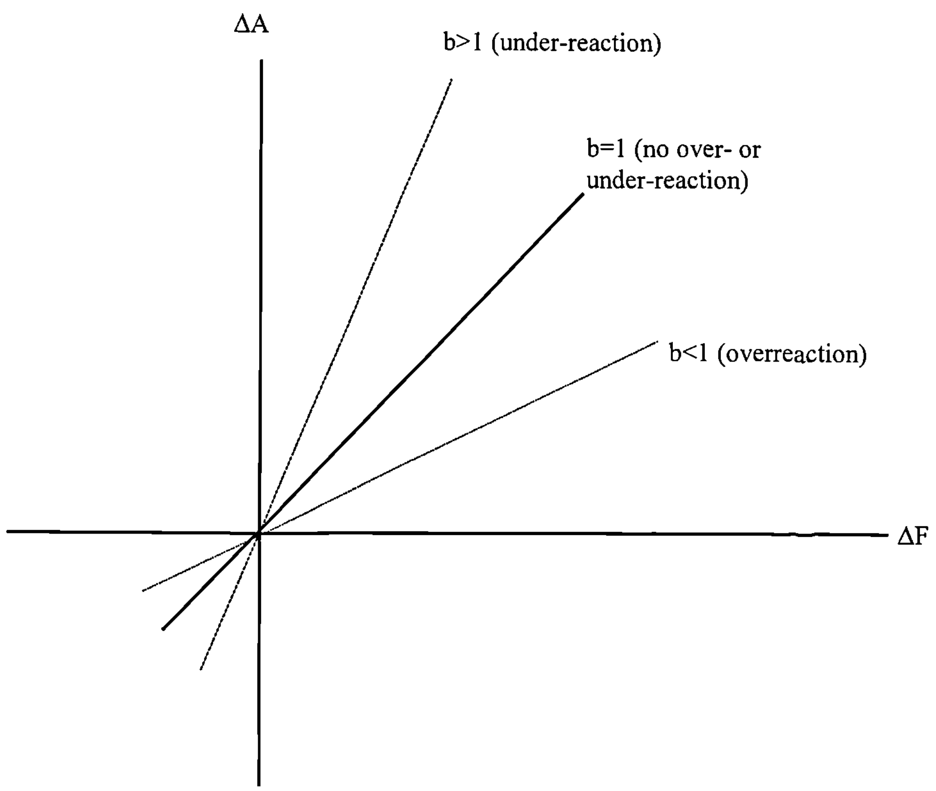
b = slope coefficient;

e_t = disturbance term (E (e_t) = 0).

Efficient forecasts generate an intercept of zero and a slope of unity (see Figure 2-1). A positive (negative) intercept indicates bias towards pessimism (optimism), while a slope greater than (less than) unity indicates under-reaction (overreaction).

De Bondt and Thaler examine earnings forecasts on the International Brokers Estimate System (IBES) tapes, made at horizons of 1 and 2 years. They use a number of different deflators for actual and forecasted changes in earnings, including the standard deviation of past earnings. Their regressions generate results consistent with a bias towards optimism and overreaction when forecasting earnings, although the degree of overreaction is less at a 1-year horizon than at a 2-year horizon. De Bondt and Thaler interprete these results as evidence of possible overreaction to earnings news, behaviour which they suggest may be mirrored in stock prices.

Figure 2-1: Overreaction and under-reaction to earnings changes



However, Abarbanell and Bernard (1992) argue that the extreme forecasted changes identified by De Bondt and Thaler need not indicate an overreaction to earnings but could indicate an overreaction to other information sources or may be related to the 'incentives structure faced by analysts' (p. 1205). They describe the De Bondt and Thaler analysis as an investigation of generalised overreaction, rather than overreaction specifically related to earnings. To investigate whether analysts overreact to earnings information (prior earnings changes), Abarbanell and Bernard carry out regression 2-15, using the stock price as the deflator;

$$A_t - F(A_t) = a + b[A_{t-1} - A_{t-2}] + e_t \qquad (2\text{-}15)$$

where A_t = actual earnings-per-share for year t;

$F(A_t)$ = forecast of earnings-per-share for year t;

a = intercept term;

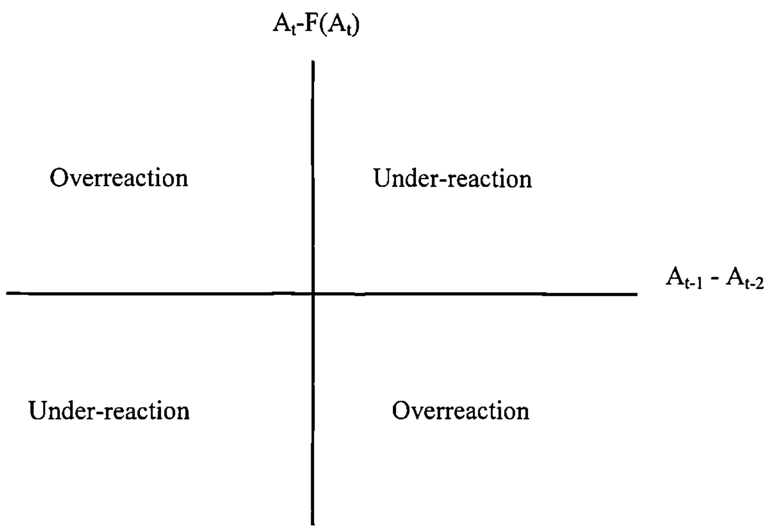
b = slope coefficient;

e_t = disturbance term ((E (e_t) = 0).

The regression will identify whether analysts place too much weight, or to little weight, on past earnings performance when forecasting future changes in earnings. For example, if prior earnings changes are positive (negative), and analysts overreact, then forecasts of earnings will be greater (less than) realised earnings. When analysts under-react, positive (negative) prior earnings changes will lead to forecasts of earnings being less than (greater than) realised earnings (see Figure 2-2). If analysts' forecasts are efficient, then the slope is zero. A slope coefficient greater than (less than) zero indicates an under-reaction (overreaction) to prior earnings changes.

Figure 2-2: Overreaction and under-reaction to prior earnings changes

Prior earnings change	Analysts reaction	
	Under-reaction	Overreaction
$A_{t-1} - A_{t-2} > 0$	$A_t - F(A_t) > 0$	$A_t - F(A_t) < 0$
$A_{t-1} - A_{t-2} < 0$	$A_t - F(A_t) < 0$	$A_t - F(A_t) > 0$



Abarbanell and Bernard carry out regression 2-15 for forecasts made at 1-quarter, 2-quarter, 3-quarter and 4-quarter horizons. The regression coefficients indicate that US analysts under-react to prior earnings changes, although this under-reaction reduces over time. Results do not differ significantly between large and medium size firms, although large firms display slightly more under-reaction. They therefore conclude that the overreaction identified by De Bondt and Thaler is not easily characterised as an overreaction to earnings.

2.4.5: Evidence of overreaction in non-US markets

Since De Bondt and Thaler's (1985, 1987) papers, other researchers have replicated the study to test for overreaction hypothesis in other stock markets. In the UK, Power, Lonie and Lonie (1991), MacDonald and Power (1991), Power (1992) and Dissanaike (1993, 1997) find evidence which support the hypothesis. Power *et al.* (1991), for example, reports that the loser portfolio earns a Cumulative Abnormal Return (CAR) of 86 percent during the 5-year period subsequent to the companies being identified as 'non-excellent', while winner portfolio earns -47 percent over the same period. MacDonald and Power (1991) use a 3-year test period to study this contrarian investment strategy, and find that the strategy yields an excess returns of 29 percent on average. More recently, Dissanaike (1997) confirms the existence of investor overreaction in the UK stock market. Using methods employed by Chan (1988) and Ball and Kothari (1989) to control for time-varying risk, he finds little evidence to support the claim that price reversals are due to changes in betas. Moreover, he claims that his sample restriction, i.e., using large and better-known companies, minimises the biases created by the bid-ask effect and infrequent trading, and reduces the possibility that reversals are primarily a small-firm phenomenon. Another UK study by Clare and Thomas (1995), however, has a different conclusion. The authors find that though losers outperform winners by a statistically significant 1.7% per annum, this phenomenon is actually due to the size effect, as claimed by Zarowin (1990). Their findings, therefore, provide little evidence to support overreaction in the UK stock market.

In Australia, the evidence of successful contrarian investment strategy by means of exploiting overreaction, is weak. An investigation by Brailsford (1992) using Australian stocks between 1958 to 1987 reveals that there is no mean reversion in the returns of extreme portfolio of losers or winners. This evidence, therefore, fails to support the overreaction hypothesis in Australia. A Canadian study by Kryzanowski and Zhang (1992) also finds weak evidence of overreaction. Using monthly returns of stocks listed on the Toronto Stocks Exchange from 1950 to 1988, they use a formation/test periods of 1, 2, 3, 5, 8 and 10 years. Their results revealed that for one- and often two-year test periods, there is a statistically significant continuation behaviour for winners and losers. For longer test periods (i.e., 3, 5, 8, and 10 years), there are evidence of mean reversions, but statistical tests performed reveal that these reversals are not significant. Also, they do not find any statistical evidence that the market overreaction effect is a manifestation of either the size or January effects.

Evidence in a Spanish study by Alonso and Rubio (1990) supports the overreaction hypothesis. The authors find that after controlling for size when estimating excess returns, the losing stocks in the Spanish equity market earn 24.5 percent more than the winning stocks 12 months after portfolio formation. The hypothesis is also supported in a Brazilian study by de Costa (1994). The study shows that two years after the portfolio formation date, losers outperform the market by 17.63 percent, while winners underperform the market by 20.25 percent. It also shows that differences in risk do not account for the performance differentials.

In the Far-East, a study of (long-run) overreaction is conducted by Wang (1997). Three markets are looked at - the Tokyo Stock Exchange, the Stock Exchange of Hong Kong, and the Taiwan Stock Exchange. The author finds that both winner and loser portfolios exhibit share price reversals in all of the different 3-year non-overlapping test periods in the Japanese and Taiwanese markets. The same is also true for Hong Kong, though abnormal returns earned from contrarian strategy are not uniformed across all sub-periods. This is due to the high volatility of this market. She also claims that risk factor cannot explain the results of her analyses. Overall, the study concludes that the behaviour of losers and winners in the Japanese, Taiwanese and Hong Kong stock markets is consistent with the overreaction hypothesis.

Richard (1997) conducts quite a different study. He uses the total returns of 16 national market indices to create portfolios of loser and winner indices, assuming the markets are well-integrated with common international risk factors. Using methodology similar in many respects to that of De Bondt and Thaler, he finds that for horizons of one year or less, test-period returns show statistically insignificant positive autocorrelation. However, for horizons of more than one year, and especially 3 and 4 years, losers outperform winners. A contrarian strategy (defined as returns on losers less returns on winners) yields an average 6.4% and 5.8% for 3- and 4-year horizons respectively. He also observes that winner-loser reversals are larger among the smaller markets, which he suggests may be due to market imperfections there.

According to Power and Lonie (1993) in their review article on overreaction, the (long-run) overreaction effect may be more important than other anomalies such as firm-size and seasonality effects. There are some reasons for this. First, the overreaction anomaly is easy to exploit even by the average investors. This is done simply by buying firms experiencing extremely bad performance ('loser') over the past 3-5 years, and selling short firms experiencing good performance ('winner' stocks). Since the holding period is more than 3 years, transaction cost is minimal. Secondly, the return from exploiting overreaction or winner-loser effect is much more substantial. De Bondt and Thaler documented 24.6 percent over 3 years by buying 'loser' stocks and selling 'winner' stocks short. Whereas, a much smaller return is earned from exploitation of other anomalies.

2.5: Related Studies on the Malaysian and Far-Eastern Markets

Fewer studies have been carried out in the Malaysian and other Far-Eastern markets, as compared with those in the US and the UK. They are also carried out fairly recently, and are mostly replication and extension of what have been done in the US. This section will first review some studies on the efficiency and anomalies in the Malaysian market, followed by the other markets.

2.4.1: Studies on the KLSE

a. Market efficiency

A relatively small number of studies have been done on the KLSE to examine its efficiency, with mixed findings. Lanjong (1983) studies the efficiency of the KLSE in the weak form, i.e., whether prices follow a random walk. Using a serial correlation test to examine the monthly returns during the period 1974 -1980, for the 104 most actively traded stocks as appeared in *Gazette*[19], he finds no significant serial correlation between the successive time lags. He also employs the runs test, and observes that the results from the test corroborate the results using serial correlation tests. He therefore concludes that there is indication of market efficiency (in the weak form) in the KLSE.

Barnes (1986) also concludes that overall, the KLSE "exhibited a surprisingly high degree of (weak-form) efficiency, in view of its thinness and its age as a stock exchange" (p.616). Like Lanjong, he also employs the serial correlation test and runs test on 30 relatively well-traded stocks, and spectral analysis on 6 sectoral indices for the six years ended 30th June 1980, using the first differences of the monthly share prices' natural logarithms. Using the serial correlation test, only 2 stocks exhibit a departure from the random walk model at a 1 percent level of significance[20]. Using the runs test, Barnes finds that only one stock exhibits non-randomness at the 1 percent level.

Laurence (1986) examines weak-form efficiency and the distribution of daily returns of 16 KLSE's most consistently traded shares during the period 1973-1978. For lag 1, 5 of the shares had significant non-zero serial correlation. For lag 2, there are also 5 shares. Using the runs test, he finds that 3 out of 16 shares exhibit non-randomness at the 3 standard errors. He also observes that the distribution of successive price changes over time on the exchange is leptokurtic and distinctly non-normal. He concludes that the characteristics of the weak form market efficiency of the KLSE

[19] This is a monthly magazine published by the KLSE

parallel closely those found in the NYSE, and suggests that differences in relevant information sets may be more apparent than real, i.e., in small market price-forming information may be disseminated very rapidly without sophisticated communication technology, hordes of analysts, large numbers of business journal and intensive market regulations.

Another study on the weak-form efficiency of the KLSE is done by Yong (1987), who examines all 170 stocks that are traded on a weekly basis from January 1977 to May 1985, as reported by *Utusan Malaysia* and the *New Straits Times*[21]. Using the serial correlation test for individual lag (lags 1, 2, ..., 8), he discovered that each stock classification[22] exhibits a high percentage of independence between the percentage price change at time t and at time t + k, for k = 1, 2, ...8. This is confirmed by the Q-statistics test which tests the serial correlation for all lags combined. However, results from the runs test indicate that a high percentage of stocks exhibit non-randomness in their percentage price changes. The main explanation given for this is that these stocks are inactively traded. Like Laurence(1986), he also observed the non-normality of the distribution of the percentage changes of stock prices. Overall, the study concludes that the KLSE is less efficient (in the weak sense of the EMH) than the previous studies suggest.

More evidence of weak-form market inefficiency on the KLSE is documented by Mohd. Ariffin and Power (1996), who examine short-run overreaction of the market. The authors look at the weekly performance of loser and winner portfolios of 10

[20] Barnes did not specify the lag of the serial correlation of his study.

[21] These are widely-circulated daily newspapers in Malaysia. The former is written in Malay language while the latter is in English.

companies each, using market-adjusted excess returns to form the portfolios. They observe that during their study period from January 1990 to December 1994, the contrarian strategy of buying losers and selling winners would earn investors positive returns only during the first two weeks after portfolio formation dates. The short-run overreaction effect seems to disappear after that period.

Published studies on semi-strong market efficiency tests on the KLSE are scarce. Dawson (1981) analyses returns earned by investors who buy the 'Stock of the Month' as recommended by *Malaysian Business*, a widely circulated business magazine in Malaysia. This study covers the period 1973-1980, using 85 stocks. During the first six months following the recommendations, the stocks are able to beat the market even after adjusting for market changes. These high abnormal returns are not due to the risk associated with the stocks since after calculation, it is found that the stocks are not riskier than the average. After 6 months up to month 12, this advantage disappears. Since it takes some months for the prices to adjust to the information, Dawson concludes that the KLSE is not yet (semi-strong) efficient.

Nassir and Mohamad (1993) also analyse the behaviour of prices following the 'Stock of the Month' recommendation by *Malaysian Business*. Their study uses 128 stocks recommended between 1975 to 1989. The price movements are measured in terms of abnormal returns which are estimated using the market-adjusted and risk-adjusted return approaches. Their results using the first approach reveal that several months, especially the last 2 months before the announcement month, the stocks' prices already start to rise. The post-announcement returns are positive, but are not

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[22] The stock classifications are: 1) Industrial, 2) Finance, 3) Hotel, 4) Property, 5) Plantation, and 6) Tin

significant. Using the risk-adjusted return approach, the cumulative abnormal return (CAR) in period -11 to 0 is close to zero. However, 3 months after the announcement month up to month 9, the abnormal returns are positive. In fact, the CAR after 9 months is 5.34 percent. Estimating transaction costs of 2.7 percent, investors can still make excess profit by following professional analysts' share recommendation. Like Dawson (1981), they conclude that the KLSE is not efficient in the semi-strong form in relation to analysts share recommendations.

Nassir and Mohamad (1993) also analyse the effect of annual earnings and dividend announcements on prices of shares listed on the KLSE. 699 earnings announcements are collected from a sample of 233 stocks. For dividend announcements, 300 dividend increases and 202 dividend decreases are included. The behaviour of the monthly closing prices of these stocks are observed for the period January 1975 to December 1989. Two classes of earnings and dividend announcements are investigated, i.e., earnings and dividend increases and decreases. The results reveal that for earnings and dividend increases, the abnormal returns are significantly positive several months before the announcements, but are not significantly different from zero during the post-announcement periods. For earnings and dividend decreases, the abnormal returns are negative several months before the announcement months, but are not significantly different from zero during the post-announcement periods. Evidence also suggests that market reaction to information contained in the announcement is almost, if not fully, reflected in share prices by the end of the announcement months, especially for the frequently traded stocks. Furthermore, there is no significant difference between the average excess returns of earnings and dividend changes for less frequently and more frequently traded samples, suggesting that the market does not discriminate the price adjustment between thinly and 'thickly' traded stocks. Overall, the KLSE appears to be near efficient in the semi-strong form for both earnings and dividend announcements.

b. Market anomalies

There are also a few studies done on the KLSE investigating some anomalies to market efficiency. Nassir and Mohamad (1987) examine the January effect using 2 broad market and 6 sectoral indices of the KLSE between 1970 and 1986. They find that the average returns for January are significantly positive and higher in magnitude as compared with those for the other months during the period under study. However, the tax-loss selling hypothesis is not relevant here since there is no capital gains tax arising from transaction of securities in Malaysia.

Contradictory evidence is reported by Yong (1989) who also examines the January effect in the KLSE. Using monthly returns of 6 sectorial indices, he finds that 5 out of 6 sectors exhibit higher returns in January compared to the other months. However, using F-statistics, these higher returns are not significant. Therefore, he concludes that there is no January seasonality in Malaysia.

Ho (1990), using the KLSE Composite Index from 1977 to 1987, documents significant negative Monday returns in Malaysia. However, the lowest return of the week is on Tuesday, while the highest return occurs on Friday. He also observes that the January return is higher than the returns in the other months, and the difference is significant at a 5 percent level. Investigating the day-of-the-week effect in January versus non-January, he finds that Monday and Tuesday returns are positive in January, but are not significant. However, for non-January, the returns are significantly negative. In addition, Ho also documents the turn-of-the-lunar-year effect in Malaysia[23].

The January effect is also found in the KLSE by Wong *et al.* (1990). Six of the market's sectoral indices, namely industrials, finance, hotels, properties, tins and plantations have significantly higher January returns compared to the other months. However, a Chinese New Year (CNY) effect is also detected. Measuring returns in the Chinese Lunar Calendar year, the authors observe that the CNY effect rally starts as early as two months prior to the first day of the new year.

2.4.2: Empirical studies on other Far-Eastern markets

It is usually perceived that the institutional characteristics of a market, such as the stringencies of disclosure requirements, control on inside trades, thinness and volatility of markets, discontinuities of trade, lack of supply of securities, etc., may significantly affect the main function of the resource allocation of funds, and hence the efficiency of the market[24]. In this sense, we can expect that share prices in the Asian Emerging Markets (AEMs) would demonstrate greater deviation from a random walk, since the degree of structure and organisation is, supposedly, lesser in the AEMs than in the US or other developed economies. In order to ascertain this belief, the following paragraphs will briefly review some of the studies examining the characteristics and efficiency of each individual market and the markets as a whole.

[23] The Lunar year is the new year for the ethnic Chinese, who are the dominant investors in the Malaysian market. The beginning of this lunar year occurs mostly in February (see Table 3-1, in Chapter 3)

a. Interdependence among AEMs and between AEMs and the developed markets

The general findings are that, with few exceptions, there is a low degree of interdependence among AEMs, compared to those among the developed markets, suggesting an opportunity for portfolio diversification. Divecha *et al.* (1992) found that most markets in emerging countries have lower correlation with each other, compared to those among the developed countries. Not only that, the correlation between AEMs and those in the developed markets is also smaller than that among the developed markets (Cheung & Ho, 1991). Lee *et al.* (1990) claim that inconsistent with the existence of important 'world' market factors, the returns on the markets under their study[25] seem to be generated by a process that implies a good deal of underlying independence.

The highest degree of interdependence is observed in the Singapore-Malaysia cluster, whose correlation was found to be 0.90 in Divecha *et al.* (1992). Cheung & Ho (1991) also found that this cluster has the highest correlation (0.669), but it seems that the cluster breaks down in the last two years of their study[26]. Another study which documents high correlation between Malaysia and Singapore is Ball (1992), with a coefficient of 0.78. According to the author, this is attributable to the close relation between the economies of these two countries. Other markets which have relatively high correlation with each other are Hong Kong-Singapore-Japan (Ko & Lee, 1991; and Lee *et al.* 1990) and Malaysia-Singapore-Hong Kong (Divecha *et al.* 1992). Among the AEMs, the Korean market emerges as the market with the lowest correlation with the others, while Taiwan is only weakly correlated with Singapore

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[24] See Drake (1985) for further and related discussion.

[25] These are Korea, Hong Kong, Taiwan, Singapore, Japan and the US

and Japan (Ko & Lee, 1991)[27]. The same study also finds relatively weak cross-correlation between AEMs and the US market[28]. However, when one-day lagged correlation with the US is examined, the coefficients increase significantly (except for Korea). Similar results are found in Ball (1992). This suggests that the US market leads the Asian markets by a one-day interval.

b. Volatility and risk-return trade-off

There is also evidence that the returns and their standard deviations in the emerging markets are generally higher than those in the developed markets, reflecting the higher volatility in the former. The following table is extracted from Claessens *et al.* (1995) which shows the data ending December 1992.

Table 2-1: Summary statistics of monthly percentage changes in total return indexes

Country	Starting date	Mean	Std. deviation	Sharpe ratio[a]
Indonesia	Jan 1990	-0.019	9.397	-0.108
Malaysia	Jan 1985	1.154	7.606	0.152
South Korea	Jan 1976	1.772	9.335	0.190
Philippines	Jan 1985	3.775	11.023	0.343
Taiwan	Jan 1985	2.835	15.271	0.186
Thailand	Jan 1976	1.861	7.435	0.250
Japan	Jan 1976	1.02	5.20	0.196
UK	Jan 1975	2.04	6.87	0.297
US	Jan 1976	1.19	4.39	0.271

Note:

a. The Sharpe ratio is the ratio of the mean return (column 3) to the standard deviation (column 4)

Source: Adapted from Claessens, S., Dasgupta, S., and Glen J. (1995)

[26] They study the markets in Hong Kong, Korea, Malaysia, the Philippines, Thailand, Singapore, Taiwan, Japan, Australia, the UK and the US between 1977 to 1988

[27] The most recent study by Wu (1997), however, reveals that after Taiwan liberalises the market by allowing foreign institutional investors to directly invest in its stock market in 1991, the movement of the market is affected by the markets in Tokyo, New York and Hong Kong

The table clearly shows that the standard deviations are higher in all AEMs, and the returns are on average, also higher, notably for the Philippines and Taiwan, compared to the three developed markets of Japan, the UK and the US. The Sharpe ratio, defined here as the ratio of mean return to the standard deviation, indicates that the AEMs, (except the Philippines) have lower risk-return tradeoff than the markets in the US and UK. Though not included in Claessens *et al.* (1995), it should be mentioned that the Hong Kong market is also one of the most volatile in AEMs. This evidence can be found in Ko *et al* (1991).

c. Random walk tests

Ang & Pohlman (1978) test the serial correlation of weekly stock prices in Hong Kong, the Philippines and Singapore, together with Australia and Japan[29]. Their results reveal that the average serial correlations for Hong Kong, the Philippines and Singapore markets are higher than for the US. Interestingly, however, the degree of serial correlation for these markets is generally very similar to those in Europe. As the lag increases, the deviation from the random walk decreases, implying that market thinness has indeed delayed the price adjustment to relevant information. Overall, the author concludes that these newer and less established markets are at least efficient in the weakest sense, and therefore, the degree of institutional organisation which is supposedly less developed in most smaller markets, may not be a requisite for an efficient market.

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[28] Surprisingly, Malaysian market has the highest correlation among the developing markets with the US, i.e., 0.70, according to Divecha, *et al.* (1992)

[29] The time periods of study are as follows; Hong Kong (9/97 - 11/74), the Philippines (9/73 - 11/74), Singapore (5/72 - 11/74), Australia (5/70 - 11/74) and Japan (5/70 - 11/74)

Claessens *et al.* (1995), also examine the serial correlation of prices in emerging markets[30]. They found that of the six AEMs in their sample (see Table 2), only the Philippines exchange, which has a first-order serial correlation of 0.338, exhibits significant predictability in the rates of return. The second-order serial correlations for all six markets, including the Philippines, however, are not significant.

Yang (1991) finds that the Taiwan Stock Exchange (TSE) is not weak form efficient in terms of 1-day interval. For a 1-month interval, however, only a small number of stocks display systematic behaviour. Similar results are found by Chu (1991), who observes the random movements of the TSE stocks for longer returns horizons, such as monthly, but not daily. However, Lock (1996) does not find any evidence of a random walk even when using weekly or monthly price changes. Results of regression, runs and variance ratio tests on the value-weighted index indicate that the TSE is not weak-form efficient. The result of the efficiency of the TSE are therefore quite mixed.

The efficiency of the Korean Stock Exchange (KSE) is more conclusive. At least four studies reveal that the exchange is not efficient in the weak form. Kim (1991), Ayadi & Pyun (1994), Kim (1992) and Koh (1989) document results inconsistent with the random walk behaviour of KSE stocks. Another study by Lee (1989) rejects the hypothesis of weak-form efficiency for daily returns, but does not reject the hypothesis for monthly returns. The study also concludes that though less efficient than the US or

[30] Emerging markets and AEMs are used interchangeably because many studies do not just concentrate on the markets in the developing Pacific Rims, but all the developing markets in the world. AEMs are therefore only parts of the emerging markets.

other major European markets, the KSE is as weak-form efficient as the other less developed countries' markets.

Besides Ang & Pohlman (1978), there are a few other studies on the Stock Exchange of Singapore (SES). D'Ambrosio (1980) examines six daily closing indices[31] from January 1973 to December 1975 to test for the random walk hypothesis in the SES. Employing runs tests and serial correlation tests, he discovers that three of the indices, i.e., Industrials, Hotels and Tins, do not conform to the hypothesis. Moreover, the runs tests indicate that these indices are dependent. Overall, the SES has higher serial correlations compared to those in western markets, and therefore the author concludes that the prices in the exchange do not behave in the manner consistent with a random walk. This result is consistent with Ko & Lee (1991), who claim that daily share price returns in Singapore exhibit very high dependent structure. Contradictory evidence is found in a study by Laurence (1986). Using 24 stocks as samples, the runs test and serial correlation test reveal mixed results. Some stocks exhibit random walk behaviour, while some others deviate from it. The distribution of successive price changes are observed to be leptokurtic and distinctly non-normal. Overall, he claims that the weak-form efficiency characteristics of SES parallel closely those found in the NYSE. Another study by Ruth *et al.* (1995) suggests that SES is not efficient in the semi-strong form.

In the Stock Exchange of Thailand (SET), Surmsrisuwan (1996) uses spectral analysis to examine the time series behaviour of stock returns. He discovers that there is no recognisable or significant pattern in the returns of stocks. The Durbin-Watson test

[31] They are Industrials, Hotels, Tins, Plantations, Construction and Finance

used also indicates that there is low autocorrelation in the samples. Therefore, the author concludes that SET is weak-form efficient.

d. Seasonalities and other anomalies

As more and more studies document various types of anomalies to the Efficient Market Hypothesis in the western markets, researchers replicate the studies using data from the developing markets. One of the most popular anomalies studied is the stock market seasonality. This includes the investigation of the day-of-the-week effect and turn-of-the-year, or January effect.

Claessens *et al.* (1995) found that for the AEMs in their study, only Korea exhibits the January effect. For Indonesia, the months which are significantly different from the others are February and September. In the Philippines, the months are June, August and September, while in Malaysia, they are May and August. No one particular month in Taiwan and Thailand is observed to yield significantly different returns from the other months.

In contrast to Claessens *et al.* (1995), Tong (1992) does not find any January effect in Korea. The same observation is reported for Taiwan. However, there is a February effect in the Taiwan Stock Exchange. Saturday returns are significantly positive but Monday returns are non-negative in both Korea and Taiwan. Chang (1991) documents significantly higher average returns on Friday and Saturday in the Korean Composite Stock Price Index. He also detects significant positive January returns (at the 10 percent level), but it is not the highest in the year.

Another study on stock return seasonalities in the AEMs is Ho (1990). Friday emerges as the day with the highest returns in Hong Kong, Malaysia, the Philippines, Singapore and Thailand, while Saturday and Wednesday have the highest returns in Korea and Taiwan respectively. Tuesday yields the most negative returns in Korea, Malaysia, Singapore and Thailand. For Hong Kong and the Philippines, the lowest return is observed on Monday. Besides the day-of-the-week effect, the author also documents January effects in Hong Kong, Malaysia, the Philippines and Singapore. This cannot be explained by the tax-loss selling hypothesis since there is no capital gains tax in these countries. Returns are lowest in September in Hong Kong, and August in the Philippines. Malaysia and Singapore, the two most closely related markets, have the lowest returns in November. The highest return in Thailand is in October, while the lowest return is in April. Ho also observes a significant Chinese New Year effect in Malaysia and Singapore.

Further evidence of stock market seasonalities in Japan, Korea, Taiwan, Hong Kong and Singapore market are documented in Lee (1992). His results indicate the presence of a January effect in Japan, Taiwan and Singapore. In Korea, there are significant positive returns in December, but negative returns in January. Returns in Hong Kong are significantly positive in January and December.

Lee *et al.* (1990) examine the daily closing price indices of Korea, Hong Kong, Taiwan, Singapore, Japan and the US markets. Day-of-the-week effects seem strong and persistent in most Asian markets except Taiwan. Negative Monday returns are observed in Japan, Hong Kong and Singapore, but the magnitude is less than that in the US. Wednesday and Friday returns rank first and second in order of magnitude in most of the countries, except Taiwan. In Korea, Saturday returns contribute about one-half of the returns generated over the 9-year period of study[32].

Chan *et al.* (1996) investigate seasonality and cultural influences on four Asian stock markets, namely the KLSE, SES, SET and SEB[33], using the main market indices in each country, and in the case of SET, some individual stocks. On all four markets, a strong day-of-the-week effect is observed. In the KLSE, Monday returns are significantly negative and the lowest in the week (-3.8%), while Friday returns are significantly positive and the highest (15.9%). In fact, Friday yields the highest returns for the Bombay and Thai markets too (27.4 % and 29.0% respectively). The highest return for Singapore is on Thursday (12.1%), which is only slightly more than Friday (11.1%). The lowest return in Singapore is on Tuesday (-7.2%), which is significant at the 5 percent level. *F*-statistics also reject the hypothesis of equal monthly returns in the KLSE and SES, but not for SET and SEB. January and December effects are present in both KLSE and SES which, the authors suggest, reflect the higher level of integration of the SES and KLSE with the international investment community. Higher January returns in Singapore is in fact consistent with Gultekin & Gultekin (1983), who also find that the month yields the highest returns. Besides the January and December effects, the Chinese New Year effect is also evident on the SES and KLSE, but not on SET and SEB.

[32] The study covers the period 1980-88

2.5: Summary and Conclusion

This chapter introduces the Efficient Market Hypothesis (EMH), and reviews works related to the hypothesis, market anomalies and mean reversions (or overreaction) in the stock markets. Evidence is reviewed from both the US and Western developed markets, as well as the Malaysian and other Far-Eastern markets. Based on the evidence, a conclusion can be made that market efficiency issues are far from fully resolved. More evidence, including that from smaller and developing markets, is needed to answer whether or not markets are efficient, and hence whether or not share prices are predictable.

[33] Stock Exchange of Bombay, India

CHAPTER 3

SEASONALITY IN MALAYSIA, SINGAPORE, HONG KONG AND THAILAND

3.1: Introduction

Stock market seasonality has been widely documented in the U.S. and other markets. Numerous studies have established that returns are different across the year. In particular, January has been found to consistently yield the highest return compared to the other months in most markets. The same phenomenon is generally observed in the Far-eastern countries, which in many aspects have different economic, institutional and cultural settings from the western, established markets. This phenomenon, popularly termed the January effect, is a subject of immense interest since it may provide another evidence which violates the weakest form of the Efficient Market Hypothesis.

This chapter will seek to add further evidence of stock market seasonality, and in particular, the January effect, in the Far-eastern markets by examining four relatively established markets in the region. These are the Kuala Lumpur Stock Exchange of Malaysia (KLSE), the Stock Exchange of Singapore (SES), the Stock Exchange of Hong Kong (SEHK), and the Stock Exchange of Thailand (SET). In addition, the chapter will also investigate a phenomenon peculiar to some markets in this part of the world, namely the Chinese New Year Effect. This refers to the tendency of stock prices to increase around the Chinese New Year. It would be interesting to see if country-specific factors can explain seasonal patterns in the stock markets.

3.2: The Chinese New Year and Its Effect on Stock Prices

Like the Gregorian or Western calendar, the Chinese calendar is a 12-month calendar year. However, it is not fixed. The calendar is based on a lunar year of about 50.5 weeks, with a 'leap' year of 55 weeks every three years to keep it in step with the Gregorian calendar which is based on the solar year. The first day of the year occurs on the first moon in January or February. Table 3-1 gives the date of the first day of the Chinese New Year (CNY) from 1970 to 1996 in the Gregorian calendar. As can be seen, the first day of the new year is mostly observed in the month of February. Between the period 1975 - 1996, the CNY is in February for 15 out of 21 years. Even when it falls in January, it tends to be in the last week of that month.

In Malaysia, the Chinese New Year is celebrated on a grand scale. It is not only celebrated by the Chinese, but also by the other ethnic groups. It is customary for the Chinese to give 'Ang Pows' (normally cash money) as gifts to friends and relatives which range from a few to several thousands Malaysian Ringgit during this festive season. Many companies, especially the Chinese-owned ones, would pay bonuses in occasion with the festival. The first two days are declared as national holidays by the Federal Government. Like

Government offices and other corporations, the Kuala Lumpur Stock Exchange is closed for trading for two days.

The interest in studies on the CNY effect began at the turn of this decade. The idea to study the effect of such cultural and country specific events may stem from the findings of returns seasonality documented much earlier in the western markets, such as the January effect. It may also be due to the claims in Wachtel (1942) that festive seasons such as Christmas and New Year will bring cheer and new hope. Such psychological attributes may provide an alternative, non-economic explanation to seasonalities such as the January effect.

Yong (1989), who investigates seasonality in the KLSE, observes that monthly returns are highest in January. However, December and February are not far behind. Rejecting any explanation based on tax-related trading, he attributes this seasonality to the celebration of the CNY in Malaysia. The giving of 'Ang Pows' requires some cash. One way of generating cash, according to the author, is by speculating in the stock market. He suggests that investors start to enter the market as early as December. As more investors enter the market, prices are driven up. Once the festive season is over, i.e., in February, these speculators move out from the market, and decrease prices. This suggestion is in fact consistent with Wong *et al.* (1990), who claim that share prices start to rise as early as two months prior to the CNY, though others such as Chan *et al.* (1996) and Ho (1990), also observe that several days after celebration, the prices are still high.

Therefore, it seems that the CNY rally takes place two months prior to the celebration, and continues up to several days after the new year. In the Gregorian calendar term, it means that the period will include the last weeks of December and the first two or three weeks of February, depending on the date of the CNY in the Gregorian calendar. For example, if the CNY falls in the middle of February, then the rally may start as early as the beginning of the third week of December, and finish by the end of the third week of February. This CNY effect, however, may not be the only seasonal factor here. The January effect can also be claimed to exist causing returns to be higher in January. Though the tax-loss selling hypothesis is not relevant in all these markets since there is no capital gains tax, there might also be other acceptable explanations which upheld the January effect, such as the liquidity factor (i.e., payment of bonuses at year end by corporations), and the influence of foreign investors.

It is expected that three of the markets in this study, which have a preponderance of Chinese investors, i.e., Malaysia, Singapore and Hong Kong, will show some indications of the CNY effect. However, this is not the case for Thailand. Though there is a sizeable number of them, the Chinese are not the dominant group of investors in Thailand. Even the CNY is not generally proclaimed as the official holiday in Thailand, unlike the other markets above.

Table 3-1: First day of CNY in the Gregorian calendar (1975 - 1996)

Year	Dates in Gregorian Calendar
1975	11th February
1976	31st January
1977	18th February
1978	7th February
1979	28th January
1980	16th February
1981	5th February
1982	23rd January
1983	12th February
1984	1st February
1985	20th February
1986	7th February
1987	29th January
1988	16th February
1989	6th February
1990	29th January
1991	14th February
1992	4th February
1993	22nd January
1994	9th February
1995	30th January
1996	19th February

3.3: Data and Methodology

To investigate stock market seasonality in this chapter, we employ the main index of each country's common stocks. These are the Kuala Lumpur Composite Price Index for Malaysia, the SES-All Share Index for Singapore, the Hang Seng Price Index for Hong Kong, and the SET Price Index for Thailand. These are all value-weighted indices, and are regarded as the main market barometer in each country.

Returns are obtained from *Datastream*, which records the daily value of the indices as far back as follows; KLSE from January 1980, SES from January 1986, SEHK from January 1975, and SET from January 1976. To maximise the number of observations, therefore, the period of study will start from the above starting dates as recorded in *Datastream* up to December 1996. In addition, the study period for each of the indices (except for the Singapore's SES) will also be partitioned into two sub-periods; i) from respective starting dates above to December 1986, and ii) from January 1988 to December 1996. The main reason behind this partition of periods is to avoid any effect of the worldwide October 1987 crash. Besides, stock markets in Asia generally grew very rapidly starting in the late 1980s, after a long period of stagnancy in the late 1970s and early 1980s (see Figure 3-1). It is therefore appropriate to see if seasonal patterns exist in periods of stagnancy and in periods of rapid growth. For SES, due to shorter data availability period, only two periods will be looked at; the whole period of 1986-1996, and the (post October 1987 crash) period of 1988-1996.

Monthly returns data are derived from the logarithmic daily returns, computed as follows;

$$R_{I,d} = \ln\left[\frac{I_d}{I_{d-1}}\right] \tag{3-1}$$

where $R_{I,d}$ is the return of the index at day d, I_d is the index value at day d, and I_{d-1} is the index value at day d-1. The daily returns are then cumulated to obtain the monthly returns, $R_{I,m}$, using the following equation;

$$R_{I,m} = \sum_{d=1}^{D} R_{I,d} \tag{3-2}$$

To determine whether any seasonal pattern exists, both the parametric (ANOVA) and non-parametric (Kruskal-Wallis test) will be employed. The F-statistics obtained from ANOVA will be used to test the null hypothesis that there is no difference in mean monthly returns, while the non-parametric Kruskal-Wallis statistics test the null hypothesis that there is no difference in median monthly returns of the indices, and is described in equation 3-3 below;

$$KW = \frac{12\sum n_i\left[\overline{R}_i - \overline{R}\right]^2}{N(N+1)} \tag{3-3}$$

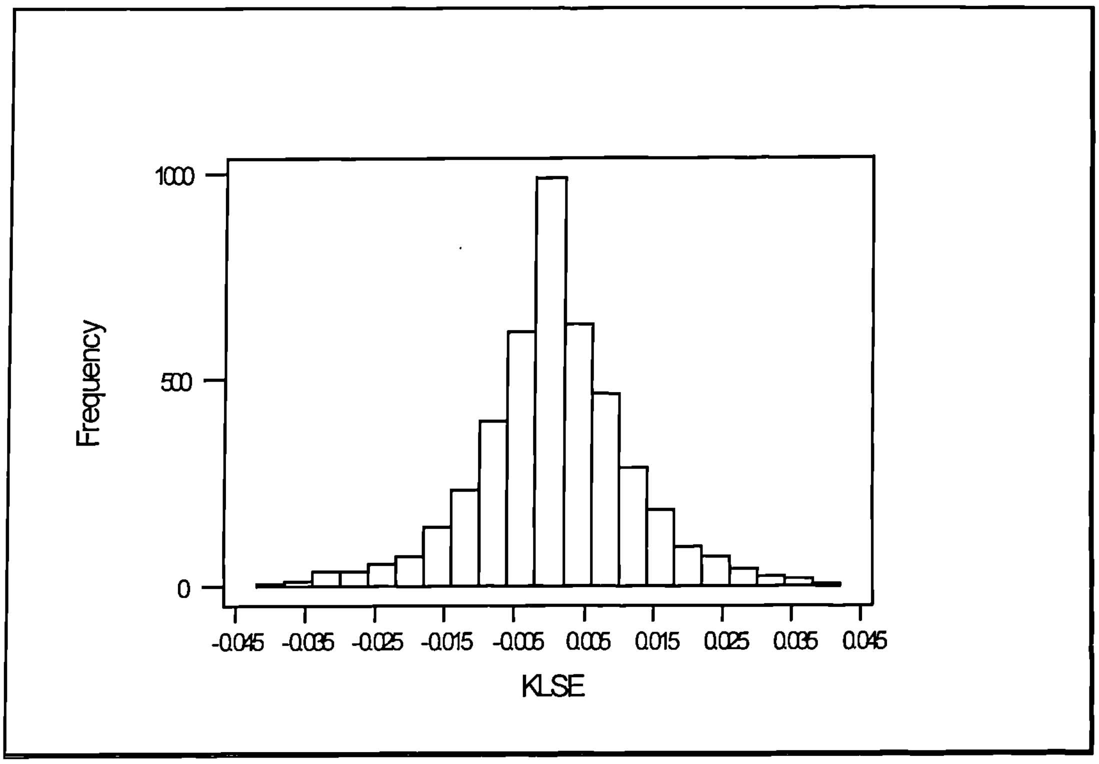
where n_i is the number of observations in each month, N is the total number of observations, $\overline{R}_i$ is the average of the ranks in month i, and $\overline{R}$ is the average of all the ranks. This test generates a statistic which tests the null hypotheses that return distributions are identical across all twelve months.

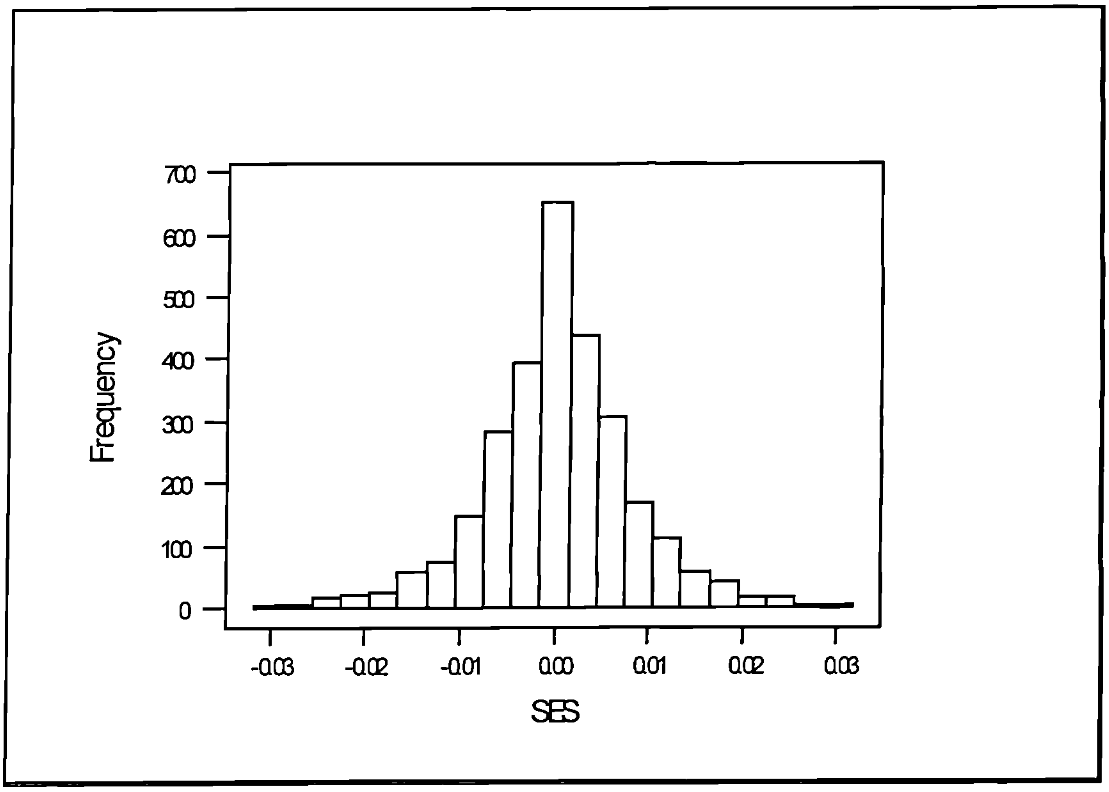
It should be noted that the parametric tests assume that the underlying distribution is normal. If this assumption holds, this test is more powerful than the non-parametric tests. Furthermore, the parametric tests are based on the sample means, so even if the population is not normal, sample means will still be approximately normally distributed. To check on the normality of the distribution of the market logarithmic returns, some descriptive statistics of the markets, including the skewness and kurtosis, are given in Table 3-2. It appears that all the four markets tend to have negative skewness. However, only SEHK returns show pronounced skewness. The skewness of KLSE returns are not as pronounced as those of the SEHK. For SES and SET, the normality of their returns cannot be rejected. The symmetrical nature of SES, SET and to some extent KLSE, are obvious from the histograms in Figure 3-1. The returns on each of the markets also tend to be more fat-tailed than would be expected from a normal distribution, as implied by the positive kurtosis values. This indicates that the distribution of returns tend to have more extreme observations, and this is especially true for SEHK. Overall, it is fairly safe to claim that the distribution of returns of most of the markets do not depart excessively form normality. Besides, the Normal Approximation Rule or the Central Limit Theorem can be imposed here which might lead to the t-test and F-test still being valid. Furthermore, to back up the results from the parametric tests in this chapter, the non-parametric tests such as the Kruskal-Wallis test (and the Wilcoxon signed ranks test and Mann-Whitney U-test in later chapters) will also be given.

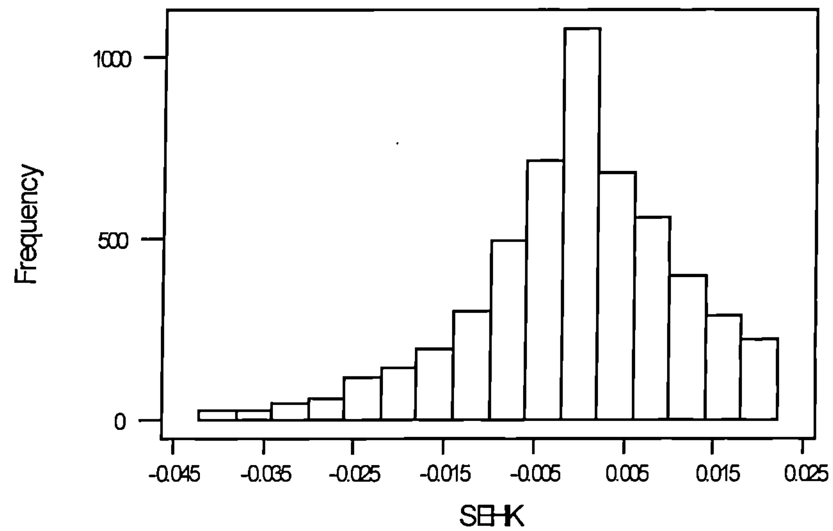
Table 3-2: Descriptive statistics of daily market logarithmic returns

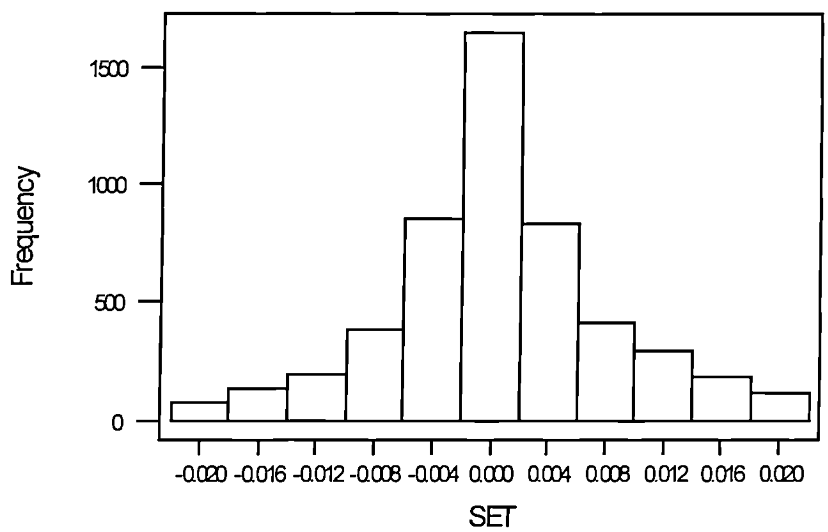
	KLSE	SES	SEHK	SET
Mean	0.00040	0.00029	0.00077	0.00042
Std. Dev.	0.01345	0.00989	0.01725	0.01251
Minimun	-0.17067	-0.09403	-0.40542	-0.09295
Maximum	0.11062	0.14313	0.14763	0.10349
Kurtosis	18.35651	28.31860	65.90470	11.00077
Skewness	-1.36556	-0.18815	-3.06607	-0.36277
No. of observation	4434	2868	5738	5479

Figure 3-1: The distribution of daily market logarithmic returns






Frequency
1000
500
0
-0.045
-0.035
-0.025
-0.015
-0.005
0.005
0.015
0.025
SEHK


Frequency
1500
1000
500
0
-0.020 -0.016 -0.012 -0.008 -0.004 0.000 0.004 0.008 0.012 0.016 0.020
SET

Once the overall differences of monthly returns are determined, further tests are employed to examine whether returns in any particular month are different from other months. This will be achieved by using two dummy-variable regressions. These regressions, however, will be carried out using the returns from the whole period only. The first regression will test whether returns in the month with the highest return is significantly higher than the return in each of the other months. Since the January effect is tested here, it is presupposed that this is the month of January. The regression, therefore, takes the following form;

$$R_t = a + b_1 Feb + b_2 Mar + \ldots\ldots\ldots + b_{11} Dec + e_t \qquad (3\text{-}4)$$

where R = the returns for each of the month of the indices;

Feb = a dummy variable, which equals 1 for February observation, and 0 elsewhere;

Mar = a dummy variable, which equal 1 for March observation, and 0 elsewhere;

....................;

a = the intercept term, which indicates the expected value R for January;

$b_1 \ldots\ldots b_{11}$ = the coefficient for February .....December, which measure the difference between February .....December returns and January returns;

e = the error term, which follows the usual OLS assumption[1].

[1] The assumptions are, i) the expected value of each e_t is zero (linearity), ii) the variance of each e_t is constant (homoscedasticity), iii) any pair of errors e_t and e_j are uncorrelated (independence), and iv) the independent variables are fixed (not random).

In cases where January is not the month with the highest return, the equation above should be adjusted accordingly. The second regression will examine if returns in that particular month are significantly higher than for the other months combined, and is given below;

$$R_t = \phi_0 + \phi_1 Jan + e_t \tag{3-5}$$

where R_t = the mean monthly returns of the indices;

Jan = the dummy variable, which is equal to 1 for observations in January and 0 otherwise;

ϕ_0 = the intercept term, which measures the mean returns for the eleven months excluding January;

ϕ_1 = the coefficient for January, which measures the difference between the mean returns in January and the other eleven months of the year;

e_t = the random error term which follow the usual OLS assumptions.

Again, if January is not the month with the highest returns, the dummy in 3-5 will be for that particular month.

To test for the Chinese New Year (CNY) effect, the appropriate 'event window' surrounding the first day of the celebration is first defined. (Table 3-1 gives the date of the first day of the CNY in the Gregorian or Western calendar). Several previous studies use different 'window'. Ho (1990) looks at the returns during the nine trading days before and the nine trading days after the first month of the CNY. Chan *et al.* (1996) examines the behaviour of returns in the six days surrounding the celebration, i.e., three days preceeding the CNY and three days after it. Wong *et al.* (1990), investigating the CNY effect in Malaysia, claim that CNY rally start two months prior to the first month of the new year. All of these studies indeed find the existence of the CNY effect.

Taking the above studies into consideration, this study will define the 'window' as two months prior to the first day of the CNY, and one week after it. To be exact, 40 daily returns preceding the CNY will be examined since a period of two months will have about 40 trading days. As for returns after the celebration, they will be examined for the first five days of trading, as all these markets have five trading days in a week. The average daily returns of both periods will be compared separately to the average daily returns for the rest of the year excluding those two periods, to determine whether the CNY effect is indeed real.

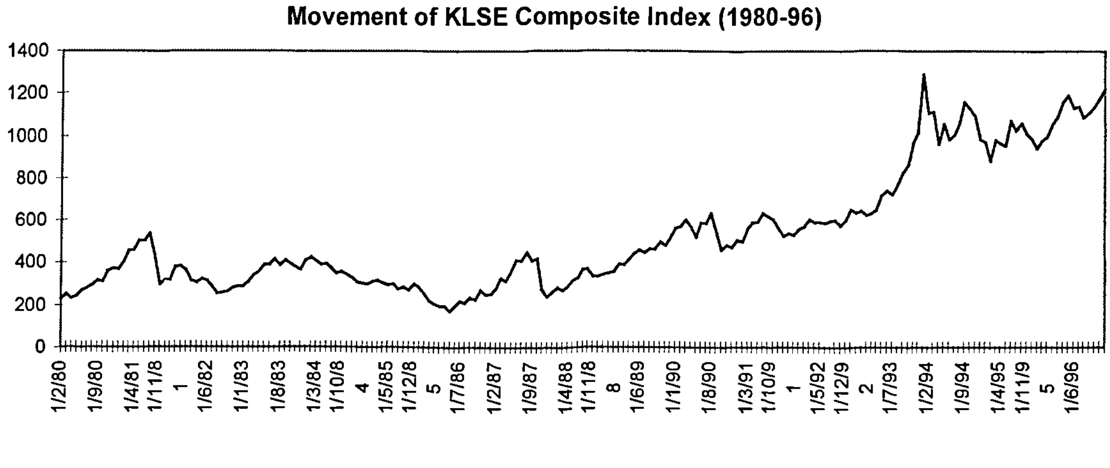
Ideally, an additional analysis on the trading volume surrounding the CNY would provide more insight into the CNY effect. However, due to unavailability of volume data from *Datastream*, such analysis could not be done. Turnover-by-volume data is only available for the KLSE Composite Index beginning March 1996. No such data is available for the SES-All Share Index, and the SEHK Hang Seng Price Index; i.e., the other two markets which are expected to show pronounced CNY effect.

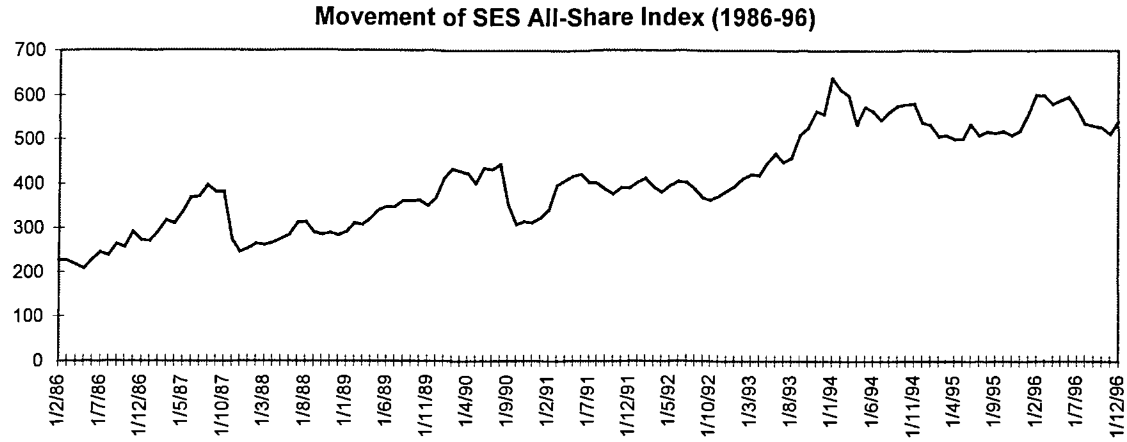
3.4: Results and Discussion

Before the details of the results of the tests described previously are presented, the time-series movements of each index in Figure 3-2 are first charted. The correlation between each pair of the indices is also calculated, and the results are presented in Table 3-3. Figure 3-2 quite clearly shows that the markets in Malaysia, Hong Kong and Thailand started to grew rapidly beginning in the late 1980s, after a quiet period in the prior years. Though it is also true, I couldn't show this for the SES since the SES-All Share Index data is only available starting 1986. It also reveals how the October 1987 crash also affected the four markets, especially Hong Kong. This is not very surprising since a lot of foreign investors are involved in the market. After the crash, the indices started to climb tremendously beginning in 1988. It is thus appropriate that the period of this study is partitioned into two, i.e., pre-1987 and post-1987.

The correlation matrix in Table 3-3 shows that the stock markets in Malaysia and Singapore are highly correlated. The correlation of 0.629 is the highest among any pairs in the sample. In fact, many previous studies such as Claessen *et al.* (1995), Cheung and Ho (1991), and Divecha *et al.* (1992), have documented similar findings. This is not surprising when one bears in mind that these two markets had many cross-listings prior to 1990. The correlation between KLSE and SEHK, and between SEHK and SES are also high (0.398 and 0.377 respectively). The SET has the lowest correlation with the others. This is most probably due to the low level of foreign investors' participation in the SET. In fact, SET is regarded as the least-open market among the four.

Figure 3-2: Time-series movement of the indices





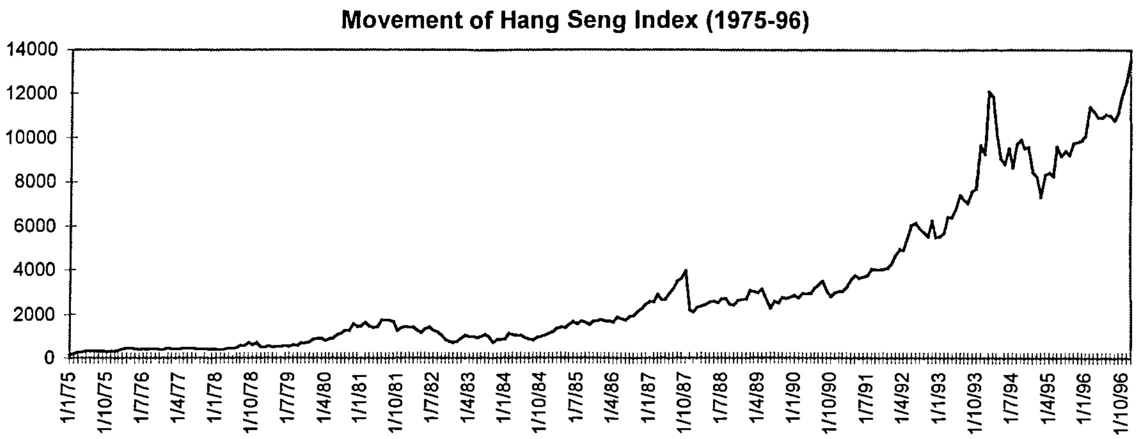


Figure 3-1 (continued)

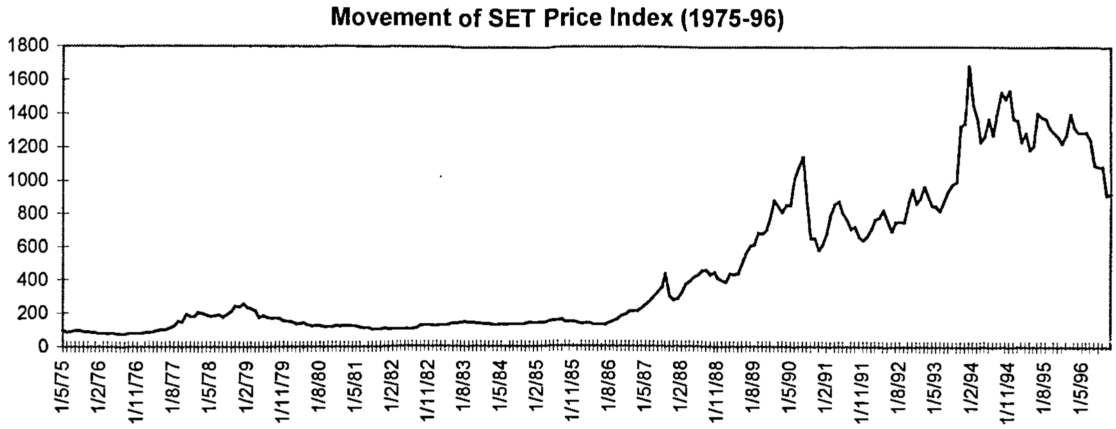


Table 3-3: Correlation matrix of the indices (1986-1996)

	KLSE	SES	SEHK	SET
KLSE	1.000			
SES	0.629	1.000		
SEHK	0.396	0.377	1.000	
SET	0.345	0.342	0.280	1.000

The results of the test described in the previous section will now be presented. Table 3-4 shows the percentage monthly returns on each indices under study. It also gives the results of the ANOVA and the Kruskal-Wallis test. For the whole period, i.e., the first panel under each country headings, returns are highest in the month of December in the KLSE, SES and SET. This is quite surprising as no study (to my knowledge), has found similar results. Only the SEHK shows the highest return in January, which is consistent with studies like Gultekin and Gultekin (1983), Lee (1992), and Ho (1990). It should be noted, however, that though previous studies do not find December to yield the highest returns in Malaysia, Singapore and Thailand, they report that the month usually ranks among the highest in generating returns (see for examples, Yong, 1989; Ho, 1990; and Chan *et al.* 1996).

Looking more closely at the KLSE, December yields an average 3.9% return in the period between January 1980 to December 1996. The second highest return is observed in February, whose average return is 3.5%. At the 0.05 level, the returns in these two months are significantly different from zero. Similar observations can be seen for the sub-period 1988-96. Monthly returns of 5.7% and 4.1% respectively for December and February rank the highest in the period. The table also reveals that overall, there is no significant difference between monthly returns, as reflected by the F-value and the Kruskal-Wallis statistics. In sub-period 1980-86, October yields the highest returns, but none of the months are actually different from zero.

In the SET, December (2.9% and 6.0% respectively) is the month with the highest returns in the whole period and in sub-period 1988-96, while October (4.3%) occupies the top spot in the sub-period 1976-86. However, all these are not significantly different from zero. The *F*-statistics and the Kruskal-Wallis statistics also reveal that there is no difference in the monthly returns. Like the KLSE, therefore, there is no January effect in the SET.

Table 3-4: Average percentage returns on country common stock indexes by month of year

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	All Month
							Malaysia						
KLSE Composite Index (1980-96)													
mean	0.014	0.035*	-0.012	0.033	0.028	0.011	-0.005	-0.026	-0.005	0.002	-0.009	0.039*	0.009
s.d	0.079	0.074	0.056	0.074	0.060	0.062	0.077	0.098	0.064	0.136	0.072	0.073	0.080
obs.	17	17	17	17	17	17	17	17	17	17	17	17	204
F (*p*-val)													1.22 (0.278)
KW (*p*-val)													14.74 (0.101)
KLSE Composite Index (1980-86)													
mean	0.023	0.010	-0.023	0.025	0.016	0.015	-0.047	-0.025	-0.003	0.033	-0.006	0.011	0.002
s.d	0.084	0.087	0.037	0.075	0.059	0.059	0.096	0.129	0.063	0.110	0.095	0.059	0.083
obs.	7	7	7	7	7	7	7	7	7	7	7	7	84
F (*p*-val)													0.55 (0.865)
KW (*p*-val)													5.41 (0.909)
KLSE Composite Index (1988-96)													
mean	-0.002	0.041*	-0.001	0.029	0.028	0.008	0.017	-0.026	-0.003	0.025	0.000	0.057*	0.014*
s.d	0.078	0.051	0.070	0.074	0.059	0.042	0.042	0.081	0.072	0.057	0.049	0.083	0.065
obs.	9	9	9	9	9	9	9	9	9	9	9	9	108
F (*p*-val)													1.12 (0.355)
KW (*p*-val)													9.83 (0.546)
							Thailand						
SET Price Index (1976-96)													
mean	0.016	0.004	-0.001	0.003	0.019	0.019	0.018	0.006	0.003	0.011	-0.017	0.029	0.009
s.d	0.072	0.060	0.061	0.068	0.065	0.052	0.061	0.088	0.089	0.133	0.066	0.078	0.076
obs.	21	21	21	21	21	21	21	21	21	21	21	21	252
F (*p*-val)													0.49 (0.907)
KW (*p*-val)													7.06 (0.794)

Table 3-4 (continued)

SET Price Index (1976-86)													
mean	0.002	-0.007	-0.009	-0.012	0.001	0.008	0.022	0.020	0.009	0.043	-0.002	0.008	0.007
s.d	0.054	0.019	0.048	0.076	0.030	0.035	0.044	0.075	0.034	0.094	0.042	0.046	0.054
obs.	11	11	11	11	11	11	11	11	11	11	11	11	132
F (*p*-val)													0.92 (0.520)
KW (*p*-val)													5.52 (0.90)
SET Price Index (1988-96)													
mean	0.033	0.019	0.000	0.013	0.034	0.022	0.000	-0.013	-0.025	0.011	-0.032	0.060	0.010
s.d	0.094	0.091	0.072	0.056	0.091	0.064	0.071	0.107	0.113	0.123	0.090	0.102	0.090
obs.	9	9	9	9	9	9	9	9	9	9	9	9	108
F (*p*-val)													0.74 (0.701)
KW (*p*-val)													7.24 (0.090)
Singapore													
SES All-Share Index (1986-96)													
mean	0.031*	0.021	-0.031	0.019	0.034*	0.003	0.005	-0.017	-0.016	-0.025	0.001	0.035*	0.007
s.d	0.048	0.056	0.045	0.045	0.032	0.050	0.040	0.084	0.050	0.113	0.050	0.040	0.060
obs	11	11	11	11	11	11	11	11	11	11	11	11	121
F (*p*-val)													1.45 (0.159)
KW (*p*-val)													17.62 (0.093)
SES All-Share Index (1988-96)													
mean	0.034*	0.014	-0.009	0.020	0.026*	-0.010	0.002	-0.028	-0.0152	0.011	0.001	0.041*	0.007
s.d	0.049	0.055	0.049	0.043	0.030	0.041	0.037	0.086	0.055	0.035	0.043	0.042	0.051
obs	9	9	9	9	9	9	9	9	9	9	9	9	108
F (*p*-val)													1.63 (0.103)
KW (*p*-val)													19.84 (0.049)

Table 3-4 (continued)

						Hong Kong							
Hang Seng Price Index (1975-96)													
mean	0.062*	0.025	-0.013	0.036*	0.020	0.010	0.025	-0.001	-0.016	0.017	-0.006	0.044*	0.017*
s.d	0.092	0.074	0.065	0.058	0.081	0.082	0.069	0.074	0.104	0.155	0.091	0.072	0.089
obs.	22	22	22	22	22	22	22	22	22	22	22	22	264
F(p-val)													1.59 (0.103)
KW (p-val)													17.32 (0.101)
Hang Seng Price Index (1975-86)													
mean	0.089*	0.009	-0.019	0.057*	0.001	0.031	0.014	0.006	-0.040	0.033	0.002	0.049*	0.019*
s.d	0.098	0.074	0.071	0.062	0.083	0.081	0.078	0.085	0.127	0.101	0.115	0.060	0.091
obs.	12	12	12	12	12	12	12	12	12	12	12	12	144
F(p-val)													1.89 (0.046)
KW (p-val)													16.91 (0.113)
Hang Seng Price Index (1988-96)													
mean	0.034	0.036	-0.001	0.013	0.037	-0.028	0.032	-0.015	0.004	0.061*	-0.011	0.034	0.016*
s.d	0.078	0.073	0.058	0.043	0.079	0.075	0.057	0.063	0.062	0.065	0.058	0.091	0.069
obs.	8	8	8	8	8	8	8	8	8	8	8	8	96
F(p-val)													1.37 (0.199)
KW (p-val)													14.44 (0.211)

Notes:
s.d. stands for standard deviation.
obs. stands for number of observations.
F refers to the F-statistics which tests the null hypothesis that all the monthly returns are equal to each other.
The asterisk * indicates significant at 0.05 level of the t-statistics for testing the mean return is equal to zero.

The January effect, however, can be observed in Singapore and Hong Kong. In the SES, the average January return of 3.1% is the third highest in the year after December, which *yields* an average return of 3.5%. The other month with a return statistically different from zero is May (3.4%). The sub-period 1988-96 reveals very similar results, whereby January yields a returns of 3.4%. In fact, the Kruskal-Wallis statistics (p-value = 0.049) suggest that monthly returns are different in this sub-period.

In Hong Kong, the January effect is most pronounced. For the whole period of 1975-96, the Hang Seng Index yields an average January return of 6.2%, followed by December (4.4%) and April (3.6%). January also ranks the highest in the 1975-86 sub-period, followed by April and December with a return of 8.9%, 5.7% and 4.9% respectively. This finding is consistent with Ho (1990) and Cheung, Ho and Wong (1994). Furthermore, higher returns in the months of January and April may be due to the close relation between the markets in Hong Kong and the UK, which also has higher returns in those months. (see for examples, Levis, 1985; Reinganum and Shapiro, 1987; Corhay, Hawawini and Michel, 1987). Not only that there is the same tax year-end in Hong Kong and the UK, but also there are 19 stocks of the 33-stock Hang Seng Index which are listed in the London Stock Exchange (LSE). The influence of the LSE, may thus contribute to the higher returns in those months. It should also be noted that since the return preceding April, i.e., March, is always negative, we can suggest that the tax-loss selling by foreign investors may be possible here. In the sub-period 1988-96, October has the highest return of 6.1% which is significantly different from zero at the 0.05 level. In all three periods, however, the *F*-value and the Kruskal-Wallis statistics indicate that overall, there is no difference in the monthly returns.

Table 3-5 gives the results of the dummy-variable regression in equation (3-4), which tests whether the month with the highest return has a significantly higher mean return than each of the other months. This means that we are testing whether December has significantly higher returns than the returns in each of the other months in Malaysia, Singapore and Thailand. For Hong Kong, the return in January is compared with the returns in the other months to determine whether it is significantly higher. The slope coefficients (b_1, b_2, ..., b_{11}) are expected to be less than zero. A one-tailed test is therefore appropriate. The Durbin-Watson statistics are also calculated to check whether there is any serial correlation in the residuals of the regressions. The results are presented in the last row of Table 3-5.

As can be seen, the mean December return is significantly higher than March and November in the KLSE, while in the SET, the month is only significantly higher than November at the 0.05 level. In the SES, the December effect is more pronounced. Its return is significantly higher than that of the other four months, namely March, August, September and October. In Hong Kong, the mean January return is significantly higher than for March, and September. It is also significantly higher than for June, August, October and November at the 0.05 level. The January effect is therefore very pronounced in Hong Kong. With regards to serial correlations in the residuals of the regressions, the

Durbin-Watson statistics indicate that generally, there is no significant serial correlation present in the residuals of the regressions.

The results for the second regression (equation 3-5) are summarised in Table 3-6. The regression is used to test whether December in the case of Malaysia, Singapore and Thailand, and January in the case of Hong Kong, have returns significantly higher than the average returns of the other eleven months. Again, a one-tail test is appropriate with the expectation that the slope coefficient (ϕ_1) is greater than zero. From the table, it is clear that the mean returns in December are not statistically different than the average returns of the other months in Malaysia and Thailand. In Singapore, however, the *t*-statistic of 1.69 indicates that the mean December return is significantly higher at the 0.05 level than the average return of the other months. Lastly, in Hong Kong, the return in January is significantly higher than the average return in the other months ($t = 2.53$).

Table 3-5: Test of equal returns in month with the highest return and in each of the other months for market indices

Month	Malaysia	Thailand	Singapore	Hong Kong
January	-0.0248	-0.0130	-0.0047	------
	(-0.91)	(-0.54)	(-0.19)	
February	-0.0038	-0.0244	-0.0145	-0.0377
	(-0.14)	(-1.02)	(-0.58)	(-1.42)
March	-0.0509	-0.0290	-0.0481	-0.0755
	(-1.86)*	(-1.22)	(-1.93)*	(-2.84)*
April	-0.0062	-0.0254	-0.0167	-0.0266
	(-0.23)	(-1.07)	(-0.67)	(-1.00)
May	-0.0110	-0.0100	-0.0017	-0.0425
	(-0.40)	(-0.42)	(-0.07)	(-1.60)
June	-0.0279	-0.0101	-0.0321	-0.0527
	(-1.02)	(-0.43)	(-1.29)	(-1.98)*
July	-0.0440	-0.0112	-0.0300	-0.0376
	(-1.61)	(-0.47)	(-1.20)	(-1.41)
August	-0.0655	-0.0224	-0.0521	-0.0633
	(-2.39)*	(-0.94)	(-2.09)*	(-2.38)*
September	-0.0440	-0.0259	-0.0515	-0.0786
	(-1.61)	(-1.09)	(-2.07)*	(-2.96)*
October	-0.0376	-0.0182	-0.0604	-0.0450
	(-1.37)	(-0.76)	(-2.42)*	(-1.69)*
November	-0.0480	-0.0454	-0.0340	-0.0685
	(-1.75)*	(-1.90)*	(-1.36)	(-2.57)*
December	------	------	------	-0.0187
				(-0.70)
D-W	1.79	1.76	1.72	1.88

Notes;
Results are based on the regression;

$$R_t = a + b_1 Feb + b_2 Mar + \dots\dots\dots + b_{11} Dec + e$$

where, R = the returns for each of the month of the indices,
Feb = a dummy variable, which equals 1 for February observation, and 0 elsewhere,
Mar = a dummy variable, which equal 1 for March observation, and 0 elsewhere,
....
a = the intercept term, which indicates the expected value R for January,
$b_1 .....b_{11}$ = the coefficient for February .....December, which measure the difference between February .....December returns and January returns,
e = the error term, which follows the usual OLS assumption.

For Malaysia, Thailand and Singapore, the month with the highest returns is December, while for Hong Kong, the month is January. The equation above should thus be adjusted accordingly for Malaysia, Thailand and Singapore.
t-statistics are in parentheses. The critical value of the *t*-statistics above is -1.65, at the 0.05 significant level, using a one-tailed test.
D-W is Durbin-Watson statistics which test the autocorrelation in the residuals of the regression above.
* indicate significant at the 0.05 level.

Table 3-6: Test of equal returns in month with the highest return and in the other months of the year combined

Market	*'Best' Month*[a] Vs. Rest of Year	
	ϕ_1	t-statistic
Malaysia	0.0331	1.63
Thailand	0.0214	1.23
Singapore	0.0314	1.69*
Hong Kong	0.0497	2.53*

Notes:

Results are based on the regression;

$$R_t = \phi_0 + \phi_1 Jan + e_t$$

where R_t = the mean monthly returns of the indices,

Jan = the dummy variable, which is equal to 1 for observations in January and 0 otherwise,

ϕ_0 = the intercept term, which measures the mean returns for the eleven months excluding January,

ϕ_1 = the coefficient for January, which measures the difference between the mean returns in January and the other eleven months of the year,

e_t = the random error term which follow the usual OLS assumptions.

[a] For Malaysia, Thailand and Singapore, the 'best' month (i.e., the month with the highest returns) is December, while for Hong Kong the best month is January. The equation above should be adjusted accordingly for Malaysia, Thailand and Singapore.

* indicates significant at 0.05 level, using a one-tailed test.

Table 3-7 summarises the results of the analysis of the CNY effect, while Figure 3-2 shows graphically the CNY effect in the markets. It seems quite clear that three of the markets which have a large number of Chinese investors, i.e., Malaysia, Singapore and Hong Kong, show signs of the CNY effect. In Malaysia, the average returns 40 days prior to the CNY are higher than the average daily returns for the whole year excluding those 40 days and 5 days after the celebration. This is consistent with Wong *et al.* (1990), who find that the CNY rally starts two months before the new year. On average, an investor will earn 0.1% daily during these 40 days. At 0.05 level, this is significant. The return after the CNY is even higher. The daily average of those five days is 0.45% ($t = 2.33$) and is statistically higher than the average for the whole year. In Singapore and Hong Kong, returns are significantly higher 40 days preceding the first day of the CNY. On average, daily returns are 0.14% ($t = 2.61$) and 0.23% ($t = 3.20$) in Singapore and Hong Kong respectively during this period. However, unlike in Malaysia, though returns are higher than the year's average 5 days after the CNY, it is not significant in Singapore. A very different result is found in Hong Kong. Investors actually earn a negative return of 0.11% daily 5 days after the celebration when trading resumes. Not surprisingly, a significant CNY effect in Thailand is not observed. This is consistent with Chan *et al.* (1996) who find a very weak CNY effect in the market, but significant evidence for the markets in Malaysia and Singapore. Although returns are higher surrounding this festive season, they are not statistically different from the returns of the rest of the year. One obvious explanation for the absence of such effect here is that the Chinese are not the dominant investors in the SET. In adition, the CNY is not declared as an official holiday in Thailand.

Table 3-7: The Chinese New Year effect

Country	N	A	B	C
Malaysia (1981-96)	16	0.00015	0.00104	0.00454
Std. dev.		0.00118	0.00213	0.00736
t-statistics			1.95*	2.23*
Singapore (1987-96)	10	0.00013	0.00142	0.00255
Std. dev.		0.00090	0.00126	0.00504
t-statistics			2.61*	1.44
Hong Kong (1976-96)	21	0.00045	0.00228	-0.00108
Std. dev.		0.00120	0.00263	0.00849
t-statistics			3.20*	-0.77
Thailand (1977-96)	20	0.00039	0.00114	0.00149
Std. dev.		0.00128	0.00219	0.00622
t-statistics			1.58	0.74

Notes:

N = number of observations.

A = average daily returns for the whole year, excluding 40 days prior to and 5 days after the first day of the CNY.

B = average daily returns 40 days prior to the CNY.

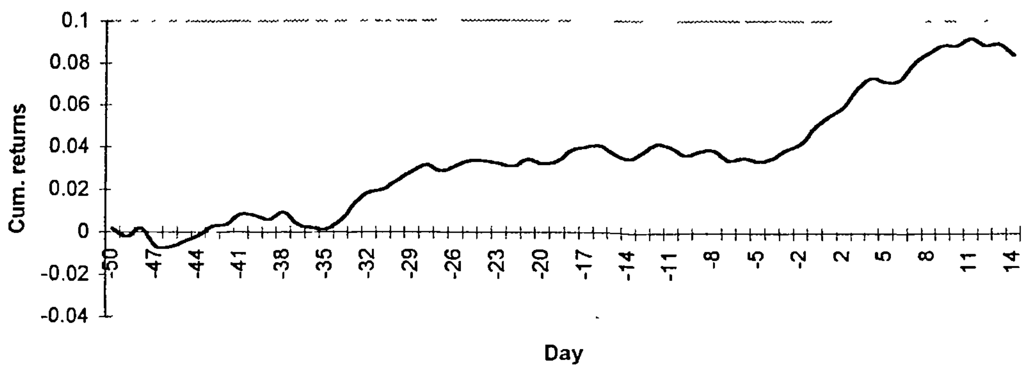
C = average daily returns 5 days after the CNY.

t-statistics test the null hypotheses that H_0: A = B and H_0: A = C, against the alternative hypotheses H_1: B > A and H_1: C > A respectively.

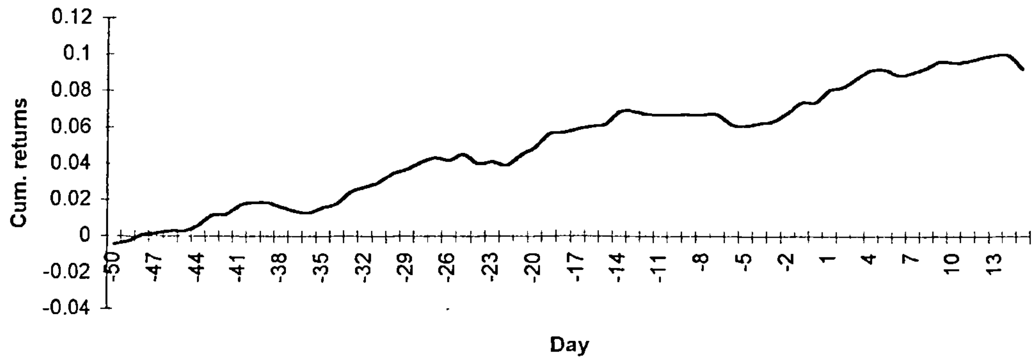
* indicates significant at 0.05 level, using a one-tailed test.

Figure 3-3: Market returns surrounding the CNY in KLSE, SES, SEHK and SET

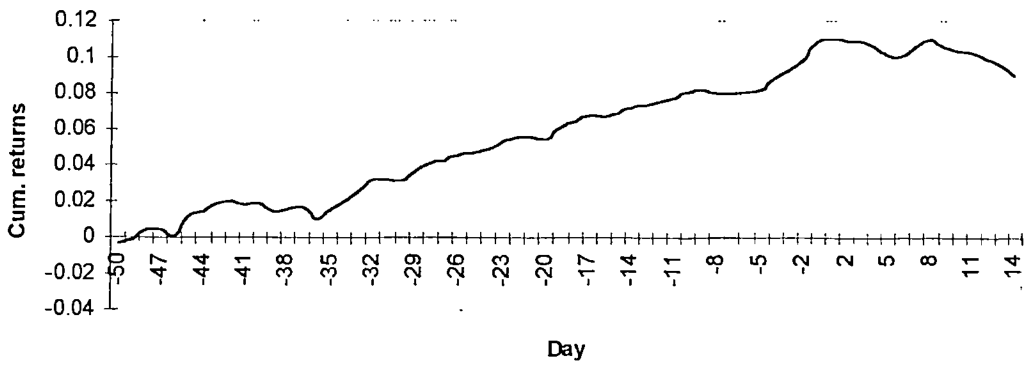
Cumulative daily returns surrounding CNY in KLSE (1981-96)

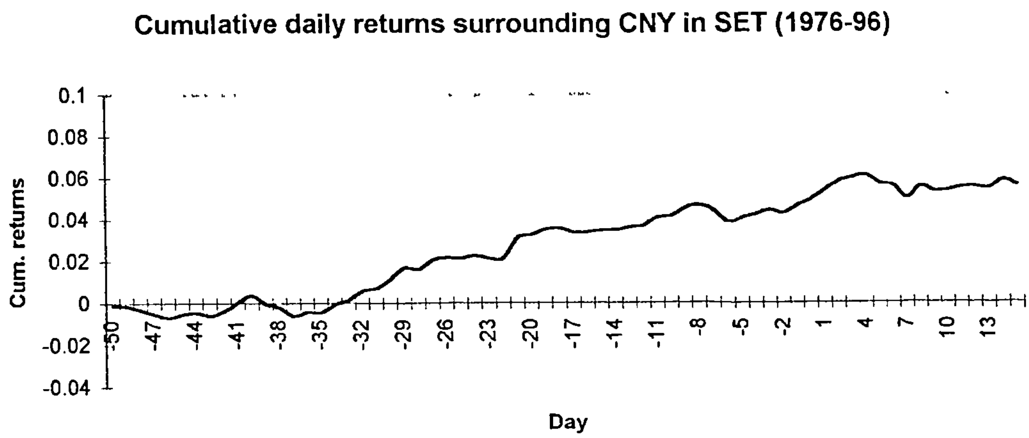


Cumulative daily returns surrounding CNY in SES (1987-96)



Cumulative daily returns surrounding CNY in SEHK (1971-96)




Cumulative daily returns surrounding CNY in SET (1976-96)
Cum. returns
0.1
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-50
-47
-44
-41
-38
-35
-32
-29
-26
-23
-20
-17
-14
-11
-8
-5
-2
1
4
7
10
13
Day

3.5: Summary and Conclusion

Stock market seasonality in four Far-Eastern markets is investigated in this chapter. Specifically, two analyses are carried out; i) analysis of the January effect, and ii) analysis of the Chinese New Year (CNY) effect. The evidence suggests that the January effect does not exist in Malaysia and Thailand. Instead, it is found that there are strong December and February effects in Malaysia. In Thailand, no month shows any different returns than the others. The January effect, however, is found in Singapore and Hong Kong. December and May also have statistically higher returns than the other months in Singapore. The January effect is most pronounced in Hong Kong. In addition, April returns are also high, which may indicate the relevance of the tax-loss selling hypothesis here.

An analysis of the CNY effect reveals that three markets which have a large Chinese involvement, show significant positive returns surrounding the celebration. In Malaysia, it is found that the effect is especially more pronounced five days after the market is open following the CNY holidays. Daily returns 40 days preceding the first day of the CNY are also high. The CNY effect is also observed in Singapore and Hong Kong. However, unlike that in Malaysia, the markets in Singapore and Hong Kong show a more pronounced CNY effect prior to the festive season. The rally starts as early as 40 days before the celebration. The effect, however, is not strong after the market re-opens. Lastly, there is no CNY effect in Thailand. One obvious reason is that this market does not have many Chinese investors.

CHAPTER 4

FURTHER EVIDENCE OF MARKET ANOMALIES IN THE KLSE: THE OVERREACTION EFFECT

4.1: Introduction

Over the past decade, a body of research has emerged suggesting that over the long term, some predictability may exist in stock returns (for examples, De Bondt and Thaler, 1985, 1987; Fama and French, 1988; and Poterba and Summers, 1988). This long term behaviour in returns is often characterised as evidence of overreaction by market participants, or linked with a possible mean-reverting returns process. As past returns are being used as the information set to make predictions, the evidence suggests that the market is not weak-form efficient.

Studies on return predictability over short intervals (weekly and monthly returns) using serial correlation tests and runs tests have already been done in the Malaysian market. The results generally confirm what has already been discovered in the US and developed markets, namely that the time-series movement of price changes is best characterised by a random walk (e.g., Yong, 1987; Barnes, 1986; Laurence, 1986; Lanjong, 1983). To my knowledge, there are no published studies examining the behaviour of returns over longer intervals, (for example, studies on the long-run overreaction effect) in Malaysia. It is the aim of this chapter to investigate stock market overreaction in the KLSE. The results would not only add to the growing evidence on stock market overreaction as a whole, but also revise any conclusion on market efficiency in the Malaysian context.

4.2: Descriptions of Data and Methodology

4.2.1: Data

Daily stock returns are calculated using data obtained from *Datastream*. This online computer database gives the daily closing prices of KLSE listed firms, adjusted for stock splits and dividends. The price given is the mid-market closing price, i.e., the bid-ask average, and is therefore not subject to the bid-ask spread bias problem noted in US studies (for examples, Kaul and Nimalendran, 1990; Conrad and Kaul, 1993). Because the KLSE is a relatively young market, and because it has developed at a considerable rate, it is decided that data from the 1970's may be rather out-of-date for this type of study. Data from the eleven year period 1986-1996 inclusive, is used here. The availability of data from *Datastream*, especially dividend data, also influences the choice of time-period for the study. Companies whose share prices and dividends are not available in *Datastream* starting 1986 are deleted from the sample. This procedure leaves 166 companies, all of which are from the main board of the exchange, to be included in the study[1] (The full list of these companies are given in Appendix 1). One result of following this procedure is that it makes sure that only long-established and perhaps the bigger companies are included in the sample; in fact 66 of them are actually constituents of the KLSE Composite Index in 1996. These 166 companies, on average, represent about 50% of the market value of the main board, and slightly less than 50% of the value of the whole market (see Table 4-1). I also ensure that every sector on the main board of the exchange is represented in the sample, as can be seen in Table 4-2. At least a 30% representation from each sector can be observed in the sample.

It should be noted that the sample selection procedure above may cause a survivorship bias in the data set. Some companies which went bankrupt (and therefore delisted) during the study period may be omitted, and this is more likely to be true for portfolio of losers (see later for definition). However, I believe that this problem will not be as serious as it may appear. A list of delisted companies is obtained from the list of suspended/delisted companies published in the KLSE's Investors Digest. Since 1986, there are only 7 Malaysian incorporated companies whose ordinary shares are delisted from the exchange. However, except for one company, these shares are delisted due to acquisition, merger, and reorganisation of the companies, and not due to bankruptcy, as described by the publication. This can be further seen in Table 1-1 (Chapter 1), which shows the number of companies listed by country of incorporation and the new listings for the period 1973-1996. It is clear that the percentage of delisted companies mentioned above is negligible in comparison to the total number of companies. Moreover, DeBondt (1985) suggests that concern over the possibility that a higher attrition rate associated with the 'winner' and 'loser' shares compared with the population attrition rate might bias the magnitude of the overreaction effect was misplaced. I therefore believe that the results in this chapter will least likely be affected by a survivorship bias.

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[1] None of the sample companies comes from the second board since the second board, which consists of

Table 4-1: Average market capitalisation of the samples and the market, in RM billions

Year	Sample	Main Board	%	Total Market	%
1986	33.1	64.5	51.3	64.5	51.3
1987	36.3	73.9	49.1	73.9	49.1
1988	49.7	98.7	50.4	98.7	50.4
1989	83.3	156.0	53.4	156.1	53.3
1990	82.3	131.1	62.8	131.7	62.5
1991	90.4	159.9	56.5	161.4	56.0
1992	103.2	242.9	42.5	245.8	42.0
1993	291.3	606.1	48.1	619.6	47.0
1994	241.3	493.0	48.9	508.9	47.4
1995	264.8	542.8	48.8	565.6	46.8
1996	330.5	665.7	49.6	705.8	46.8

Table 4-2: Sectoral profile of companies in the samples

Sector	Number in sample	Number in sectors[a]	Percentage (%)
Consumer products	29	57	50.9
Industrial products	37	85	43.5
Construction	8	20	40.0
Trading/services	24	63	38.1
Finance	14	47	29.8
Hotels	2	5	40.0
Properties	28	55	50.9
Plantations	18	39	46.2
Minings	6	11	54.5
Totals	166	382	

Note:

a. as at 28 June, 1996.

smaller firms, was only introduced in 1989.

4.2.2: Portfolio formation

Logarithmic returns are used , which are equivalent to the continuous-time returns;

$$R_{j,d} = \ln\left[\frac{P_{j,d} + D_{j,d}}{P_{j,d-1}}\right] \tag{4-1}$$

where; $R_{j,d}$ = return of security j during day d;

$D_{j,d}$ = dividend per share of security j received in day d;

$P_{j,d}$ = price of security j at the end of day d;

$P_{j,d-1}$ = price of security j at the end of day d-1.

According to Strong (1992), the logarithmic returns are both theoretically and empirically preferable. Theoretically, they are analytically more tractable when linking together sub-period returns to form returns over longer intervals, i.e., by simply adding up sub-period returns. Empirically, logarithmic returns are more likely to be normally distributed , and so conform to the assumptions of standard statistical techniques. In addition, the use of logarithmic returns is common in much of the overreaction literature.

A procedure similar to that of DeBondt and Thaler (1985) to construct portfolios, is used here. Daily market-adjusted excess returns, *ERs*, are calculated for every stock j[2], thus;

[2] DeBondt & Thaler (1985) use three types of return residuals - market-adjusted excess returns, market model residuals, and excess returns that are measured relative to Sharpe-Lintner version of CAPM. It turns out that whichever the three are used, the results are similar and do not affect their main conclusion. Therefore, they only report results based on market-adjusted excess returns. Using this type

$$ER_{jt} = R_{jt} - R_{mt} \tag{4-2}$$

where R_{jt} and R_{mt} are the returns of stock j and market respectively. The KLSE Composite Price Index, is used as a proxy for the market. Results from a number of studies (such as those of DeBondt and Thaler, 1985) indicate that evidence of overreaction is not sensitive to whether abnormal performance is measured relative to the market (as here), or relative to some other expected returns model (such as CAPM or market model). This conclusion is perhaps not surprising; a major study conducted by Brown and Warner (1980) finds that sophisticated expected returns models perform no better than simple models, for identifying abnormal performance in equities[3].

Cumulative excess returns, CERs, are then calculated over the 3 years starting January 1986 and ending December 1988, described here as the portfolio formation period (FP);

$$CER_j = \sum_{t=1}^{T} ER_{jt} \tag{4-3}$$

where T is the number of days in the three year period. Stocks are ranked based on their CERs over the 3-year period, and assigned to 10 portfolios of equal number of

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of returns, there is no risk adjustment except for movement of the market as a whole, and the adjustment is identical for all stocks.

[3] Their simulation analysis reveals that the simplest model of all in measuring abnormal performance - the mean adjusted returns model - is able to detect abnormal performance no less frequently than the other more sophisticated models, such as those which are based on the market and risk adjusted returns models. Furthermore, the power of the tests does not appear to be enhanced by using risk adjustment procedures suggested by the Asset Pricing model. In fact, the authors suggest that more complicated methodologies can actually make researchers worst off, as these models can bring their own problems.

stocks. Portfolio 1 consists of stocks with the highest CERs (winners) while portfolio 10 is made up of stocks with the lowest CERs (losers). With 166 stocks in the sample, I allocate 17 stocks each in the winner and loser portfolios[4]. According to DeBondt and Thaler (1985), overreaction effect is especially true for the extreme portfolios; not only that the movements in stock prices will be followed by subsequent price movements in the opposite direction, but also the more extreme the initial price movement, the greater will the subsequent adjustment be. I therefore concentrate only on these two portfolios.

In the following 3 years, i.e., from January 1989 to December 1991, described here as the test period (TP), the CERs of all stocks in the winner and loser portfolios are calculated. The mean of these CERs represents the cumulative excess returns for an equal weighted portfolio, with daily rebalancing. This procedure is repeated, with starting date for FP and TP being advanced by one year, i.e., January 1987, January 1988, and so on for FP, and correspondingly January 1990, January 1991, and so on for TP. This procedure yields a total of 6 FPs and TPs for the analysis, summarised in Table 4-3 below. Hereafter, for brevity, individual formation and test periods will be referenced by the numbers 1,...,6, as defined in the table. As the table reveals, overlapping periods are used in this study. However, this may not create a problem since for all statistical tests in this study, a pooled data of test periods is not used. Thus, problems such as double or even triple counting of data is avoided. Moreover, an extended period would be needed if non-overlapping periods were to be used. For

[4] Different studies have defined portfolios of winner and loser differently. DeBondt and Thaler define winners and losers as being the best and worst 35 performing stocks respectively. Zarowin (1990) uses the top and bottom quintiles , Chopra, *et al* (1992) the top and bottom 5%, and Kryzanowski and Zhang (1992) and Dissanaike (1997) the two extreme deciles . Clare and Thomas (1995) suggest that

Table 4-3: Formation period and test period for KLSE stocks

Period	Formation Period (FP)	Test Period (TP)
1	1986-88	1989-91
2	1987-89	1990-92
3	1988-90	1991-93
4	1989-91	1992-94
5	1990-92	1993-95
6	1991-93	1994-96

example, a six non-overlapping periods means that the required data set should go as far back as 1979, the year when the KLSE was just 6 years formally established, with just over 200 companies listed and no index that represented the whole market[5]. Not only that, none of the KLSE companies with 1979 data is available in *Datastream* for analysis[6]. Furthermore, as argued by Dissanaike (1997), the use of non-overlapping periods does have its own shortcomings, such as the inevitable loss of information and the failure to detect any effect of economy-wide (3-5 years) cyclical factor on the consistency of the success (or failure) of the contrarian strategy. Therefore, disaggregated results and tests for individual test periods would be given more emphasis, whilst the aggregated results would only be given to show the overall picture.

The whole procedure above (see equation 4-3) represents the 'arithmetic method' in computing cumulative excess returns, and is in fact commonly used in overreaction

differences in defining winner and loser portfolios could explain the different results in overreaction studies. The authors themselves use quintile in forming portfolios.

[5] As mentioned earlier, the KLSE Composite Index was only launched in 1986. Prior to its introduction, investors could only gauge the market based on the then existing six sectoral indices.

[6] KLSE companies' share data are only available in *Datastream* from 1985 onwards. This, however, involves very few companies

studies. However, Dissanaike (1993, 1994) argues that it is an unsatisfactory and inaccurate method in computing multi-period returns from single-period returns since the strategy involves rebalancing to equal weights in each single period. He suggests the buy-and-hold method be used. Instead of adding up together single period returns, they should be multiplied, as shown below;

$$\overline{CER}_{BH} = \frac{1}{N}\sum_{j}^{N}\left(\prod_{t=0}^{T} r_{jt} - \prod_{t=0}^{T} r_{mt}\right) , \qquad (4\text{-}4)$$

where $\overline{CER}_{BH}$ is the mean CER for winner and loser portfolios using the buy-and-hold strategy, N is the total number of stocks in the portfolios, T is the total number of time periods (days), r_{jt} is the return on stock j in day t, where the return is defined as the price-relative inclusive of dividends, and r_{mt} is the return on the market in the same period. This method does not imply any rebalancing; the success of contrarian strategy is judged purely on the basis of the one-off decision to buy or sell at the portfolio formation date. It involves lower transaction costs, and is less affected by the problem of infrequent trading. However, as pointed out by Dissanaike, the buy-and-hold method could result in a reduction of diversification as stocks whose prices have risen over time, will carry more weight in the portfolio than those whose prices have fallen.

For comparison, the results using the buy-and-hold method above will also be reported. Any differences in the results can therefore be attributable to the return metric being used. However, to be in line with most of the overreaction studies, the results using the arithmetic method of computing cumulative excess returns will be given more prominence.

4.2.3: Testing for overreaction

A number of tests are conducted to analyse overreaction in the KLSE. The tests in parts (a) and (b) in this chapter provide an initial investigation of the overreaction effect in the KLSE stocks. Part (a) investigates whether stocks with poor (good) price performance over a three-year period, become relatively better (worse) performers over the following three-year period. This process would be consistent with overreaction by market participants, and suggests a possible mean reverting component in the generating process for KLSE stock returns. The potential for exploiting these patterns through arbitrage is investigated in part (b), where test period excess returns are compared between winner and loser portfolios. The next chapter (Chapter 5) will analyse, in more detail, the results of the initial investigation of overreaction patterns examined in parts (a) and (b) above by looking at two possible factors which have been proposed as an alternative explanation for overreaction, namely time-varying risk and the size effect. Chapter 6 will examine any potential seasonal patterns in the excess returns profile for winner and loser portfolios.

The test procedures used here include both parametric and non-parametric methods. Although parametric tests are more powerful, non-parametric tests are generally more robust to non-normal distributions and extreme observations.

a. <u>Differences between formation period and test period CERs for a specific portfolio</u>

For all individual winner and loser portfolios, a comparison is made between CERs in the formation period and in the test period. Are good/poor CER values in the first three years (the formation period, FP) followed by a reversal of fortunes in the next three years (the test period, TP)?

The winner and loser portfolios for a particular period p (p = 1, 2, ..., 6) each contain 17 stocks and therefore there are 17 FP and TP CER values. Since changes in CERs for a specific portfolio are tested here, two tests for related samples are used; the parametric paired *t*-test and the non-parametric Wilcoxon Signed Ranks test. The hypotheses for the *t*-test are as follows, relating to the mean CER values in the FP and TP;

For winner portfolios:

H_0: $\overline{CER}_{FP} = \overline{CER}_{TP}$

H_1: $\overline{CER}_{FP} > \overline{CER}_{TP}$

For loser portfolios:

H_0: $\overline{CER}_{TP} = \overline{CER}_{FP}$

H_1: $\overline{CER}_{TP} > \overline{CER}_{FP}$

The Wilcoxon Signed Ranks test is employed in a similar manner, although it tests for general shifts in the distribution rather than concentrating on the mean of the distribution. For additional information, median CER values are also calculated. These tests are conducted for each of the six periods ($p = 1, 2, \ldots, 6$).

b. Differences between winners' and losers' CERs in the test periods

Assuming no transaction costs, an arbitrage portfolio, created by short selling winners and buying losers generates cumulative excess returns for the portfolio, CER_A, i.e.;

$$CER_A = CER_L - CER_W \tag{4-5}$$

where the cumulative excess returns are the values obtained over the test period for winners (CER_W) and losers (CER_L). Under a random walk process, such an arbitrage portfolio would not be expected to generate excess returns. Significant differences in test period CERs for winners and losers would indicate potential profits from the contrarian based arbitrage trading strategy. Differences in winners' and losers' test period CERs are examined here using tests for independent samples; the parametric *t*-test for two independent samples, and the non-parametric Mann-Whitney *U*-test. Here we are concentrating only on the test period CERs; we examine the CER differentials for winners and losers for each period (p = 1, 2, ..., 6). Both the winner and loser portfolios for a particular period contain 17 stocks and thus 17 CERs. The hypotheses for the *t*-test are that, in the test period;

H_0: $\overline{CER_L} = \overline{CER_W}$

H_1: $\overline{CER_L} > \overline{CER_W}$

The Mann-Whitney *U*-test is not based on the mean CER values but examines general differences in central tendency. Median CER values are also calculated. The results of the initial test of stock market overreaction in parts (a) and (b) above will be given in section 4.3 below.

4.3: Initial Evidence of Mean Reversion in KLSE Stock Returns

Table 4-4 gives the CER differentials between formation period and test period for both winner and loser portfolios. It shows that in all period, winners' mean and median CER values are higher in the formation period than in the test period, as reflected in the positive CER differentials in column 2. The differences in the formation period and test period CERs for this portfolio are all significant at the 0.05 level. The reverse is true for loser portfolios; in all periods, the mean and median CER values are significantly greater in the test period than in the preceding formation period. These results are therefore consistent with those in the US and the UK studies reviewed earlier in Chapter 2. For comparison, the results of the same analysis using the buy-and-hold method are also reported in Table 4-5. No major differences are observed between the results in Table 4-4 and Table 4-5, even though using the buy-and-hold method generally yields less significant results (except for periods 2 and 6 for winner portfolio) than using the arithmetic method.

Both tables therefore give a strong indication that there are significant return reversals in KLSE stocks. Specifically, stocks which perform very well in a three-year period relative to the market, will experience a reversal of fortune in the next three years as their prices decline. The reverse is true for those which experience a price decline in the three-year formation period. Their returns in the next three-year are higher relative to the market. This evidence is therefore consistent with returns patterns which may be expected in the presence of market overreaction or mean reverting behaviour in stock returns.

Figure 4-1 illustrates the mean reversions in the level of CERs of winners and losers in each of the 3-year formation period (year -3 to year -1) and 3-year test period (year 1 to year 3). As can be seen, the performance differential of winners and losers diverges in the formation period. Roughly towards the end of the third year of the formation period, however, the CER values tend to converge; winners' CERs start losing the momentum and is decreasing at a fast rate, while losers' CERs is improving and is increasing at a fast rate, too. As predicted by the overreaction hypothesis, the fortune of both portfolios reverses in the test period, as revealed by the figure. Losers start to outperform winners as early as the first half of the first year in the test period. The rate of divergence in performance increases until the end of the first year. The performance of losers slow down thereafter, while winners start to pick up again at a steady rate. Roughly towards the end of the third year into the test period, the CER values of the portfolios converge again. Consistent with the claim made by DeBondt and Thaler, the figure reveals that, winners' and losers' fortune changes in an interval of three years.

Table 4-4: CER differentials between formation period and test period for winner and loser portfolios, using the arithmetic method

A. Winner portfolios

Period	Mean CER_{FP} - Mean CER_{TP}	*t*-value	Median CER_{FP} - Median CER_{TP}	Wilcoxon test statistic
1	0.63	5.19*	0.60	149.0*
2	1.50	13.14*	1.48	153.0*
3	0.99	5.40*	1.02	147.0*
4	0.75	4.96*	0.82	144.0*
5	0.74	3.50*	0.74	135.0*
6	2.15	9.66*	2.14	153.0*

B. Loser portfolios

Period	Mean CER_{TP} - Mean CER_{FP}	*t*-value	Median CER_{TP} - Median CER_{FP}	Wilcoxon test statistic
1	1.87	11.88*	1.93	153.0*
2	1.09	5.58*	0.93	153.0*
3	1.73	7.86*	1.60	153.0*
4	1.37	10.48*	1.36	153.0*
5	0.54	5.18*	0.52	153.0*
6	0.60	6.66*	0.59	153.0*

Notes:

CER_{FP} = cumulative excess returns over 3-year formation period;

CER_{TP} = cumulative excess returns over 3-year test period;

t-value = *t*-statistic for paired *t*-test of differences in sample means;

Wilcoxon = Wilcoxon Signed Ranks test statistic for testing differences in sample median between two related samples;

* indicates significant at the 0.05 level.

Table 4-5: CER differentials between formation period and test period for winner and loser portfolios, using the buy-and-hold method

A. Winner portfolios

Period	Mean CER_{FP} - Mean CER_{TP}	*t*-value	Median CER_{FP} - Median CER_{TP}	Wilcoxon test statistic
1	0.593	3.29*	0.645	133.0*
2	1.532	15.95*	1.527	133.0*
3	0.905	2.07*	1.224	118.0*
4	0.539	1.68*	0.804	114.0*
5	0.658	1.95*	0.773	124.0*
6	2.062	11.89*	2.078	153.0*

B. Loser portfolios

Period	Mean CER_{TP} - Mean CER_{FP}	*t*-value	Median CER_{TP} - Median CER_{FP}	Wilcoxon test statistic
1	1.552	7.40*	1.478	153.0*
2	1.009	3.41*	0.629	153.0*
3	4.360	2.93*	2.186	150.0*
4	1.139	4.02*	0.943	152.0*
5	1.071	5.78*	0.909	153.0*
6	0.050	5.48*	0.446	153.0*

Notes:

CER_{FP} = cumulative excess returns over 3-year formation period;

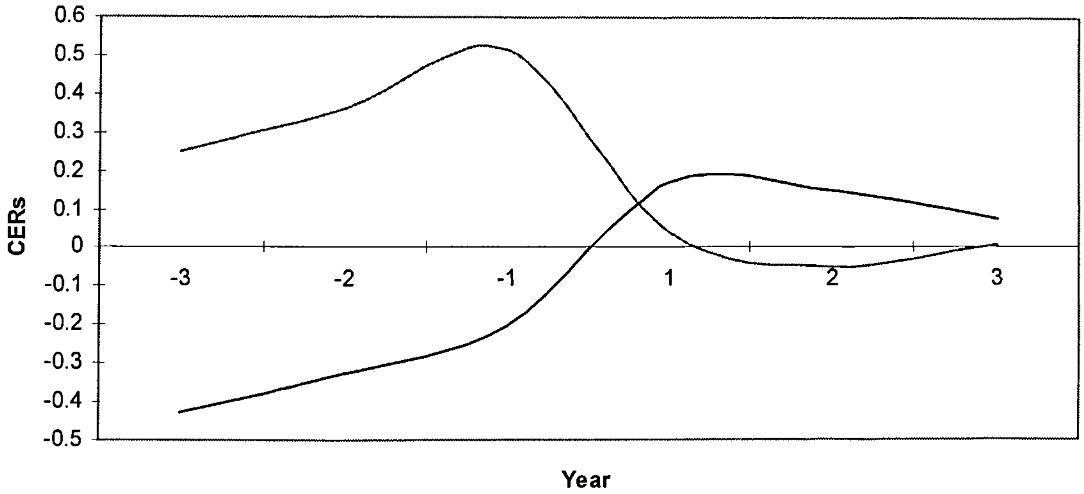
CER_{TP} = cumulative excess returns over 3-year test period;

t-value = *t*-statistic for paired *t*-test of differences in sample means;

Wilcoxon = Wilcoxon Signed Ranks test statistic for testing differences in sample median between two related samples;

* indicates significant at the 0.05 level.

Figure 4-1: Mean reversions in the level of winners' and losers' CERs in the formation and test periods, pooled across six periods



Following on from the results in Tables 4-4 and 4-5, the results in Tables 4-6 and 4-7 provide some evidence of the CER differentials between winners and losers in the three-year test periods. It actually summarises how much profit an arbitrageur would reap (or losses he will suffer) by using a contrarian investment strategy of buying losers and short-selling winners.

Table 4-6 clearly shows that losers consistently outperform winners in all six test periods. As predicted by the overreaction hypothesis, mean and median CER values are greater for losers than for winners. However, only in three periods are the differences significant at a 0.05 level, i.e., periods 2, 3 and 6. Thus, the potential profits from an arbitrage portfolio may not always exist (or be worth exploiting) once transaction costs are taken into account. The results of the analysis using the buy-and-hold method are given in Table 4-7. Though there are some differences, there are also some striking similarities in the results. The most notable difference is that losers no longer outperform winners consistently in the test period, as is observed in periods 1, 4 and 5 where winners actually perform better. However, statistically, this is not significant at any conventional level; the observed *t*-values of -0.96, -0.53 and -0.85 are considered small. The similarity of the results can be seen in terms of the periods where losers outperform winners, and the significance of these superior performances. In periods 2, 3 and 6, losers significantly outperform winners, just as they do when the arithmetic method is used (see Table 4-6), though the *t*-values and the Mann-Whitney *U*-statistics are comparatively smaller. Therefore, we can claim that though the use of different return metric may change the CER values of some winner and loser constituents, it does not significantly affect the overall results regarding mean reversions of both portfolios. Hereafter, therefore, only the results based on the

Table 4-6: Differences between winners' and losers' CERs in the test periods, using the arithmetic method

Period	Mean CER_L	Mean CER_W	Mean CER_L - Mean CER_W	*t*-value	Median CER_L - Median CER_W	M-W-U
1	0.075	-0.008	0.083	0.45	-0.021	306.0
2	0.067	-0.397	0.464	2.67*	0.176	371.0*
3	0.922	0.072	0.850	3.44*	0.049	388.0*
4	0.607	0.376	0.231	1.25	0.014	330.0
5	0.540	0.356	0.184	1.03	0.721	320.0
6	0.153	-0.424	0.577	3.07*	0.314	377.0*

Notes:

CER_L = losers' cumulative excess returns over 3-year test period;

CER_W = winners' cumulative excess returns over 3-year test period;

t-value = *t*-statistic for *t*-test of differences in sample means for two independent samples;

M-W-U = Mann-Whitney *U*-test statistic for testing differences in sample medians between two independent samples;

* indicates significant at the 0.05 level.

Table 4-7: Differences between winners' and losers' CERs in the test periods, using the buy-and-hold method

Period	Mean CER_L	Mean CER_W	Mean CER_L - Mean CER_W	*t*-value	Median CER_L - Median CER_W	M-W-U
1	-0.248	0.025	-0.223	-0.96	-0.248	255.0
2	-0.012	-0.429	0.441	1.61**	0.013	330.0
3	3.551	0.161	3.390	2.19*	1.400	371.0*
4	0.374	0.590	-0.216	-0.53	0.253	284.0
5	0.162	0.442	-0.280	-0.85	0.051	274.0
6	0.049	-0.336	0.385	2.60*	0.636	397.0*

Notes:

CER_L = losers' cumulative excess returns over 3-year test period;

CER_W = winners' cumulative excess returns over 3-year test period;

t-value = *t*-statistic for *t*-test of differences in sample means for two independent samples;

M-W-U = Mann-Whitney *U*-test statistic for testing differences in sample medians between two independent samples;

* indicates significant at the 0.05 level;

** indicates significant at the 0.10 level.

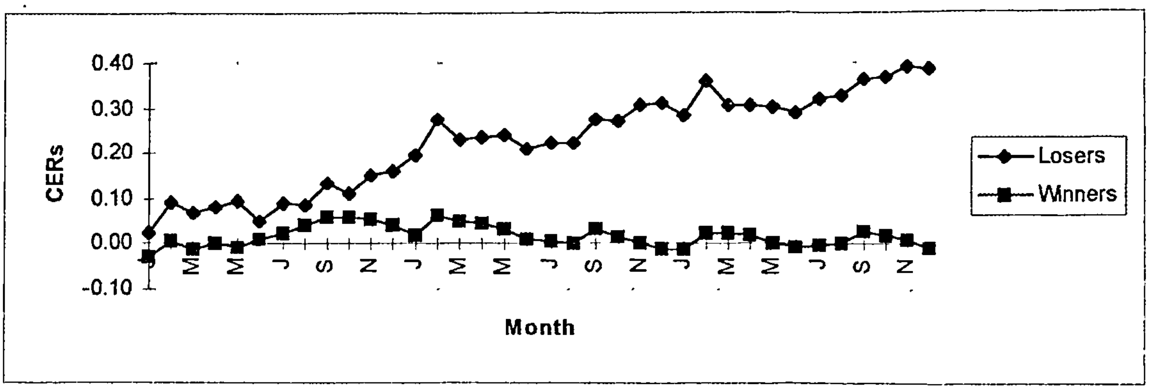
arithmetic method for computing excess returns will be reported.

Table 4-6 also indicates a degree of asymmetry regarding the test period CERs for winner and loser portfolios. Mean CERs for losers are positive for all six periods, indicating above-market performance as expected. However, CERs for winners are negative for only three periods (p = 1,2,6). Winners' CERs in periods 3, 4 and 5 are still positive. Thus, the under-performance of winners in the test periods is not as dramatic as the above-market performance of losers. This may be due to the fact the KLSE was booming tremendously in these periods, especially in 1993, so that it offsets some effect of overreaction for winners (i.e., by reducing their price decline) while at the same time, it amplifies the overreaction effect for losers (i.e., by increasing their excess returns). That is why overreaction is more pronounced for the loser stocks in this market. The asymmetry mirrors results from the US (De Bondt and Thaler, 1985), and the UK (Power, 1992) studies of overreaction, and can be seen in the graphical representation of the KLSE data in Figure 4-2. Panel A shows the CERs of winners and losers, cumulated over the 36 months test period for the whole periods combined, while Panel B the cumulated CERs for each test period. With the exceptions of the first 20 months in test period 3 and the first 14 months in test period 4, the panels generally reveal the superiority of performance of losers over winners in all six test periods.

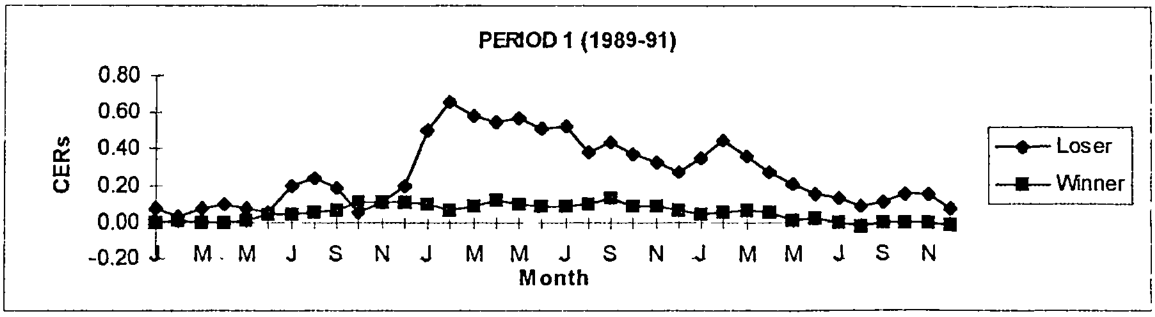
There are two possible (rational) explanations for this observed phenomenon. One is that, the systematic risk (beta) of losers and winners have changed from the formation to test periods, and that there may be some risk differences between losers and winners in the test periods. Secondly, it may be that this overreaction effect is just another reincarnation of the size effect. Losers yield higher excess returns because they have become smaller in the test periods, while winners have become bigger in the test periods. These two possibilities are explored in the next chapter.

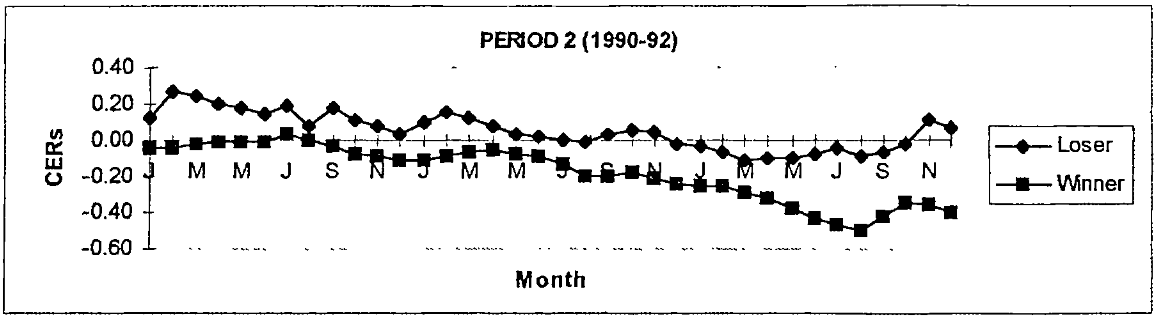
Figure 4-2: CERs for winner and loser portfolios, cumulated over 3-year test period

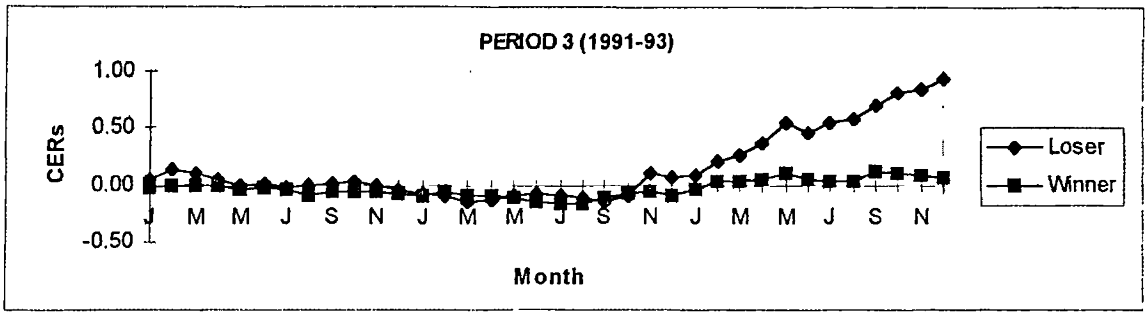
A. All period

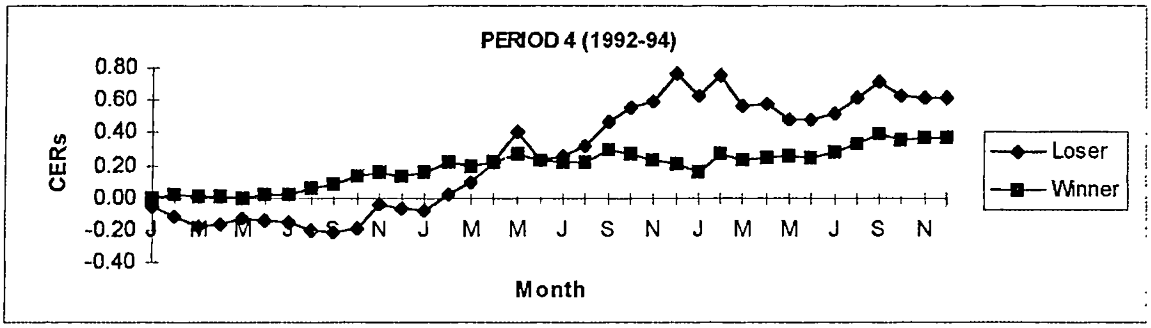


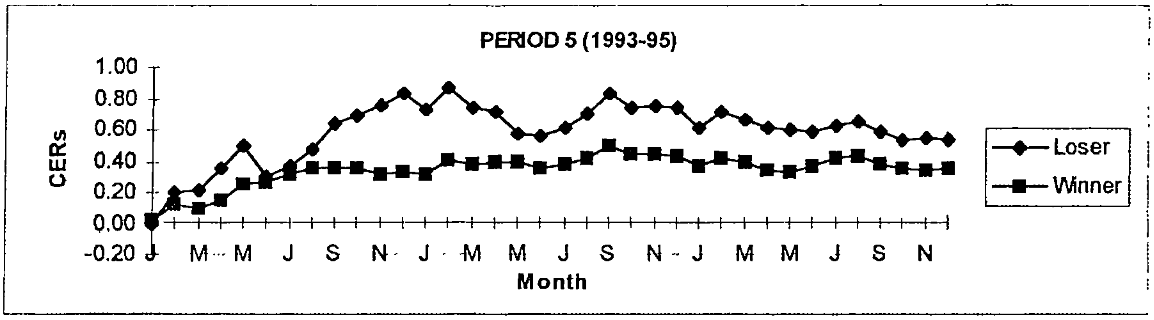
B. Subperiods 1 6

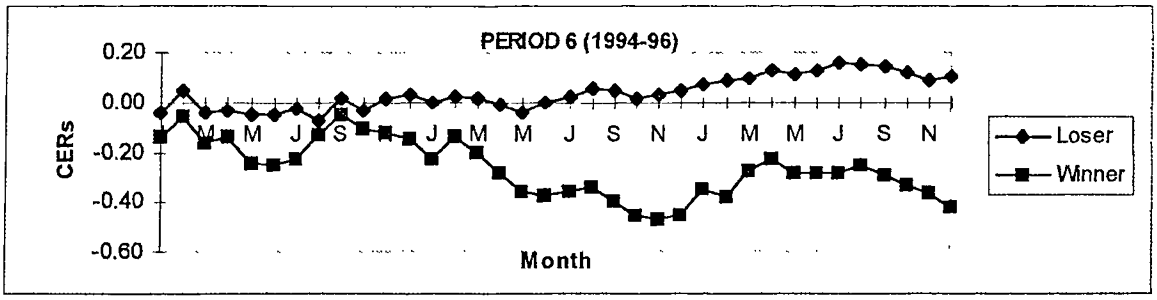





PERIOD 3 (1991-93)
1.00
0.50
0.00
-0.50
CERs
J M M J S N J M M J S N J M M J S N
Month
Loser
Winner


PERIOD 4 (1992-94)
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
CERs
J M M J S N J M M J S N J M M J S N
Month
Loser
Winner


PERIOD 5 (1993-95)
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
CERs
J M M J S N J M M J S N J M M J S N
Month
Loser
Winner


PERIOD 6 (1994-96)
0.20
0.00
-0.20
-0.40
-0.60
CERs
M M J S J M M J S N J M M J S N
Month
Loser
Winner

4.4: Limitation: Transaction Costs for Daily Returns

This chapter's analysis of KLSE stocks utilises daily returns. However, realising such returns would require daily trading, which would incur substantial transaction costs. As described in Chapter 1, there are some costs associated with trading on the KLSE, such as the brokerage fees (see section 1.3.1). Therefore, the potential for profitable exploitation of the overreaction effect documented in the study may be severely limited. Even though the buy-and-hold method used in the previous section, to some extent, has already reduced transaction costs, this section will look at another way to reduce transaction costs, using the arithmetic method in computing returns. The comparison of winner and loser portfolios, used in section 4.3, is therefore repeated , but using annual returns data also obtained from *Datastream.* This low frequency trading will incur relatively small transaction costs, since only three times the costs are incurred in the three-year period. Because transaction costs are taken into consideration, any profit earned will therefore be more realistic. The results are summarised in Table 4-8. It appears that the use of annual returns does not change the results substantially. The results indicate that the contrarian trading strategy offers potential profits for each of the six test periods, although winner-loser differences are only significant at the 0.05 level for two of these periods, i.e., periods 2 and 3. Recalling the results from the analysis using daily returns, the differences in CERs is also significant for period 6, besides the two periods above. In period 2 and 3, employing a contrarian strategy will earn an investors a gross profit of 34.9 % and 71.3% respectively. Therefore, it can be argued that, the contrarian investment strategy of buying losers and selling winners is worth undertaking. The winner-loser anomaly is indeed worth exploiting.

Table 4-8: Differences between winners' and losers' CERs in the test periods, using annual returns

Period	Mean CER_L	Mean CER_W	Mean CER_L - Mean CER_W	*t*-value	Median CER_L - Median CER_W	M-W-U
1	0.236	0.008	0.228	1.30	0.118	330.0
2	0.150	-0.199	0.349	2.15*	0.176	353.0*
3	0.759	0.046	0.713	3.06*	0.666	373.0*
4	0.583	0.350	0.233	1.27	0.022	331.0
5	0.472	0.325	0.147	0.85	0.002	320.0
6	0.119	-0.172	0.291	1.54	0.318	340.0

Notes:

CER_L = losers' cumulative excess returns over 3-year test period;

CER_W = winners' cumulative excess returns over 3-year test period;

t-value = *t*-statistic for *t*-test of differences in sample means for two independent samples;

M-W-U = Mann-Whitney *U*-test statistic for testing differences in sample medians between two independent samples;

* indicates significant at the 0.05 level.

4.6: Conclusion

The analyses in this chapter provide strong evidence that there are patterns of mean reversions in KLSE stock returns. Stocks which underperform the market in a three-year period (losers) are found to fare better than the market in the following three years. The opposite is true for stocks which have outperformed the market (winners); they find that their fortune reverses in the subsequent three-year period. There is also evidence of potential profits from arbitrage trading based on short selling winners and buying losers. Using different methods in calculating cumulative excess returns does not change the results significantly. Although the main analysis using daily returns makes an assumption that there is no transaction costs, further analysis using annual returns and buy-and-hold returns suggests that profitable opportunities are still there to be exploited.

CHAPTER 5

DO TIME-VARYING RISK AND SIZE EXPLAIN OVERREACTION?

5.1: Introduction

Preliminary findings in Chapter 4 are consistent with the findings in US and UK studies that there are mean reversions in stock returns over the long-term in the KLSE. Winner and loser stocks over the past 36 months will experience reversals in their fortunes in the following 36 months. The argument, as advanced by De Bondt and Thaler (1985), is that investors overreact to new information, such as earnings announcements, due to wave of optimism and pessimism, and subsequently correct themselves. This irrational behaviour of market participants is the reason why stock prices take temporary swings away from their fundamental values, and leads De Bondt and Thaler to investigate the overreaction hypothesis.

However, two major arguments have been advanced against the hypothesis. Firstly, as claimed by Chan (1988) and Ball and Kothari (1989), there is a measurement error in beta estimated from the rank period as done by DeBondt and Thaler; since losers' betas increase during the rank period, the rank period beta underestimates the test period beta. Secondly, mean reversions are claimed to be the consequences of changes in the size of winners and losers (Zarowin, 1989, 1990). An increase in the winner's price in the formation period will result in an increase in its market value. Likewise, a decrease in the loser's price in the formation period will result in a decrease in its market value. It may be that differences in the market value for winners and losers explain any return differentials, as predicted by the size effect. In other words, overreaction is really a reincarnation of the size effect.

The objective of this chapter is to provide additional evidence which will help to resolve the above issues. An analysis of the relationship between risk and mean reversions will first be carried out, followed by an analysis of the size effect and its interaction with mean reversions in the KLSE stock returns.

5.2: Description of Methodology

5.2.1: Testing the relationship between overreaction and changes in systematic risk

Any excess returns which are identified in tests (a) or (b) in section 4.2.3, may be explained by changes in systematic risk (beta). For example, for firms experiencing significant price appreciation (i.e., winners), the market value of equity rises and gearing falls - assuming no changes in the market value of debts - thus reducing beta. The reverse process applies to losers. These changes may explain the apparent overreaction in stock returns, detected in part (a). It may also be that there exist significant risk differentials between loser and winner portfolios in the test period. This may explain excess return differentials identified in part (b) of the analysis.

In order to determine whether time-varying risk and risk differentials play a role in the performance of winner and loser portfolios, the following test is carried out. Systematic risk is first estimated for winner and loser portfolios for both formation and test periods, using the market model as below;

$$R_{it} = \alpha_i + \beta_i R_{mt} + e_{it} \tag{5-1}$$

where R_{it} is the return of stock i, R_{mt} is the return of the market, α_i is a constant term, and e_{it} is the error term. The slope coefficient, or β_i, represents the systematic risk of the stock. Estimated betas are then examined for evidence that (i) the beta for specific portfolios changes from the formation period to the test period, and (ii) that the test period beta is greater for losers than for winners, thus explaining return differentials.

For parts (i) and (ii), tests for related samples and independent samples are employed respectively. These tests are identical to those used to examine differences in CERs for tests (a) and (b) in Chapter 4. Thus, for the first analysis, two tests for related samples are used here; the parametric paired t-test and the non-parametric Wilcoxon Signed Ranks test - to examine changes in a portfolio's beta values over time. The hypotheses for the t-tests are as follows, relating to the mean beta values in the test period (TP) and the formation period (FP);

For winner portfolios:

H_0: $\overline{BETA}_{FP} = \overline{BETA}_{TP}$

H_1: $\overline{BETA}_{FP} > \overline{BETA}_{TP}$

For loser portfolios:

H_0: $\overline{BETA}_{TP} = \overline{BETA}_{FP}$

H_1: $\overline{BETA}_{TP} > \overline{BETA}_{FP}$

The Wilcoxon Signed Ranks test is employed in a similar manner, as a non-parametric alternative. The second analysis concerns beta differential between winners and losers in the test periods. Differences in winner and loser test period betas are examined here using tests for independent samples; the parametric *t*-test for two independent samples, and the non-parametric Mann-Whitney *U*-test. The hypotheses for the *t*-test are that, in the test period;

H_0: $\overline{BETA}_L = \overline{BETA}_W$

H_1: $\overline{BETA}_L > \overline{BETA}_W$

The Mann-Whitney *U* test is also utilised to examine differences in winners' and losers' beta values in the test periods, as a non-parametric alternative to the *t*-test. Section 5.3 will discuss the results obtained from the test in this section.

5.2.2: Testing for size effect and and its interaction with overreaction

In order to determine whether size effect has any influence on the mean reversion of CER values for winner and loser portfolios, an investigation is first carried out to determine whether a size effect is present in the KLSE stocks. All of the same 166 firms are first ranked based on their market values at the end of each formation period. The market value data is obtained from *Datastream*. The largest and smallest 17 firms are placed into two extreme portfolios. Test periods CERs for these small firms and large firms portfolios are examined for evidence of the size effect. Tests for independent samples are employed (*t*-test and Mann-Whitney *U*-test) to examine whether, on average, the small firm portfolio generates greater CERs than the large firm portfolio. The hypotheses for the *t*-test are that, in the test period;

H_0: $\overline{CER}_{small} = \overline{CER}_{large}$

H_1: $\overline{CER}_{small} > \overline{CER}_{large}$

To examine whether there is any interaction between overreaction and firm size effect, the number of common firms between the winner/loser and small/large firm portfolios is described. The potentially profitable portfolios are the small firms portfolio and the loser portfolio. To examine any potential interaction, the following bi-variate regression models are used. For the loser firms portfolio, the importance of firm size (at the end of the formation period) is examined using the regression;

$$CER_{TP,j} = \phi_1 + \phi_2 . SIZE_{FP,j} + \upsilon_j \qquad (5\text{-}2)$$

where $SIZE_{FP,j}$ is the market value of firm j at the end of the formation period and υ_j is a random error term following usual OLS assumptions. The influence of the formation period CERs is therefore controlled for whilst investigating the effect of size on the test period CERs. If size has additional explanatory value, then the slope coefficient should be negative and significant. The non-parametric Spearman rank correlation coefficient for these two variables is also computed.

For the small firm portfolio, the importance of being a (formation period) loser is examined using the regression;

$$CER_{TPj} = \gamma_1 + \gamma_2.CER_{FPj} + \xi_j \tag{5-3}$$

where CER_{TPj} and CER_{FPj} are the test period and formation period CERs for stock j, and ξ_j is a random error term following the usual OLS assumptions. The main idea of regression 5-3 is to study the relationship between formation period CERs on test period CERs while controlling for firm size, so that any excess return reversals observed could not be attributed to size differentials. Since all firms in this portfolio are small, the loser effect should be indicated by a significant negative slope estimate. The non-parametric Spearman rank correlation is also computed for these two variables.

For regressions 5-2 and 5-3, significant overreaction and size effects will lead to negative values for ϕ_2 and γ_2 respectively; thus one-tail t-tests are employed here. The null and alternative hypotheses for these regressions are as follow;

H_0: $\phi_2 = 0$

H_1: $\phi_2 < 0$

H_0: $\gamma_2 = 0$

H_1: $\gamma_2 < 0$

5.3: Time-Varying Risk and Mean Reversions

This section reports the results of the analysis in section 5.2.1. Recall that CER values for winners are significantly greater in the formation period than in the following test period (see Table 4-4, Chapter 4). The opposite is true for losers. However, this apparent evidence of overreaction or mean reverting behaviour could be the result of changes in systematic risk between formation period and test period. If winners' beta values decrease and losers' beta values increase, this may explain the results in Table 4-4. The results in Table 5-1 below provide some evidence on beta changes.

It reveals that for winners, the mean and median beta values are generally greater in the formation period than in the test period. However, this difference is only significant for one of the six periods ($p = 3$). More interestingly, for the final period ($p = 6$), the average formation period beta is significantly *less than* the test period beta. It would be difficult to suggest that the beta changes reported here could explain the significant evidence of mean reversion for winners reported in Table 4-4, Chapter 4. For losers, it is found that test period betas are greater than formation period betas; this difference is significant for four out of six periods under study ($p = 1,2,4,5$)[1]. While these changes may explain

[1] For period 5, the parametric t-test and the non-parametric Wilcoxon signed ranks test produce quite inconsistent results insofar as significance is concerned. However, this is in fact, not a major inconsistency. The p-value of the Wilcoxon signed ranks test (not reported in the table) is actually 0.054 - very closed to being accepted at the 0.05 level of significance.

Table 5-1: Systematic risk (beta) differentials between formation period and test period for winner and loser portfolios

A. Winner portfolios

Period	Mean $BETA_{FP}$ - Mean $BETA_{TP}$	*t*-value	Median $BETA_{FP}$ - Median $BETA_{TP}$	Wilcoxon test statistic
1	0.03	0.59	0.03	86.0
2	0.02	0.26	0.02	73.5
3	0.23	3.47*	0.22	133.5*
4	0.11	1.29	0.11	102.0
5	0.08	0.72	0.09	82.0
6	-0.35	-3.80*	-0.34	138.0^{x}

B. Loser portfolios

Period	Mean $BETA_{TP}$ - Mean $BETA_{FP}$	*t*-value	Median $BETA_{TP}$ - Median $BETA_{FP}$	Wilcoxon test statistic
1	0.47	8.92*	0.46	153.0*
2	0.36	3.18*	0.36	121.5*
3	0.01	0.07	-0.01	73.0
4	0.56	5.52*	0.58	148.0*
5	0.21	1.90*	0.14	111.0
6	0.05	1.07	0.05	91.0

Notes:

$BETA_{TP}$ = Beta estimated over 3-year test period;

$BETA_{FP}$ = Beta estimated over 3-year formation period;

t-value = *t*-statistic for paired *t*-test of differences in sample means;

Wilcoxon = Wilcoxon Signed Ranks test statistic for testing differences between two related samples

* indicates significant at 0.05 level;

^{x} indicates that this test statistic is the 'wrong sign' in relation to the one-tail test. Using a two-tail test, this *t*-value is highly significant (even at 0.01 level).

increased returns in the test period, the changes for the two non-significant period (p = 3, 6) would unlikely explain the significant overreaction pattern for losers identified for these periods (see Table 4-4). Thus, the mean-reverting behaviour identified in Table 4-4 may be partly explained by time-variation in beta values, particularly for losers, but beta changes do not appear to offer a full explanation of this effect.

The results in Table 4-6 in the previous chapter indicate that, over the three-year test periods, losers generate larger CERs than winners. This could be attributed to the differences in test period betas for winners and losers. In fact, Table 5-2 below reveals that for three of the six test periods (p = 1,4,5), betas for loser firms are significantly greater than for winners. This may partly explain the CER differentials in Table 4-6.

Recalling the results in Table 4-6, the largest loser-winner CER differentials are found to be in periods 2, 3 and 6. However, Table 5-2 indicates that the beta differentials are not significant for periods 2 and 3, and even shows that for period 6, the losers' beta is smaller than the winners' beta, as indicated by the negative sign. Instead, beta differentials are largest for periods 1, 4 and 5, where the CER differentials are not significant (see Table 4-6). These results suggest that changes in systematic risk of winners and losers, and risk differentials between the two, are unlikely to provide a complete explanation for overreaction effects in the KLSE, as documented in Chapter 4.

Table 5-2: Differences in systematic risk (beta) between winners and losers in the test periods

Period	Mean $BETA_L$ - Mean $BETA_W$	*t*-value	Median $BETA_L$ - Median $BETA_W$	M-W-U
1	0.736	8.08*	0.81	436.0*
2	0.059	0.37	0.27	327.5
3	0.024	0.24	0.08	308.0
4	0.559	6.35*	0.60	423.5*
5	0.517	5.26*	0.57	406.5*
6	-0.378	-3.15^{x}	-0.40	380.0^{x}

Notes:

$BETA_L$ = losers' beta estimated over 3-year period;

$BETA_W$ = winners' beta estimated over 3-year period;

t-value = *t*-statistic for t-test of differences in sample means for two independent samples;

M-W-U = Mann-Whitney *U* test statistic for testing differences between two independent samples

* indicates significant at the 0.05 level;

^{x} indicates that this test statistic is the 'wrong sign' in relation to the one-tailed test. Using a two-tailed test, this *t*-value is highly significant (even at the 0.01 level).

As reviewed earlier in Chapter 2, Jones (1993) suggests that the apparent overreaction in stock returns may be due to the time-varying risk premia as a results of the movement in a three-year real business cycle. However, the calculations of meaningful correlations and autocorrelations for three-year non-overlapping periods requires a time series of data greater than that available for the KLSE. Thus, similar calculations to those of Jones (p. 129, Table 3 and footnote 3) are not possible at this stage of the KLSE history.

5.4: Size Effect and Overreaction

Table 5-3 summarises the mean market value and CERs of portfolios constructed using the stocks of the 17 largest and smallest firms, in each of the six periods. A huge difference in size, as represented by the market value at the end of the formation period, between both portfolios can clearly be observed in columns 2 and 5. There are also some indication of mean reversions in the CER values for both portfolios which take place in the formation and test periods. For small firms, all but one period (p = 6) record positive CER values in the test periods, suggesting a better performance than in previous periods. For large firms, the performance is generally worse in the test period, with the exception of period 5. Like those in the winner-loser analysis, these observations therefore suggest that there is also some indication of 'mean reversion' in the performance of portfolios formed on the basis of size.

Table 5-4 presents test period CER differences for both size-extreme portfolios. This process is similar to the test of overreaction in Section 4.2, except that portfolios are

Table 5-3: Mean market value and CERs of small and large firms portfolios

Period	Small			Large		
	MV	FP_{CER}	TP_{CER}	MV	FP_{CER}	TP_{CER}
1	19.6	-1.2140	0.3500	1585.0	0.2846	0.0734
2	42.4	-0.3730	0.0106	2451.0	0.2926	-0.0875
3	40.4	-0.2671	0.8679	2419.3	0.4539	-0.1771
4	47.4	-0.1410	0.8705	2596.0	0.3085	0.0392
5	50.5	-0.4872	0.8172	2982.6	0.2271	0.2524
6	251.7	0.4726	-0.0572	7444.6	0.6204	-0.1318

Notes:

MV = Market value in RM millions at the end of the formation period;

FP_{CER} = Cumulative excess returns in the formation period;

TP_{CER} = Cumulative excess returns in the test period.

Table 5-4: The firm size effect: CER differentials between small firms and large firms portfolios in the test periods

Period	Mean CER_{small} - Mean CER_{large}	*t*-value	Median CER_{small} - Median CER_{large}	M-W-U
1	0.28	1.36	0.35	350.0*
2	0.10	0.43	0.07	315.0
3	1.05	4.57*	1.08	405.0*
4	0.83	4.35*	0.58	400.0*
5	0.57	3.83*	0.60	391.0*
6	0.08	0.48	0.05	307.0

Notes:

CER_{small} = Small firms' cumulative excess returns over 3-year test period;

CER_{large} = Large firms' cumulative excess returns over 3-year test period;

t-value = *t*-statistic for *t*-test of differences in sample means for two independent samples;

M-W-U = Mann-Whitney *U*- test statistic for testing differences between two independent samples;

* indicates significant at the 0.05 level.

based on size rather than on formation period CERs. It reveals that there is evidence of the firm size effect for KLSE stocks. All periods show positive differentials between small firms' CER values and large firms' CER values, indicating that on average, the former yields higher returns than the latter. For three periods, i.e., periods 3, 4 and 5, the evidence of size effect are significant at 0.05 level. It may be that the apparently strong performance of loser firms as found in Table 4-6, may be a manifestation of the size effect. Losers outperform winners because they may have become smaller in the test periods. Therefore, a preliminary analysis is done to investigate whether winners have become smaller and losers have become larger in the test period. The results of this preliminary analysis is presented in Table 5-5, which shows the changes in average market values of winner and loser firms from formation period to test period. It can be seen that on average, losers are smaller firms than winners; this could explain why losers outperform winners over the test period. However, it is also obvious that except for period 6, losers are smaller than winners in the formation periods. Therefore, it seems that the change in performance of the winner and loser stocks as reflected in their return reversals is not due to the change in size as asserted by Zarowin (1989,1990). In other words, the overreaction effect observed in the KLSE is not a manifestation or reincarnation of the well-known size effect.

Why then are losers outperformed by the winner stocks? It may be that the overreaction effects and the firm size effects operate independently. Further evidence of this can be seen in Table 5-6 where the number of firms which are both the constituents of loser and small firms portfolios at the beginning of the test period, is counted[2]. It would be interesting to know if losers are actually small firms. The same procedure is done with winner and large firms portfolios. The results reveal that, on average, only 25 percent overlap occur between loser and small firm portfolios. The figure is slightly higher for winner and large firms portfolios, i.e., 29 percent. It can therefore be suggested that losers are not the smallest firms, and winners are not the largest firms.

[2] Using the argument put forward by Zarowin (1989, 1990) who argues that losers are becoming smaller by the end of formation period (or equivalently at the beginning of test period), and winners are becoming bigger, we can look at small firms portfolio as losers, since at the end of formation period, their share price is at the lowest level. Likewise, large firms portfolio is winner portfolio since at the end of formation period, their price is at the highest level.

Table 5-5: Market value of the winner and loser portfolios during formation periods and test periods

Period	Winner			Loser		
	FP	TP	Change (%)	FP	TP	Change (%)
1	693	1496	116	65	226	248
2	379	649	71	82	141	72
3	764	1769	132	135	498	269
4	909	2369	161	284	847	198
5	822	2995	264	358	1061	196
6	1127	2479	120	1322	2038	54
Average	782	1959	151	374	802	114

Notes:

FP = 3-year formation period;

TP = 3-year test period;

Market values (in RM millions) are the three-year average across FP and TP.

Table 5-6: Number and percentage of losers in the small firms portfolio, and winners in the large firms portfolio

Period	Losers in small firms portfolio	Percentage	Winners in Large firms portfolio	Percentage
1	5	29%	8	47%
2	5	29%	3	18%
3	3	18%	6	35%
4	4	24%	5	29%
5	8	47%	3	18%
6	0	0%	4	24%
Average	4.17	25%	4.83	29%

Note:

There are 17 companies in each portfolios

Table 5-7: Results of OLS regressions on CER_{TP} against SIZE for loser portfolio

Period	ϕ_1	ϕ_2	R^2 (%)	Spearman
1	-0.235	0.00137	50.1	0.283
	(-1.85)	(3.88)^x		
2	-0.204	0.00192	16.9	0.277
	(-0.98)	(1.74)		
3	0.605	0.00064	9.7	0.150
	(1.89)	(1.27)		
4	0.641	-0.00004	0.7	0.172
	(3.86)*	(-0.32)		
5	0.665	-0.00012	12.8	-0.373
	(5.07)*	(-1.49)		
6	0.174	-0.00001	0.3	0.002
	(1.32)	(-0.20)		

Notes:

Results are based on the OLS regression;

$$CER_{TP,j} = \phi_1 + \phi_2 . SIZE_{FP,j}$$

where $CER_{TP,j}$ = cumulative excess returns over 3-year test period for loser firm *j*;

$SIZE_{FP,j}$ = market value of loser firm *j*, at the end of formation period;

Spearman = Spearman rank correlation coefficient;

t-statistics are in parentheses;

* indicates significant at the 0.05 level;

^{x} indicates that this test statistic is the 'wrong' sign in relation to the one-tailed test. Using a two-tailed test this *t*-value is highly significant (even at the 0.01 level).

Table 5-8: Results of OLS regression on CER_{TP} against CER_{FP} for the smallest firm portfolio

Period	γ_1	γ_2	R^2 (%)	Spearman
1	0.059	-0.240	4.5	-0.240
	(0.15)	(-0.84)		
2	-0.034	-0.121	0.8	-0.088
	(-0.14)	(-0.35)		
3	0.562	-1.147	34.7	-0.542*
	(2.80)*	(-2.83)*		
4	0.749	-0.862*	28.0	-0.569*
	(4.95)*	(-2.42)		
5	0.688	-0.266	15.7	-0.324
	(5.14)*	(-1.67)		
6	-0.048	-0.020	0.1	-0.039
	(-0.32)	(-0.10)		

Notes:

Results are based on the regression;

$$CER_{TP,j} = \gamma_1 + \gamma_2 . CER_{FP,j}$$

$CER_{TP,j}$ = cumulative excess returns over 3-year test period for small firm *j*;

$CER_{FP,j}$ = cumulative excess returns over 3-year formation period for small firm *j*;

Spearman = Spearman rank correlation coefficient;

t-statistics are in parentheses;

* indicates significant at the 0.05 level.

The regression results and Spearman coefficients in Tables 5-7 and 5-8 examine the size effect for loser firms, and the overreaction effect for small firms. If these effects are in operation, the slope coefficients and Spearman coefficients should be negative.

Table 5-7 shows that for loser firms, the slope coefficient is negative for three out of the six periods (p = 4,5,6), but never significant, and the Spearman rank correlation coefficient is negative for only one period (p = 5). This suggests that when formation period performance is controlled for (i.e., all similar losers), the size effect offers little additional explanation for test period CERs. In fact, it may suggest that there is a positive relationship between test period CERs and firm size when prior period CERs are controlled for. This can be seen in the significant slope coefficient for period 1, with a high R^2 value (50.1%). Furthermore, five periods show a positive Spearman rank correlation coefficients. For small firms (Table 5-8), there is stronger evidence for the presence of an overreaction effect. For all six periods, both the slope coefficients and the Spearman coefficients are negative, and for two periods (p = 3,4), the slope is significant at the 0.05 level. Thus, even when size is controlled for, formation period CERs contain explanatory power for test period CERs.

5.5: Limitation: Thin Trading and Beta Estimation

As noted by many previous studies (for examples, Dimson, 1979; Brown and Warner, 1980), the systematic risk or beta estimated from stocks which are traded infrequently may be biased downward. This is especially true for high frequency data such as daily returns, since the chances of infrequent trading are greater for such data. The infrequent trading of these stocks may induce negative serial correlation in return series. Small firms are argued to suffer more from this beta misestimation, since they are less frequently traded. Therefore, returns for small firms are overestimated.

Although the use of daily returns data in this study greatly increases the number of observations (and degrees of freedom) for regression analysis, the presence of thin trading in the KLSE presents potential problems for the estimation of the beta. However, a number of arguments can be made here. Even though a number of 'beta correction' techniques have been suggested (for examples, Scholes and Williams, 1977; Dimson, 1979), empirical studies which have used these corrections in thinly traded markets have noted that these corrections can bring their own problems. These problems are noted in Canadian stock market studies by Fowler and Rorke (1983), and Boabang (1996). In addition, none of the formation period (FP) and test period (TP) beta values for winner and loser portfolios, presented in Table 5-9 below, appear overly extreme.

Table 5-9: Mean beta estimates for winners and losers during formation period (FP) and test period (TP)

Period	Winners' mean beta		Losers' mean beta	
	FP	TP	FP	TP
1	0.85	0.82	1.08	1.55
2	1.16	1.14	0.84	1.20
3	1.11	0.88	0.90	0.91
4	0.97	0.86	0.86	1.42
5	1.02	0.94	1.25	1.46
6	0.95	1.30	0.87	0.92

5.6: Summary and Conclusion

Following on from the initial results in Chapter 4, further analyses are performed to examine if time-varying risk, or beta, and size could explain the observed mean reversions in the KLSE stocks returns. It is found that generally, the betas of the winners (losers) decrease (increase) from formation period to test period, and that the change is more dramatic for loser portfolios. However, significant beta differentials between winner and loser portfolios in certain test periods do not correspond to the significant performance differentials of the portfolios in those periods. Therefore, the observed patterns of mean reversions in the KLSE are not fully explained by the changes in the systematic risk.

The evidence in this chapter also suggests that there exists a size effect in the excess returns of small and large KLSE firms. Small firms are found to outperform large firms in all periods of the study. However, the overreaction effect, as manifested in the return reversals of winner and loser portfolios detected in Chapter 4, is not explained by this size effect. Initial evidence confirms that the constituents of loser and small firms portfolios are not the same. The same is true for winner and large firms portfolios. Furthermore, it is also found that losers are generally smaller, and winners are generally larger in both formation and test periods.

Results from regression analyses suggest that when prior period returns are controlled for, there is no clear relationship between test period returns and firm size. However, when firm size is held constant, it is found that prior period returns do have predictive value on test period returns, suggesting the presence of an overreaction effect which is independent of the size effect. To conclude, there is a separate firm size effect acting upon KLSE stocks. However, this effect does not explain the overreaction effect in the market.

CHAPTER 6

SEASONALITY AND OVERREACTION IN THE KLSE

6.1: Introduction

One of the most common findings in the literature on stock market overreaction is that there is a strong pattern of seasonality in the abnormal performance of the stocks (e.g. DeBondt and Thaler, 1985, 1987; Chopra, *et al.*,1992; Zarowin, 1990). In particular, mean reversions in returns are observed to occur mostly in the month of January, and that this seasonal pattern is more pronounced for the losers. This is perhaps not surprising as it may relate to the January effect widely documented in stock market seasonality literature.

As for the Malaysian market, the evidence on stock market seasonality is quite mixed. Though there are a few studies which do not document January effect (e.g. Claessen, *et al.*, 1995), most studies generally find that the effect does exist there. However, the significance of the January effect is not unanimously agreed. Nassir and Mohamad (1987) and Ho (1990), for instance, claim that the effect is significant, but this is refuted by Yong (1989). The results in this very study (Chapter 3), find that although the mean January return is positive, it is not significantly different from zero. Instead, as previously reported, December and February record the highest returns for the period 1980-96.

Seasonality in the excess returns profile of KLSE stocks is the subject of analysis in this chapter. The same portfolios of winners and losers from the previous chapter are studied to determine whether excess returns are concentrated in any particular months. In addition, the relationship between seasonality and the size effect is also investigated. The following section will describe the test procedure.

6.2: Description of Methodology

6.2.1: Seasonality and mean reversion in the winner and loser portfolios

To test for any seasonal pattern in the excess returns detected in the previous chapter, a number of tests will be performed. The first tests are descriptive in nature and use data pooled across six test periods. This is to produce an 'overall picture' of any possible seasonal patterns which might be present. Here, monthly CERs are presented in tabular and graphical forms for both winner and loser portfolios, and casually inspected for any abnormal monthly performance. As will be seen later, in this chapter, it appears that CERs for February are larger than for the other eleven months. This is consistent with a possible Chinese New Year effect in the general level of market returns, as suggested by Ho (1990), Wong *et al.* (1990), and Chan *et al.* (1996), and also by the evidence in this study in Chapter 3.

The second set of tests are then introduced, which are applied to each test period individually. This ensures no 'double counting' which can occur with pooled data. In order to test the existence of a possible February effect, two Ordinary Least Square (OLS) linear regressions are carried out using daily excess returns, averaged across all seventeen firms in the winner and loser portfolios. The models employ dummy variables to investigate seasonalities in the pattern of excess returns, and are described by equations 6-1, and 6-2 below;

$$ER_t = \Psi_1 + \Psi_2 FEB_t + e_t \tag{6-1}$$

where ER_t = the mean daily returns across all 17 firms in the loser and winner portfolios;

FEB_t = the dummy variable, which is equal to 1 for observations in February and 0 otherwise;

Ψ_1 = the intercept coefficient, which measures the mean returns for the eleven months excluding February;

Ψ_2 = the coefficient for *FEB*, which measures the difference between the mean returns in February and the other eleven months of the year;

e_t = the random error term which follows the usual OLS regression assumptions

$$ER_t = \phi_1 + \phi_2 JAN + \phi_3 MAR + \ldots\ldots\ldots + \phi_{12} DEC + \varepsilon_t \qquad (6\text{-}2)$$

where, ER = the mean daily excess returns across all 17 firms which make up the winner or loser portfolios;

JAN = a dummy variable, which equals 1 for January observation, and 0 elsewhere;

MAR = a dummy variable, which equals 1 for March observation, and 0 elsewhere, and so on through December observations;

ϕ_1 = the intercept term, which indicates the expected value for February;

ϕ_q = model parameters (q = 1, …., 12);

ε_t = the error term, which follows the usual OLS assumption.

Regression 6-1 investigates whether there is a significant difference between daily excess returns earned in February, and those earned in non-February periods. The estimated intercept parameter (Ψ_1) is the average daily excess return in the non-February periods, while the dummy slope (Ψ_2) indicates the February-differential for daily excess returns. It is the sign, and significance of the dummy slope which is important from the viewpoint of investigating seasonalities in excess returns. The hypothesis test is stated here in the form of a one-tailed test;

H_0: $\Psi_2 = 0$

H_1: $\Psi_2 > 0$

The second regression, i.e., equation 6-2, also investigates seasonalities in excess returns, but the dummy slopes (ϕ_2, ..., ϕ_{12}) indicate the differential between daily excess returns for each of the individual non-February months, compared to daily excess returns for February. Again, the hypothesis test is stated in the one-tail form;

H_0: $\phi_2 = 0$

H_1: $\phi_2 < 0$, conducted separately for $q = 2, \ldots.., 12$.

Of course the regression analyses are parametric in nature, so to provide additional evidence of seasonalities in excess returns, a non-parametric approach is also used here. The CERs for each month are investigated for each of the six pest periods, for both winner and loser portfolios. For each portfolio and test period, three monthly CERs can be calculated for each of the seventeen stocks (i.e., three January CERs, three February CERs, and so on) since all test periods span three years. Thus, for each portfolio and test period, 51 CERs can be obtained for each month. For each portfolio and test period, median CERs are calculated and the distribution for each set of 51 monthly CERs are compared using the Kruskal-Wallis test, described earlier by equation 3-3 and reintroduced in the equation below;

$$KW = \frac{12\sum n_i\left[\overline{R}_i - \overline{R}\right]^2}{N(N+1)} \qquad (6\text{-}3)$$

where n_i is the number of observation in each month, N is the total number of observations, $\overline{R}_i$ is the average of the ranks in month i, and $\overline{R}$ is the average of all the ranks. This test generates a statistic which test the hull hypotheses that CER distributions are identical across all twelve months. In addition, there is an opportunity to test how the mean rankings for observations in the twelve groupings differ from the mean rank for all observations, using the z-calculation below;

$$z_g = \frac{\overline{X}_g - \frac{(N+1)}{2}}{\sqrt{(N+1)\left(\frac{N/(n_g-1}{12}\right)}} \tag{6-4}$$

where z_g = z-value for group g,

$g = 1, 2, \ldots.., 12$ (i.e., Jan, Feb, …., Dec);

X_g = average of the ranks in group g;

N = total sample size;

n_g = number of observations in group g.

A number of statistical programmes generate this statistic automatically with the Kruskal-Wallis output (e.g. *MINITAB*). The critical values for z_g may be obtained from a standard normal distribution table. However, a two-tail test is employed here because of the nature of the procedure. Unlike the regression analyses which compare 'other' months with February, the z-test used here compares each month with the average for the whole sample. Although we can hypothesise that 'other' months will have lower CERs than

February, it is difficult to hypothesise how each month's CERs will compare to the overall mean, with the exception of February which we would expect to be greater than the mean. For this reason, a two-tailed test is employed for the z-test.

It should be noted that both the parametric and non-parametric tests employed here examine seasonalities in excess returns for winner and loser portfolios, rather than testing for seasonalities in the general level of returns. This chapter is concerned with the overreaction effect, and some of the factors that may influence it, rather than seasonalities per se, as we have seen in Chapter 3.

6.2.2: Seasonality and size effect

A lot of evidence have been established from the US studies that the January effect is primarily a small-firm effect; abnormally higher January returns are observed mostly among the smaller firms. This study therefore investigate whether higher February excess returns have any links with the size of firms. The dummy-variable regression in equation 6-1 is used again, except that portfolios are constructed on the basis of size, instead of prior period returns. The two extreme-size portfolios, i.e., the small and large firms portfolios in each of the six test periods, as described in section 5.2.2, Chapter 5, are used. The regression is described below;

$$ER_t = \lambda_1 + \lambda_2 FEB_t + e_t \qquad (6\text{-}5)$$

where ER_t = the mean daily excess returns across all 17 firms in the small and large firms portfolios;

FEB_t = the dummy variable, which is equal to 1 for observations in February and 0 otherwise;

λ_1 = the intercept coefficient, which measures the mean returns for the eleven months excluding February;

λ_2 = the coefficient for *FEB*, which measures the difference between the mean returns in February and in the other eleven months in the year;

e_t = the random error term which follows the usual OLS regression assumptions.

Regression 6-5 investigates whether there is a significant difference between daily excess returns earned in February, and those earned in non-February months, within the small and large firms portfolios. The estimated intercept parameter (λ_1) is the average daily excess return in the non-February periods, while the dummy slope (λ_2) indicates the February-differential for daily excess returns. The sign and significance of the dummy slope will determine whether there is any relation between February and size effects. The hypothesis test is stated in the form of a one-tailed test;

H_0: $\lambda_2 = 0$

H_1: $\lambda_2 > 0$.

6.3: Seasonal Patterns in the Mean Reversions of Winners and Losers

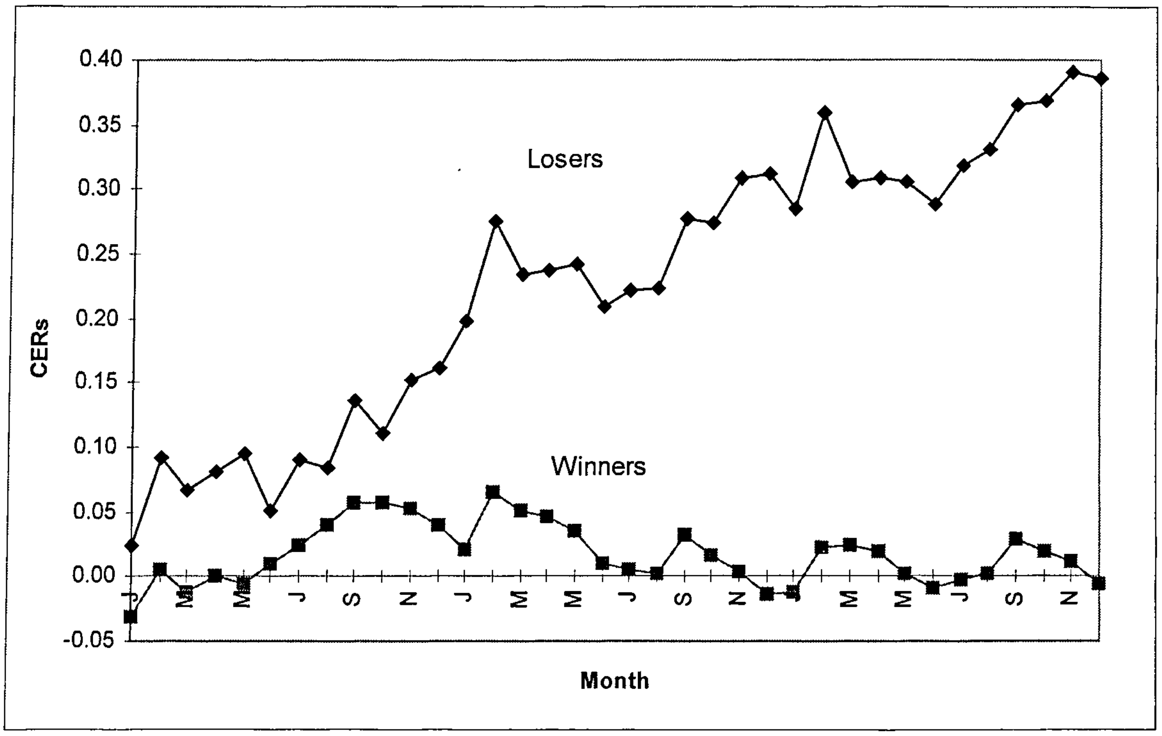
Table 6-1 shows both the mean monthly CERs and cumulative CERs for winners and losers, for each month in the three year test period, pooled across all six periods in this study. Figure 4-2, panel A, from the previous chapter is also reproduced in Figure 6-1 below, to illustrate graphically the existence of seasonal pattern in excess returns. Pooling CER values across all six test periods (p = 1, 2,..., 6) is problematic because of the overlapping time periods (see Table 4-3), which could result in double or triple counting of some firms' CER values; firms in the winner portfolio for period 1989-91, for example, may likely be in the same portfolio for period 1990-92. For this reason, the pooled sample is only used for descriptive analysis, providing an 'overall picture' of the behaviour of excess returns. The pooling procedure provides a compact method of illustrating returns patterns which appear to exist in the KLSE.

The most noticeable aspect of these results are; (i) the absence of any January effect, and (ii) the presence of a strong February effect, possibly related to the Chinese New Year effect as described in Wong, *et al.* (1990), Ho (1990) and Chan, *et al.* (1996). This process may be illustrated with reference to Figure 6-1 which shows monthly CERs for winner and loser portfolios in the test periods. Table 6-1 indicates that for losers, the largest monthly increases in CERs occur during the first, second and third February in the test period. Indeed, these three February CER values (6.8%, 7.7%, and 7.5%) represent more than half of the total CERs for losers over the three year test period (39.2%). However, it is unlikely that February effect explains fully the observed mean reversions in

Table 6-1: Average monthly CERs and average cumulative CERs for winners and losers pooled across all six test periods

Month	Winner		Loser	
	Mean CER for month *i*	Monthly cumulative CER	Mean CER for month *i*	Monthly cumulative CER
J	-0.031	-0.031	0.024	0.024
F	0.037	0.006	0.068	0.092
M	-0.018	-0.012	-0.026	0.066
A	0.013	0.000	0.015	0.082
M	-0.006	-0.005	0.014	0.095
J	0.015	0.010	-0.044	0.052
J	0.015	0.025	0.039	0.090
A	0.015	0.040	-0.006	0.084
S	0.017	0.057	0.052	0.136
O	0.000	0.057	-0.026	0.110
N	-0.004	0.053	0.042	0.152
D	-0.014	0.039	0.009	0.162
J	-0.018	0.021	0.036	0.198
F	0.044	0.065	0.077	0.275
M	-0.015	0.050	-0.041	0.234
A	-0.004	0.046	0.004	0.238
M	-0.012	0.035	0.005	0.242
J	-0.025	0.010	-0.034	0.209
J	0.005	0.006	0.013	0.221
A	-0.003	0.003	0.002	0.223
S	0.030	0.033	0.055	0.278
O	-0.016	0.017	-0.004	0.274
N	-0.013	0.004	0.035	0.309
D	-0.017	-0.013	0.004	0.313
J	0.001	-0.013	-0.027	0.286
F	0.036	0.023	0.075	0.361
M	0.00	0.024	-0.053	0.308
A	-0.003	0.020	0.002	0.310
M	-0.018	0.002	-0.003	0.307
J	-0.011	-0.008	-0.015	0.292
J	0.005	-0.003	0.031	0.323
A	0.006	0.003	0.012	0.335
S	0.026	0.029	0.034	0.369
O	-0.009	0.020	0.004	0.373
N	-0.009	0.011	0.024	0.397
D	-0.017	-0.006	-0.005	0.392

Figure 6-1: CERs for winner and loser portfolios, cumulated over 3-year test period, pooled across 6 periods



excess returns; excluding the month will still leave losers with a substantial CER value of 17.2%. This result contrasts with US findings suggesting that most overreaction occurs during January. The same observation, i.e., higher CER values in February, also appears to be present for winners. Monthly CER values for the three Februarys are all positive (3.7%, 4.4% and 3.6%) despite there being an overall negative value for the three-year CER (-0.6%). Over a 36-month period, losers outperform the market by 39.2%, while winners underperform the market by 0.6%, so that a contrarian trading strategy of buying losers and selling winners short could earn an arbitrageur a profit of 39.8%[1].

It is likely that these results are related to the Chinese New Year (CNY) effect suggested by other studies reviewed in Chapter 2, and also by the findings in Chapter 3 in this study. The findings in Chapter 3 reveal that returns are higher surrounding the CNY holidays in the KLSE, especially 5 days after trading resumes. As the CNY occurs mostly in the first half of February (see Table 3-1), I believe there are some possible links between the celebration and the excess returns of losers and winners here. In the absence of capital gain taxes in Malaysia, a behavioural-based explanation might provide the answer for this phenomenon. For example, it may be that for countries where there is a strong Chinese cultural influence like Malaysia, the end of the Chinese new lunar-year acts as a focal point for investors' 'mental accounts'[2]. However, more research is needed to examine this possibility.

[1] However, it should be noted that as assumed in Chapter 4, there is no transaction cost here. In reality, all transactions in the KLSE do incur such costs, which vary according to the amount transacted as described in Section 1.2 in Chapter 1.

[2] See the discussion on 'mental accounting' on page 44

It should be noted that here this chapter investigates the contribution of the February effect, or Chinese New Year effect, to the overreaction profile of stocks rather than the general level of returns on those stocks. Plotting CERs for winners and losers, for all 36 months of the test period (pooled across all six test periods) illustrates these effect. The plot in Figure 6-1 also, as mentioned earlier, illustrates the winner-loser asymmetry for test period CERs.

In order to assess the statistical significance of any February effect on daily excess returns, two separate regressions are carried out for both portfolios. This procedure is carried out for each of the six test periods individually; using pooled data could be problematic for statistical testing, as previously mentioned. Regression 6-1 investigates the differences between daily excess returns if February and daily excess returns in other months. The results are presented in Table 6-2.

The results in the table provide some evidence of a February effect in the daily excess returns of Malaysian stocks. For both winners and losers, the results are similar. The slope coefficient for the February dummy variable (Ψ_2) is positive for five of the six test periods; only period 4 for losers and period 1 for winners generate a negative coefficient, and this is not significant at any reasonable probability level. For winners, the coefficient is positive and significant for three periods (p = 3, 5, 6), and a similar result is found for losers (p = 1, 5, 6). This pattern is also evident from the results of regression 6-2, which investigates daily excess returns in each non-February month, compared to February. These results are presented in Table 6-3. The Durbin-Watson statistics are also reported for all regression results. Generally, they confirm that there is no serial correlation in the residuals of the regressions.

Since overreaction effects tend to be asymmetric in nature, it is perhaps not surprising that the February impact is more noticeable for the loser portfolio than for the winner portfolio. However, in both cases, slope coefficients are almost always negative for non-February dummy variables, although the number of significant results varies between test periods.

Table 6-2: Test of equal mean daily returns in February and in the other 11 months of the year

Period	Ψ_2(losers)	Ψ_2(winners)
1	0.0037*	-0.0001
	(1.70)	(-0.21)
2	0.0025	0.0012
	(1.62)	(1.31)
3	0.0022	0.0016*
	(1.38)	(1.77)
4	-0.0029	0.0000
	(-1.22)	(0.03)
5	0.0072*	0.0039*
	(3.05)	(3.58)
6	0.0022*	0.0030*
	(2.34)	(1.91)

Notes:

Results are based on the regression;

$$ER_t = \Psi_1 + \Psi_2 FEB_t + e_t$$

where ER_t = the mean daily returns across all 17 firms in the loser and winner portfolios;

FEB_t = the dummy variable, which is equal to 1 for observations in February and 0 otherwise;

Ψ_1 = the intercept coefficient, which measures the mean returns for the eleven months excluding February;

Ψ_2 = the coefficient for *FEB*, which measures the difference between the mean returns in February and the other eleven months in the year;

e_t = the random error term which follows the usual OLS.

t-values are in parentheses;

* indicates rejection of the null hypothesis that $\Psi_2 = 0$, at the 0.05 level using a one-tail test (H_1: $\Psi_2 > 0$)

The critical value is $\pm$ 1.65.

Table 6-3: Test of equality between daily excess returns in February and daily excess returns in each of the other months

a. Loser Portfolio

Month	Period 1	2	3	4	5	6
Jan	0.0031	-0.0001	-0.0030	-0.0057*	-0.0110*	-0.0030*
ϕ_2	(1.09)	(-0.03)	(-1.40)	(-1.81)	(-3.44)	(-2.40)
Mar	-0.0055*	-0.0045*	-0.0040*	-0.0051*	-0.0098*	-0.0037*
ϕ_3	(-1.91)	(-2.21)	(-1.87)	(-1.65)	(-3.16)	(-2.99)
Apr	-0.0049*	-0.0038*	-0.0025	-0.0005	-0.0066*	-0.0018
ϕ_4	(-1.67)	(-1.85)	(-1.19)	(-0.15)	(-2.06)	(-1.42)
May	-0.0045	-0.0037*	-0.0007	-0.0007	-0.0075*	-0.0032*
ϕ_5	(-1.59)	(-1.82)	(-0.34)	(-0.22)	(-2.37)	(-2.65)
Jun	-0.0056*	-0.0033	-0.0044*	-0.0054*	-0.0110*	-0.0013
ϕ_6	(-1.91)	(-1.63)	(-2.07)	(-1.73)	(-3.36)	(-1.07)
Jul	-0.0017	-0.0019	-0.0029	-0.0018	-0.0050	-0.0011
ϕ_7	(-0.61)	(-0.92)	(-1.38)	(-0.56)	(-1.57)	(-0.86)
Aug	-0.0055*	-0.0054*	-0.0030	-0.0007	-0.0041	-0.0016
ϕ_8	(-1.93)	(-2.66)	(-1.43)	(-0.22)	(-1.31)	(-1.32)
Sep	-0.0032	-0.0001	-0.0013	0.0006	-0.0040	-0.0012
ϕ_9	(-1.08)	(-0.06)	(-0.59)	(0.20)	(-1.22)	(-0.98)
Oct	-0.0059*	-0.0027	-0.0009	-0.0025	-0.0088*	-0.0037*
ϕ_{10}	(-2.04)	(-1.32)	(-0.41)	(-0.78)	(-2.78)	(-3.01)
Nov	-0.0033	-0.0014	-0.0007	0.0004	-0.0061*	-0.0016
ϕ_{11}	(-1.14)	(-0.69)	(-0.33)	(0.13)	(-1.93)	(-1.33)
Dec	-0.0042	-0.0051*	-0.0032	-0.0007	-0.0065*	-0.0014
ϕ_{12}	(-1.43)	(-2.51)	(-1.51)	(-0.23)	(-2.08)	(-1.12)
DW	1.96	2.02	1.79	2.02	2.04	1.99

B. Winner Portfolio

Month	Period					
	1	2	3	4	5	6
Jan	-0.0003	-0.0015	-0.0014	-0.0036*	-0.0051*	-0.0040*
ϕ_2	(-0.38)	(-1.25)	(-1.15)	(-2.77)	(-3.54)	(-1.91)
Mar	0.0038	-0.0007	-0.0020*	-0.0043*	-0.0049*	-0.0032
ϕ_3	(0.42)	(-0.56)	(-1.66)	(-3.37)	(-3.45)	(-1.50)
Apr	0.0003	-0.0008	-0.0015	-0.0025*	-0.0040*	-0.0025
ϕ_4	(0.35)	(-0.67)	(-1.26)	(-1.97)	(-2.78)	(-1.18)
May	-0.0004	-0.0016	-0.0018	-0.0023*	-0.0024*	-0.0057*
ϕ_5	(-0.48)	(-1.25)	(-1.45)	(-1.76)	(-1.67)	(-2.70)
Jun	0.0006	-0.0017	-0.0024*	-0.0035*	-0.0040*	-0.0026
ϕ_6	(0.63)	(-1.33)	(-1.91)	(-2.74)	(-2.80)	(-1.22)
Jul	-0.0001	-0.0014	-0.0024*	-0.0027*	-0.0020	-0.0016
ϕ_7	(-0.13)	(-1.14)	(-2.00)	(-2.08)	(-1.39)	(-0.74)
Aug	0.0001	-0.0026*	-0.0026*	-0.0019	-0.0028*	-0.0002
ϕ_8	(0.11)	(-2.13)	(-2.11)	(-1.46)	(-1.95)	(-0.10)
Sep	0.0009	0.0002	0.0007	-0.0009	-0.0037*	-0.0025
ϕ_9	(1.02)	(0.16)	(0.61)	(-0.67)	(-2.59)	(-1.17)
Oct	0.0003	0.0002	-0.0011	-0.0033*	-0.0051*	-0.0046*
ϕ_{10}	(0.34)	(0.13)	(-0.93)	(-2.54)	(-3.51)	(-2.18)
Nov	0.0003	-0.0016	-0.0018	-0.0032*	-0.0046*	-0.0031
ϕ_{11}	(0.27)	(-1.30)	(-1.46)	(-2.45)	(-3.22)	(-1.44)
Dec	-0.0003	-0.0019	-0.0025*	-0.0038*	-0.0040*	-0.0035
ϕ_{12}	(-0.31)	(-1.57)	(-2.03)	(-3.00)	(-2.77)	(-1.59)
DW	2.14	2.00	1.97	1.89	2.04	1.89

Results are based on the regression;

$$ER_t = \phi_1 + \phi_2 JAN + \phi_3 MAR + \ldots\ldots\ldots + \phi_{12} DEC + \varepsilon_t$$

where, ER = the mean daily excess returns across all 17 firms which make up the winner or loser portfolios;
JAN = a dummy variable, which equals 1 for January observation, and 0 elsewhere;
MAR = a dummy variable, which equals 1 for March observation, and 0 elsewhere, and so on through December observations;
ϕ_1 = the intercept term, which indicates the expected value for February;
ϕ_q = model parameters (q = 1, …., 12);
ε_t = the error term, which follows the usual OLS assumption;

t-values are in parentheses; * indicates rejection of the null-hypothesis that $\phi_q = 0$, at the 0.05 level using a one-tailed test (H_1: $\phi_q < 0$ where q = 2, 3, …., 12). The critical value is ± 1.65.
DW is Durbin-Watson statistics which test the serial correlation in the residuals of the regressions.

The results for the non-parametric Kruskal-Wallis and z-value tests on monthly CER values, shown in Table 6-4, also display an apparent February effect, especially for the loser portfolio. Looking at the results for losers first, it can be seen that there are a number of months which, for specific periods, generate excess returns significantly greater than the norm for the whole sample. However, only February generates positive median CER values and z-values which are significant at the 0.05 level, for all six test periods. This pattern is less noticeable for winner stocks, but February still generates significantly positive CERs for four out of the six test periods. The Kruskal-Wallis statistics at the bottom of each table also indicate that for losers, the hypothesis of identical CERs distributions across all 12 months is rejected at the 0.05 level for all periods. For winners, only period 1 indicates that the CERs distribution is identical across all 12 months.

Table 6-4: Monthly CERs of the loser and winner portfolios, using the Kruskal-Wallis test

Test Period 1 (1989-91)

Month	Winner		Loser	
	Median	z-value	Median	z-value
Jan	-0.010	-1.43	0.100	7.16
Feb	-0.002	-0.41	0.040	3.66
Mar	-0.004	0.50	-0.050	-1.97
Apr	0.012	0.46	-0.050	-1.39
May	-0.020	-1.99	-0.030	-1.23
Jun	0.020	1.21	-0.050	-2.76
Jul	-0.010	-0.28	0.010	2.38
Aug	-0.003	0.07	-0.050	-3.35
Sep	0.016	1.95	-0.010	0.26
Oct	-0.001	0.35	-0.060	-2.58
Nov	0.008	0.72	0.000	0.53
Dec	-0.020	-1.16	-0.040	-0.72
	KW_{winner} = 12.78 (p=0.310)		KW_{loser} = 95.27 (p=0.000)	

Test Period 2 (1990-92)

Month	Winner		Loser	
	Median	z-value	Median	z-value
Jan	-0.010	-0.26	0.050	3.94
Feb	0.010	1.85	0.020	2.42
Mar	-0.010	0.97	-0.040	-2.44
Apr	-0.020	0.70	-0.050	-2.00
May	-0.040	-1.65	-0.010	-1.05
Jun	-0.020	-0.82	-0.030	-1.08
Jul	-0.010	0.34	0.020	1.91
Aug	-0.040	-2.50	0.050	-3.79
Sep	0.020	2.71	0.040	3.96
Oct	-0.010	2.11	0.020	0.92
Nov	-0.030	-1.30	0.000	1.21
Dec	-0.030	-2.14	-0.060	-4.01
	KW_{winner} = 30.01 (p=0.002)		KW_{loser} = 78.52 (p=0.000)	

Test Period 3 (1991-93)

Month	Winner		Loser	
	Median	z-value	Median	z-value
Jan	0.020	0.90	0.000	-0.29
Feb	0.020	2.71	0.040	2.49
Mar	-0.010	-0.55	0.000	-1.75
Apr	-0.010	-0.46	-0.010	-0.53
May	-0.020	-0.86	0.000	0.52
Jun	0.000	-0.78	-0.020	-1.78
Jul	-0.030	-1.31	-0.010	-0.47
Aug	-0.010	-1.67	-0.010	-0.75
Sep	0.020	2.72	0.020	1.64
Oct	0.010	1.40	0.020	2.57
Nov	-0.010	-0.19	0.000	0.67
Dec	-0.020	-1.90	-0.040	-2.33
	KW_{winner} = 25.28 (p=0.009)		KW_{loser} = 26.67 (p=0.006)	

Test Period 4 (1992-94)

Month	Winner		Loser	
	Median	z-value	Median	z-value
Jan	-0.010	-0.86	-0.060	-4.62
Feb	0.040	4.05	0.030	2.24
Mar	-0.020	-2.78	-0.060	-4.39
Apr	-0.010	-0.69	0.010	1.83
May	0.010	0.97	0.000	0.19
Jun	-0.010	-0.96	-0.040	-3.33
Jul	0.010	0.46	0.010	1.50
Aug	0.010	0.76	0.010	1.25
Sep	0.030	1.99	0.050	3.45
Oct	0.000	-0.65	-0.010	-0.70
Nov	-0.010	-0.59	0.010	1.94
Dec	0.000	-1.70	-0.010	0.63
	KW_{winner} = 32.69 (p=0.001)		KW_{loser} = 73.69 (p=0.000)	

Test Period 5 (1993-95)

Month	Winner		Loser	
	Median	z-value	Median	z-value
Jan	-0.020	-1.82	-0.080	-4.23
Feb	0.070	5.15	0.130	7.31
Mar	-0.030	-2.11	-0.060	-4.22
Apr	-0.030	-1.56	-0.020	-0.58
May	0.040	1.75	-0.050	-1.75
Jun	-0.010	-0.64	-0.030	3.29
Jul	0.030	2.70	0.040	3.39
Aug	0.010	1.66	0.010	2.26
Sep	0.000	-0.51	0.040	2.55
Oct	-0.030	-2.51	-0.060	-2.82
Nov	-0.020	-1.74	0.020	1.24
Dec	-0.010	-0.37	0.000	0.14
	KW_{winner} = 54.94 (p=0.000)		KW_{loser} = 124.66 (p=0.000)	

Test Period 6 (1994-96)

Month	Winner		Loser	
	Median	z-value	Median	z-value
Jan	-0.030	-0.84	-0.040	-2.28
Feb	0.050	3.28	0.050	3.86
Mar	-0.050	-2.13	-0.030	-3.63
Apr	-0.010	0.09	0.020	0.63
May	-0.060	-3.80	-0.020	-2.76
Jun	-0.010	0.72	0.020	1.57
Jul	0.000	2.67	0.030	2.72
Aug	0.000	2.87	0.000	0.03
Sep	-0.010	1.18	0.010	1.35
Oct	-0.060	-3.18	-0.040	-3.49
Nov	-0.030	-0.36	0.010	0.84
Dec	-0.020	-0.51	0.020	1.16
	KW_{winner} = 53.34 (p=0.000)		KW_{loser} = 61.65 (p=0.000)	

Notes (for Table 6-4):

Figures are obtained from monthly observations in the three year test periods from all 17 companies which make up each of the Winner and Loser portfolios.

KW = Kruskal-Wallis statistic testing the null hypothesis of identical CER distributions across 12 months;

z-value = statistic for comparing each month with the rest of the sample;
critical value: ± 1.96 for a two-tailed test;

p-values are in parentheses.

6.4: Size-February Effect in Excess Returns

Table 6-5 below summarises the results of equation 6-5, where the relationship between the February effect and the size effect is examined. Similar to the results reported for the January effect in US studies, the table reveals that seasonality is more pronounced for small firms than for large firms. Out of the six periods, the daily excess returns in February are higher than the mean daily excess returns in the other months in five periods, as indicated by the positive slope coefficient (λ_2) of the dummy variable *FEB*. In periods 2, 5 and 6, the higher returns in February are significant at the 0.05 level (t = 2.46, t = 2.51 and t = 1.89 respectively) for the small firms portfolio. Though not significant at the 0.05 level, the *t*-value of 1.41 in period 1 is also high. Only in period 4 are February returns lower than the average for the other months, but this is not significant.

For the large firm portfolio, there are two periods, i.e., periods 5 (t = 2.42) and 6 (t = 2.46) where February yields significantly superior returns than the other months.

Table 6-5: Test of equal mean daily excess returns in February and in the other 11 months for small and large firms portfolios

Period	λ_2 (small)	λ_2 (large)
1	0.0028	-0.0009
	(1.41)	(-1.57)
2	0.0036	-0.0006
	(2.46)*	(-1.08)
3	0.0017	-0.0001
	(1.10)	(-0.03)
4	-0.0023	0.0003
	(-1.10)	(0.35)
5	0.0060	0.0020
	(2.51)*	(2.42)*
6	0.0037	0.0023
	(1.89)*	(2.46)*

Notes:

Results are based on the regression;

$$ER_t = \lambda_1 + \lambda_2 FEB_t + e_t$$

where ER_t = the mean daily excess returns across all 17 firms in the small and large firms portfolios;

FEB_t = the dummy variable, which is equal to 1 for observations in February and 0 otherwise;

λ_1 = the intercept coefficient, which measures the mean returns for the eleven months excluding February;

λ_2 = the coefficient for *FEB*, which measures the difference between the mean returns in February and in the other eleven months in the year;

e_t = the random error term which follows the usual OLS regression assumptions.

t-values are in parentheses;

* indicates rejection of the null hypothesis that $\lambda_2 = 0$, at the 0.05 level using a one- tailed test (H_1: $\lambda_2 > 0$).

However, February does not consistently outperform the other months in producing superior returns for this portfolio in the six periods tested. In fact, in periods 1, 2 and 3, the returns in February are actually lower than the mean daily returns in the other months, as indicated by the negative slope coefficient (λ_2). Thus, it appears that the February effect in the KLSE is more pronounced for the small firms. This may be due to higher level of local individual investors participation in smaller firms. Any 'local factor' effect, such as the Chinese New Year in February may thus cause a significant movement in prices of stocks. As for larger firms, it is presumed that they attract more foreigners. Such effect, therefore, would not leave significant impact on the prices of these companies.

6.5: Summary and Conclusion

The chapter seeks to detect the presence of seasonality in the context of mean reversion in KLSE stocks. Both parametric and non-parametric tests are employed. The results of the analyses suggest that mean reversions in the cumulative excess returns (CERs) profile of the KLSE stocks contain a seasonal pattern. Specifically, it is found that CER values are significantly higher in the month of February than in the other months. This is true for both the winner and loser portfolios, though the evidence is more pronounced for the later. This so-called February effect could be related to the Chinese New Year effect in the general level of market returns identified in Chapter 3 and other studies. Though seasonality is detected, the finding in this chapter is not consistent with those in the US and UK studies in the sense that it does not document a January effect in the abnormal returns of winners and losers, but a February effect.

A further analysis reveals that the February effect above is influenced by firm size. Though it can be observed for both large and small firms, the February effect is more pronounced for small firms than for large firms.

CHAPTER 7

THE ASIAN ECONOMIC TURMOIL OF 1997 AND ITS EFFECTS ON THE KLSE: A POST-SCRIPT

7.1: Introduction

The analyses so far in this thesis have been based on the data from January 1986 to December 1996 period. Especially true for the KLSE, this period can be characterised by a tremendous growth in the number of companies listed, market value of listed companies, and volume traded. This growth is in line with the good overall performance of the Malaysian economy (see Table 7-1 and Figure 7-1). However, since summer 1997, an unexpected and dramatic economic turmoil has hit many Asian countries, including Malaysia. Within a few months, prices plunged to their lowest level in almost a decade (see stock indices in Figure 7-2). Trading started to slow down, high premiums for initial public offerings disappeared, foreign investors pulled out funds from these countries, and people started to talk about recession.

The objective of this chapter is to continue to investigate whether the overreaction effect still remains in the KLSE when the bearish year of 1997 is included in the test period. As mentioned above, most stocks record a substantial decline in their prices. If the overreaction effect, as documented in the previous chapters, is valid, it can be expected that winners in the formation period 1992-94 to suffer yet an even worse performance in the test period 1995-97. A more interesting question, however, is; can losers reverse their fortune in this turbulent test period?

7.2: The Chronicle of and Reasons Behind the Asian Economic Turmoil

There are a number of possible reasons which are argued to cause the turmoil. The most popular argument advanced by many analysts and economists is the deterioration of Asian economic fundamentals and competitiveness. High and prolonged current account deficits, slower export growth, imprudent supervision in the banking and financial industry, inefficient and unproductive use of capital, shortage of technical skills, and a failure to upgrade technology which leads to export decline are among some of the suggested causes. Another popular suggestion is the conduct of greedy, foreign currency speculators. This argument is mostly advanced by the government of the countries affected. All these arguments and suggestions have been widely published in news magazines, such as the Far Eastern Economic Review, Asiaweek and Newsweek.

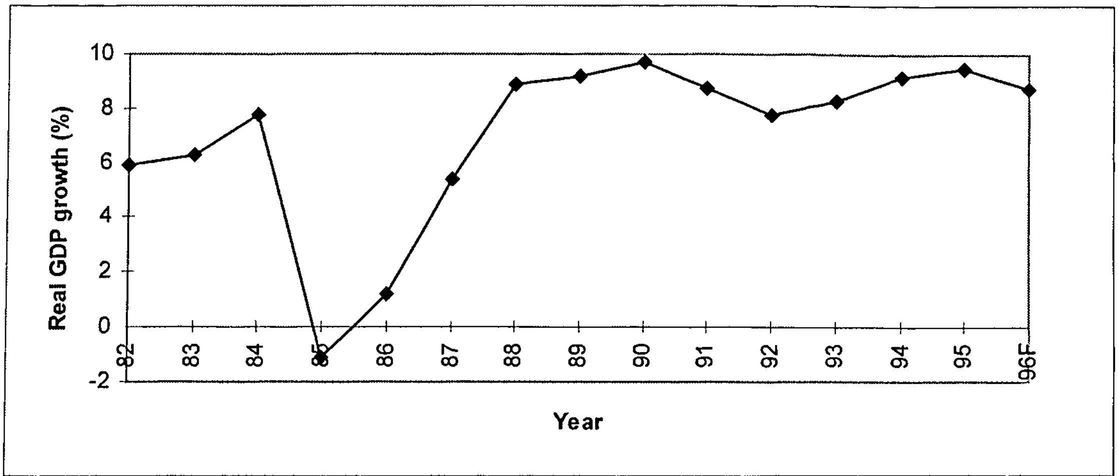
Despite the argument by various parties over what really causes the crisis or who is to blame for it, the fact is the Asian economic turmoil was triggered by the devaluation of the Thailand's baht in summer 1997. The genesis of the Thai crisis lay in the way the country opened its door to foreign capital. Thailand liberalised by allowing domestic investors access to cheap funds through the Bangkok International Banking facility,

Table 7-1: Economic growth rates in Malaysia (1982-1996)

Year	Real GDP growth rates (%)
1982	5.9
1983	6.3
1984	7.8
1985	-1.1
1986	1.2
1987	5.4
1988	8.9
1989	9.2
1990	9.7
1991	8.7
1992	7.8
1993	8.3
1994	9.2
1995	9.5
1996F	8.7

Source: Ministry of Finance and Malaysian Institute of Economic Research (reproduced in *Investing in the Stock Market in Malaysia*, June 1996, p. A3)

Figure 7-1: Malaysia: Recession, recovery and growth (1982-1996)



Source: Ministry of Finance and Malaysian Institute of Economic Research (reproduced in *Investing in the Stock Market in Malaysia*, June 1996, p. A3) launched in 1992. Being flooded by huge amounts of cheap, largely short-term foreign capital, the surfeit of cash led to ill-advised investment in unproductive sectors, such as luxurious property, producing an asset bubble that inevitably burst, leaving banks with massive bad loans. These funds were also invested in industries that provide meagre returns, such as the capacity-glutted steel and petrochemical industries. Faced with the choice of deflating the economy or devaluing the currency, which was previously pegged to a basket of currencies dominated by the American dollar, the government chose the first course, keeping interest rates high and effectively imposing currency controls by limiting access to baht by currency traders.

However, with the balance-of-payment deficits running at US$600-700 million, that strategy risked depleting reserves, which already shrank from the previous year. Moreover, at that time, the government had spent about US$2 billion defending the baht, a currency thought to be overvalued by speculators. The subsequent massive selling of baht by speculators therefore was inevitable. The net outflow of capital and declining returns on equity at Thai companies also exacerbated the perception that the economy was unhealthy, and that in turn added pressure to devalue the currency. Faced with these market pressures, the government finally decided to float the currency on July 2, 1997.

The effect of baht devaluation was later felt by other neighbouring countries, even though they did not face a similar financial crisis to Thailand. However, many analysts already believed there would be regional spillover, since countries like the Philippines, Indonesia and Malaysia were all facing similar prolonged current-account deficits, which could be vulnerable to currency speculators. On average, the current account deficit was about 5%

of the GDP for Thailand, Malaysia and the Philippines, and about 4% for Indonesia in 1997. As a matter of fact, statistics revealed by the International Monetary Fund (IMF) show that these countries have suffered from current account deficits since 1990 (IMF Financial Statistics, Feb. 1988). Speculators have long believed the governments of these countries have valued their currencies higher than the market would justify. Consequently, like in Thailand, speculators in the foreign exchange market started attacking these weak currencies with a wave of selling, starting with the Philippines, Malaysia, and Indonesia, and to a lesser extent Singapore and South Korea. The subsequent effect of currency devaluation in these countries led to the economic crisis. For Thailand, the baht devaluation did not revive their economy but led to recessionary effect as more expensive imports dampen domestic consumption. Thai companies also suffer since a lot of their borrowings are dollar-denominated, which are mostly unhedged.

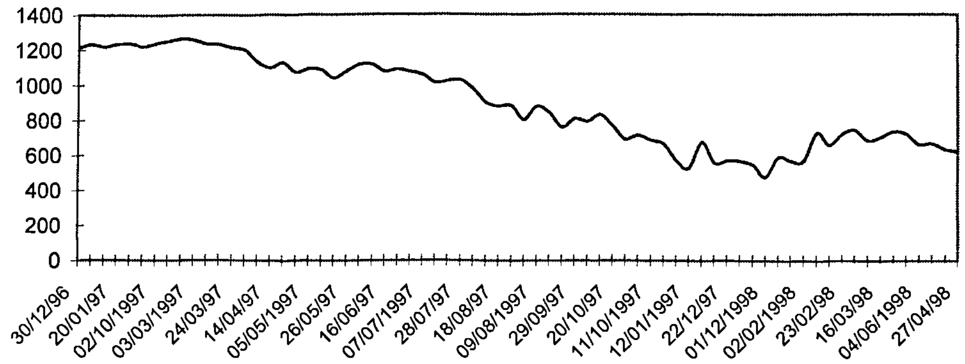
For Malaysia, most analysts and economists initially doubted that the country would face the Thai-like financial crisis. Comparatively, Malaysia has a more stable political climate and a sturdier banking system with reasonably efficient regulation. The country's banking and financial institutions boast the highest capital-adequacy ratio in South-East Asia outside of Singapore. It has a continuing high inflow of long-term capital as opposed to Thailand's short-term capital flows, and a more flexible floating currency instead of a fixed one like Thailand. However, in addition to some effects of direct spillovers from Thailand and the Philippines, Malaysia's financial crisis and economic downturn are also the results of pre-emptive measures taken by the authorities to avoid similar problems. When the Thai baht was first under heavy speculative attack in May 1997, the Malaysian ringgit also experienced heavy selling pressure. To protect the currency, the central bank,

Bank Negara Malaysia, sold close to $US1.5 billion in the foreign exchange market. The success of the strategy, however, resulted in Bank Negara soaking up an estimated 3.5 billion ringgit in liquidity. This has, in effect, pushed interest rates up. The one-month interbank rates, for instance, increased to about 9% from the usual rate of 7.25%. Besides the direct consequence of Bank Negara's intervention to protect the ringgit, higher interest rates were actually desired by the central bank to curb escalating property prices and excessive stock market speculation and avoid an asset-inflation bubble and a Thai-like financial crisis. Among others, lending for stock and property investments were restricted to 15% and 20% respectively. The stock market, consequently, has been in the doldrums ever since. Meanwhile, Bank Negara also gave up protecting the ringgit on July 14, and let market forces determine its value. The currency plunged dramatically thereafter; from about 2.517 ringgit to a dollar in June, 1997, the ringgit dropped to 2.744 in August and plunged further to 3.769 in December (IMF Financial Statistics, February 1998).

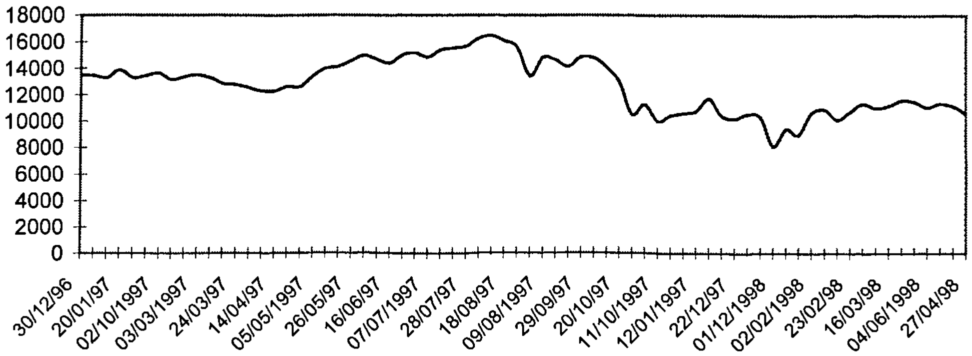
From what began in the foreign exchange market, the turmoil spread very quickly to the stock market in each of the countries affected. The effect on stock markets was first seen in Thailand, followed by Malaysia and later Hong Kong and Singapore (see Figure 7-2). In Malaysia, confidence in the economy started to erode as the value of ringgit deteriorated at a very fast rate. The situation has resulted in an exodus of foreign funds to more lucrative countries, and this, coupled with less retail interest following the curb, has dampened market sentiment. The KLSE Composite Index fell sharply from its 1997 high of 1270 points at the end of February, to just over 1000 points in mid-July, and between 550 to 580 points by the end of December 1997 (see Figure 7-2). In several desperate attempts to reverse the situation, the government made controversial ad hoc policies and statements, which not only failed to change the direction of the market, but also further dampened investors' confidence. Among these, the government ordered state-run agencies to start buying shares and announced plans to create a multibillion dollar fund to shore up the stock market. It also threatened to ban currency trading, and accused certain currency speculators of sabotaging the economy. Rules to dissuade stocks selling were also introduced, such as requiring sellers to deliver physical scrip to brokers before selling. However, the most damaging measure taken by the authorities was the drastic decision to ban short-selling of 100 blue-chip stocks that make up the Composite Index. This has trapped and angered many American and European fund managers, and further eroded their confidence in the KLSE. Although the government subsequently abandoned the ban on short-selling, and introduced other positive measures to restore confidence, such as scaling back the stock-price-support plan and postponing giant infrastructure projects to reduce imports and deficits, they did not bring back foreign capital and investors' confidence as soon as expected. In the end, the KLSE lost more than half of its value within several months of the crisis.

<u>Figure 7-2: Effect of Asian economic turmoil on countries' indices</u>

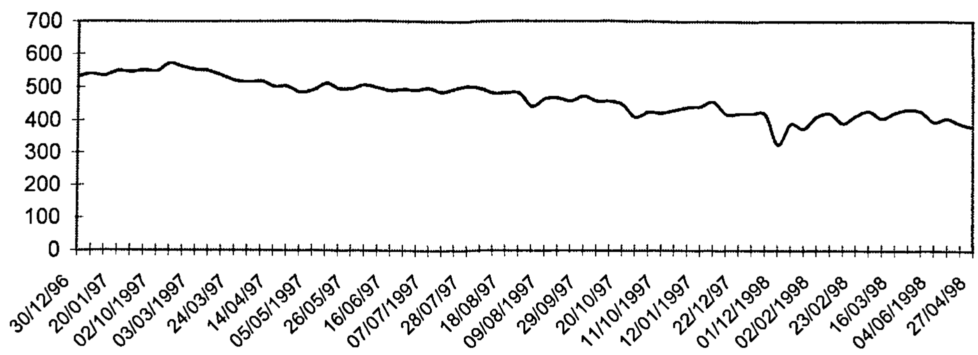
Movement of KLSE Composite Index (Jan 1997 - Apr 1998)



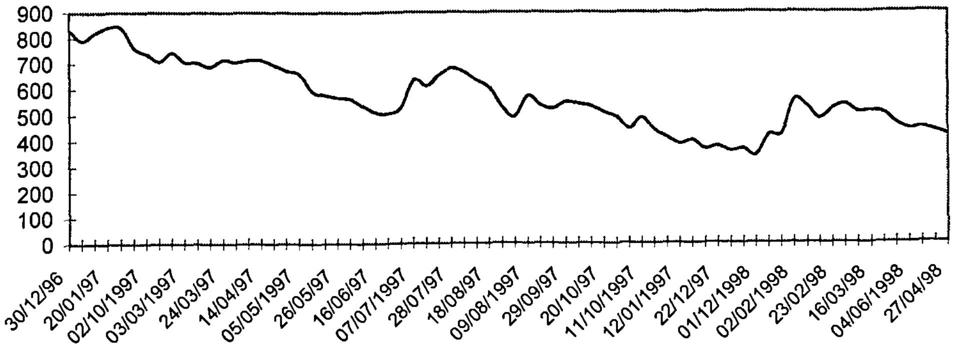
Movement of Hang Seng Price Index (Jan 1997 - Apr 1988)



Movement of Singapore All-Share Index (Jan 1997 - Apr 1998)



Movement of SET Price Index (Jan 1997 - Apr 1998)



7.3: Does Overreaction Effect Still Remain when the 1997 Data is Used?

The evidence of an overreaction effect for the period 1986-1996 has already been documented in the previous chapters. Losers are found to perform better than the market in the test period, while the opposite is generally true for winners, though not as dramatic. It is also observed that time-varying risk and size do not explain the phenomenon. In this post-script chapter, an investigation will be carried out to determine if the overreaction effect still remains when returns for the bearish year of 1997 are included in the sample.

7.3.1: Data, methodology and the test

As in Chapter 4, two extreme portfolios are formed, i.e., the winner and the loser portfolios. These are the 17 firms which outperform the market (winners) in the 3-year formation period 1992-94, and the 17 firms which underperform the market (losers) in the same formation period. Their market-adjusted cumulative excess return (CERs), calculated using equations 4-2 and 4-3, are then computed for the test period 1995-1997. Two separate tests are then employed to determine if mean reversions in CERs, and hence overreaction effect exists. First, I test whether there are any differences in the performance of both portfolios in the formation period (FP) and test period (TP). In addition, I also check for any changes in beta or firm size during the same periods for each portfolio. The appropriate hypotheses are as follow;

For winners, the null hypotheses are,

H$_0$: $\overline{CER}_{FP} = \overline{CER}_{TP}$

$\overline{BETA}_{FP} = \overline{BETA}_{TP}$

$\overline{SIZE}_{FP} = \overline{SIZE}_{TP}$ against the alternative hypotheses,

H$_1$: $\overline{CER}_{FP} > \overline{CER}_{TP}$

$\overline{BETA}_{FP} > \overline{BETA}_{TP}$

$\overline{SIZE}_{FP} < \overline{SIZE}_{TP}$ respectively.

For losers, the following null hypotheses are tested,

H$_0$ $\overline{CER}_{FP} = \overline{CER}_{TP}$

$\overline{BETA}_{FP} = \overline{BETA}_{TP}$

$\overline{SIZE}_{FP} = \overline{SIZE}_{TP}$ against the alternative hypotheses,

H$_1$: $\overline{CER}_{FP} < \overline{CER}_{TP}$

$\overline{BETA}_{FP} < \overline{BETA}_{TP}$

$\overline{SIZE}_{FP} > \overline{SIZE}_{TP}$ respectively.

Secondly, the CERs, beta and size of winners and losers in the test period are compared. If the overreaction hypothesis is true, the CERs of losers are expected to be higher than that of winners in the period. Furthermore, for the critiques of the hypothesis to be true, losers should have higher beta and smaller size than winners in the test period. The appropriate null hypotheses are that, in the test period;

H_0 : $\overline{CER}_{Loser} = \overline{CER}_{Winner}$

$\overline{BETA}_{Loser} = \overline{BETA}_{Winner}$

$\overline{SIZE}_{Loser} = \overline{SIZE}_{Winner}$, while the alternative hypotheses are that, in the test period,

H_A: $\overline{CER}_{Loser} > \overline{CER}_{Winner}$

$\overline{BETA}_{Loser} > \overline{BETA}_{Winner}$

$\overline{SIZE}_{Loser} < \overline{SIZE}_{Winner}$, respectively.

7.3.2: Results and Discussion

The results of the first test is given in Table 7-2 below. Panel A summarises the results of the *t*-test relating to the equality of mean CERs, beta and size in the formation period (FP) and test period (TP) for winners, while panel B summarises the results for losers. As expected, the CER value for winners decreases significantly in the test period by 240% (t=10.36). On the other hand, though still suffering a negative overall CER value, losers manage to record an improvement in performance by 8.67%. However, this is not statistically significant. The overall performance of the market in the turbulence year of 1997 may have taken a costly toll for most of the companies in the KLSE; losers in the period 1992-94 are no exceptions. However, despite the bearish sentiment, losers still manage to improve.

With regard to beta, there is no significant difference observed in both periods for winners. Quite surprisingly, the beta slightly increases in the test period by 0.01, but this evidence is insufficient to reject the null hypothesis of equal beta in the formation and test periods. The conjecture that winners underperform the market in the test period because they are less risky can therefore be rejected. In fact, their beta value increases in the test period 1995-97. More surprisingly, losers' beta has decreased in the test period when it would be expected to increase to compensate for their higher returns in the period. The losers' beta drops from 0.96 to 0.79; a statistically significant decrease of 0.17 (t = -3.03).

Last but not least, I also check if the reversal in fortunes for winner and loser portfolios is due to the changes in their size. Critiques of the overreaction hypothesis argue that due to the decline in their price, winners' size (as measured by market value) shrinks. The opposite is argued for losers. As a consequence, winners' (losers') returns would be lower (higher) in the following period. At first glance, Table 7-2 reveals that this argument seems to be true. There is an increase in winner' size, and a decrease in losers' size; however, both are not significant at any reasonable probability level. Therefore, the reverse in CER value from the formation period to the test period for winner and loser portfolios cannot be completely attributed to the changes which take place in size for both portfolios in the periods.

The results of the second test, i.e., testing for differences in losers' and winners' CERs, beta and size in the test period which includes the bearish year of 1997, are given in Table 7-3. As can be seen, losers significantly outperform winners by 54.5%. However, it should be noted that this is in absolute value terms. Applying an arbitrage strategy of

Table 7-2: Differences between formation period (FP) and test period (TP) CERs, Beta and Size of loser and winner portfolios (1992-1997)

A. Winner	FP	TP	Difference[a]	*t*-value
CERs	1.5896	-0.8145	2.4041	10.36*
Beta	1.09	1.10	-0.01	-0.12
Size (in RM million)	1165	1618	-453	-1.10
B. Loser				
CERs	-0.3567	-0.2700	0.0867	0.42
Beta	0.96	0.79	-0.17	-3.03[x]
Size (in RM million)	1377	1308	-69	-0.42

Notes:

a. For winner portfolio, the difference is obtained by subtracting the figure in TP column from FP column, while for loser portfolio, the difference is obtained by subtracting the figure in FP column from TP column.

t-value = *t*-statistic for paired *t*-test of differences in sample means.

* indicates significant at the 0.05 level.

[x] indicates that this test statistic is the 'wrong sign' in relation to the one-tail test. Using a two-tailed test, this *t*-value is highly significant.

buying losers and selling winners short will not yield any profit in this period. An arbitrageur can only reduce his losses to 54.5% by applying the strategy. A higher CER value for losers, however, is not accompanied by a higher beta. In the test period, losers' beta is smaller by 0.31, and this is significant at the 0.05 level ($t = 3.31$). In terms of size, losers are smaller in the test period than winners. This corresponds with the higher CERs for losers, and is consistent with the size effect. However, at the 0.05 level, it is not significant. From both tests, it appears that even in the bearish year of 1997, some degree of mean reversions remains. However, a further graphical analysis below actually reveals that this is only true prior to the period of economic turmoil.

Figure 7-3 illustrates how the monthly cumulative CER values of both winner and loser portfolios move 36-months into the test period. It clearly shows how the effect of economic turmoil which began in the second half of 1997 in the KLSE, affects the performance of both portfolios. For losers, the CERs start to fall in October, and underperform the market beginning in November. Winners, as expected, never outperform the market in the 1995-97 period. Their CERs plunge very substantially beginning in September 1997. The figure also reveals that the movements of CER value of winners and losers are not symmetrical in the period 1995-97. The effect of economic turmoil is stronger for the previous winners. Another point about Figure 7-3 is that, there is no pronounced seasonality in the CERs of both portfolios, although some degree of February effect can be observed for winners in the first and third years of the test period.

Table 7-3: CERs, Beta and Size differentials between loser and winner portfolios in the test period (1995-1997)

	Loser	Winner	Difference	*t*-value
CERs	-0.2700	-0.8145	0.5445	1.82*
Beta	0.79	1.10	-0.31	-3.31ˣ
Size (in RM million)	1308	1618	-310	-0.59

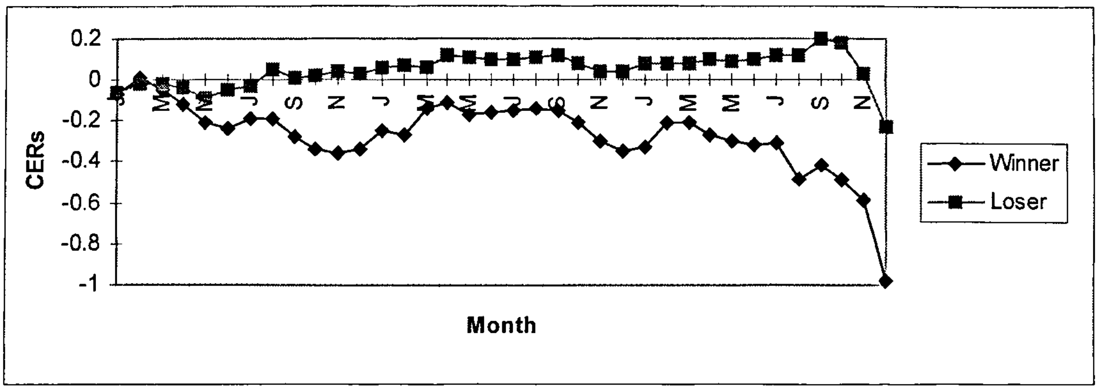
Notes:

t-value = *t*-statistic for *t*-test of differences in sample means for two independent samples,

* indicates significant at the 0.05 level,

ˣ indicates that this test statistic is the 'wrong sign' in relation to the one-tailed test. Using a two-tailed test, this *t*-value is highly significant.

Figure 7-3: CERs of winners and losers 36 months into the test period (1995-97)



7.4: Summary and Conclusion

Asia was hit by a sudden economic crisis in the summer of 1997. Deteriorating economic fundamentals and competitiveness, and speculative selling pressure by currency speculators are cited as the explanations. This Asian economic turmoil, as it is most popularly referred to, was triggered by the devaluation of Thailand's baht in early July, and spread quickly across most countries in the region, and in turn affected their economy as a whole, including the performance of the stock markets. As for Malaysia, the Kuala Lumpur Stock Exchange lost more than half of its value by the end of the year. Trading also slackened ever since, as investors lost confidence in the economy in general, and the stock market in particular.

An investigation is carried out to determine if the overreaction hypothesis is still valid in the KLSE when the bearish year of 1997 is included in the test period. Winner and loser portfolios are formed based on their 1992-94 market adjusted cumulative excess returns (CERs), and their performance in the test period 1995-97 is examined. Results from the analysis show that for losers, the reversion in CER value from the previous period can be observed up to September 1997; thereafter, their CERs started to decrease. As for winners, they never outperform the market. Comparing the performance of both portfolios in the test period 1995-97, the losers' average CERs is higher than the winners'; however an arbitrage trading strategy of buying losers and selling winners short only works up to October 1997. Size and time-varying risk do not appear to be relevant with the results above. It can therefore be concluded that when the bearish year 1997 is included in the test period, there is still some degree of mean reversion (and hence overreaction) in the

KLSE, but this is only observed up to October 1997 when the economic crisis just started; further into the crisis, this anomaly is not worth exploiting.

CHAPTER 8

SUMMARY AND CONCLUSION

8.1: Summary

This study has been concerned with documenting stock market anomalies in the Kuala Lumpur Stock Exchange (KLSE), Malaysia, with some comparisons with three other Far-Eastern markets, namely the Stock Exchange of Singapore (SES), the Stock Exchange of Thailand (SET) and the Stock Exchange of Hong Kong (SEHK). The main anomaly investigated was long-run overreaction effect as documented in DeBondt and Thaler (1985). Seasonality and firm size effects, which are usually associated with the overreaction effect, were also examined individually, and in the context of the overreaction effect. In addition, the impact of time-varying risk was also investigated.

The search for stock market anomalies is very popular among academics. This area of research has produced a great deal of evidence which is used by sceptics to attack the Efficient Market Hypothesis (EMH). Questions have been raised on the validity of the hypothesis which claims that share returns are unpredictable. To the practitioners, the evidence of stock market anomalies provides huge potential for making profits in the market place. The predictability of returns encourages the use of an active investment style in order to take advantage of the deviation of actual prices from equilibrium prices. This deviation of price from the fundamental value is perceived to be greater in a relatively small, thin and volatile market, such as that in Malaysia. It is due to these reasons that this study is undertaken.

The study started with an investigation of stock market seasonality in four Far-Eastern markets - KLSE, SES, SET and SEHK. The countries' main stock indices were used to determine whether absolute returns were different across different months of the year. Of particular interest was whether the well-known January effect, widely documented in the US studies, applied in these markets. In addition the cultural influence on returns was also investigated. With the exception of Thailand, all three markets are dominated by the Chinese investors. An investigation was carried out to determine whether the Chinese New Year celebrations affect stock prices in these markets.

A detailed examination of the overreaction effect in the KLSE was then undertaken in the next three chapters. Two portfolios of 'extreme' stocks were formed based on their past performance. The initial results appeared to be consistent with market overreaction; portfolios of stocks which performed very well (winners) relative to the market in a period were observed to underperform the market in the next period. The opposite was true for those which underperformed the market (losers). A further analysis was then done to determine whether these results were due to time-varying risk and risk differentials between winner and loser portfolios. Next, the firm size effect in the KLSE was investigated, and the impact of firm size on the overreaction effect was analysed. The profile of overreaction was then examined for any seasonal patterns. Before I concluded the study, a post-script chapter was included whereby the effect of the recent Asian economic turmoil on the markets, particularly on overreaction in the KLSE, was looked at.

8.2: Main Findings of the Study

(1) The January effect is not present in Malaysia and Thailand. The effect, however, is detected in Hong Kong and Singapore. In Malaysia, returns are highest in the months of December and February. Both are significantly different from zero at the 0.05 level. In Thailand, December has the highest returns, but overall, no months are significantly different from the others. December also is the month which yields the highest returns in Singapore. January and May are the other two months with returns significantly different from zero. In Hong Kong, the January effect is most pronounced. It is the month which yields the highest returns there, followed by December and April.

(2) The Chinese New Year effect is detected in the countries whose dominant investors are from the ethnic Chinese community, i.e., Malaysia, Singapore and Hong Kong. In Malaysia, the effect is especially significant five days after the market reopens following the holidays. Daily returns 40 days preceding the celebration are also high. The Chinese New Year effect, however, is more pronounced in Singapore and Hong Kong prior to the festive season. In these markets, the rally starts as early as 40 days before the first day of the celebration. Once the markets are open, the returns are still high, but the effect is no longer significant. As expected, the effect does not exist in

Thailand, treated as the control market in the investigation. This is most probably due to the fact that the Chinese are not dominant there.

(3) There is evidence of an overreaction effect in the KLSE. Patterns of returns, consistent with mean reversions are observed in both the winner and loser portfolios. Stocks which underperform the market (losers) in a three-year period (formation period) are found to outperform the market in the following three-year period (test period). The reverse is true for stocks which outperform the market (winners) in the formation period. Assuming no transaction costs, a contrarian investment strategy of buying losers and short-selling winners will earn an arbitrageur significant returns in three out of the six periods under study. Even when transaction costs are taken into account, the arbitrageur can still earn significant profit in two periods. Pooling all six periods under study together, on average, losers earn a positive gross return of 39.2%, while winners earn a negative return of 0.6%, so that the strategy will earn the arbitrageur a profit of 39.8%, assuming no transaction costs.

(4) The risk factor (beta) cannot fully explain overreaction in the KLSE. The evidence of overreaction here does not seem to be influenced significantly by changes in systematic risk over time, nor appear to be caused by risk differentials between winner and loser portfolios. For winners, though the beta is greater in the formation period than in the test period in five out of six periods under study, this observation is significant only in one period. In fact, in period 6, the winners' beta is significantly greater in the test period. For losers, the beta is significantly greater in 4 test periods. However, the change in risk for two non-significant periods is unlikely to explain the

significant overreaction patterns for losers identified earlier in these two periods. With regards to beta differentials between winners and losers in the test period, an analysis reveals that losers' beta is greater than winners' beta in five periods. However, in period 6, the opposite is true; the losers' beta is actually significantly smaller than winners' beta. In this period, amazingly, losers significantly outperform winners. More interestingly, significant beta differentials between these portfolios in three test periods (p = 1,4,5) nicely correspond to the insignificant performance differentials of the portfolios in those periods.

(5) A firm size effect is present in the KLSE. Portfolios constructed based on the market value of firms are observed to yields different excess returns. The smallest firms portfolio outperforms the largest firms portfolio in all six test periods. In three periods, this superior performance of small firms is statistically significant.

(6) The size effect does not appear to explain the overreaction effect. This is concluded from the following observations. First, there are few interactions between losers and small firms , and between winners and large firms, implying that losers are not always the smallest firms, and winners are not always the largest firms. Secondly, it is found that losers are always smaller than winners in both formation and test periods. Moreover, when prior period (formation period) returns are controlled for, test period returns do not appear to be explained by size. However, when firm size is held constant, it is found that prior period returns do have explanatory power on test period returns. Therefore, the overreaction effect in the KLSE appears to be independent of the size effect.

(7) There is a strong seasonal pattern in the cumulative excess returns (CERs) profile of winner and loser portfolios. CER values are found to be higher in the month of February for both portfolios than the other months. In absolute terms, losers' CERs in February are higher than those of the winners. For the loser portfolio, CERs in February contribute more than half of its total CERs in the test period. Excluding February CERs, however, still leaves losers with substantial positive returns. In the case of winners, despite having an overall negative CER value in the test periods, the CER values in February actually contribute substantial positive CERs for the portfolio. I believe that this phenomenon is related to the Chinese New Year effect since the festival occurs mostly in the month of February.

(8) Further investigation of the relation between the February effect and firm size reveals that higher February returns are more pronounced for small firms than for large firms. For small firms, there are three periods where there is evidence of a significant February effect. For large firms, there are only two periods where a significant February effect is observed. Higher proportions of local individual investors in small firms may likely explain this finding, as their trading behaviour may be influenced by local factors, such as the Chinese New Year celebration. Outside investors would most likely invest in well-researched and well-known companies, which tend to be large corporations.

8.3: Conclusion

This study provides strong evidence of the existence of several anomalies in the KLSE, and therefore concludes that KLSE share prices are predictable to some extent. The overreaction effect, which is observable in both US and the UK stock returns is also present in the stock returns of the KLSE. Stocks which underperform the market over a three-year period (losers) can be used to construct portfolios which yield significantly improved performance, relative to the market, over the following three years. For stocks which outperform the market over the initial three-year period (winners), there is a tendency for this superior performance to be reversed over the following three years, though not as dramatically as for losers. Although there is evidence of time variation in systematic risk levels, and evidence of risk differentials between winners and losers, the evidence here suggests that these factors cannot fully explain the apparent mean reverting behaviour of prices. There is also evidence of potential profits from arbitrage trading based on short selling winners and buying losers, although it is doubtful that these will always be large enough to outweigh any transaction costs.

Besides the overreaction effect, there also exists a firm size effect in KLSE stocks. Portfolios of smaller firms are found to outperform those of larger firms. However, this effect does not explain the overreaction effect. A seasonal pattern is also documented in the KLSE. The general level of returns is observed to be higher in December and February, and also around the Chinese New Year which occurs mostly in the first half of February for the period under study. Furthermore, this so-called February effect is more pronounced in the excess returns of small firms than large firms. Interestingly, higher

February excess returns also play a significant part in the seasonal pattern observed in the overreaction profile of KLSE stocks; excess returns are highest in February for both winners and losers. Because of the non-existence of capital gain tax on securities trading in Malaysia during the period studied here, an institutional or cultural explanation for this seasonal pattern in overreaction appears the most likely.

8.4: Implications of the Study

The findings of this study have several implications, both for academics and practitioners. To the practitioners in the KLSE, the results in this study provide another opportunity for them to beat the market. Devising a strategy of buying the previous 3-year loser shares and selling short the previous 3-year winner shares could earn them substantial profits in the next three years. Applying a strategy based on the market value of firms, and correct timing in buying and selling shares may also yield some profits.

At a more theoretical level, the successful trading strategy of buying losers and short selling winners could constitute a major stumbling block to the Efficient Market Hypothesis. To be more specific, since the strategy uses past returns as the information set to make future predictions, the ability of the strategy to make profit consistently has potentially violated the weakest form of the EMH. Historical information which is available publicly does actually have predictive value. Results from studies invoking market efficiency as an assumption are therefore, questionable. However, a degree of caution is in order. This study does not explicitly test the validity of the equilibrium asset pricing model. A test of market efficiency, as always acknowledged, is a joint-test of an asset pricing model. There might be some possibility that the asset pricing model is misspecified. Therefore, it cannot be concluded definitely form the results in this study that the KLSE is weak-form inefficient.

8.5: Suggestions for Future Research

One of the most puzzling observations in this study is the way in which February returns contribute to high positive excess returns for both winners and losers. I have not made any analytical attempt to investigate this phenomenon in this study. However, I believe that such a phenomenon may have some relationship with the Chinese New Year (CNY) effect, since the festival occurs mostly in February. For example, February or CNY might constitute a focal point for the 'mental accounting' of Malaysian investors. In the absence of capital gain tax in Malaysia, cultural or behavioural-based explanations could possibly provide a more acceptable explanation for abnormally high February returns. Future research should therefore look into this possibility.

Another possible extension to this study might look at the factor(s) or variable(s) that drive overreaction in the KLSE. As DeBondt and Thaler argue, investors overreact to news events, such as earnings announcements, and subsequently correct themselves. Would this be true in the KLSE? Is there any tendency for firms in Malaysia to release price-sensitive information in certain periods, such as around the Chinese New Year? Again, this would be interesting because an alternative explanation based on cultural and perhaps behavioural approaches could be offered to explain such a phenomenon.

APPENDICES

Appendix 1: List of sample companies

1. Ajinomoto
2. Amalgamated Industrial Steel
3. AMDB
4. Amsteel
5. Anson Perdana
6. Antah
7. Aokam
8. AP Land
9. Asia Pacific Holdings
10. Asiatic Development
11. Austral Amalgamated Tin
12. Austral Enterprise
13. Ayer Hitam Tin
14. Bandaraya
15. Batu Kawan
16. Berjaya Group
17. Berjaya Ind.
18. Berjaya Sports
19. Berjuntai Tin
20. Best World Land
21. Boustead
22. Carlsberg Brew.
23. CASH
24. Chemical Co.
25. Choc. Product
26. CIMA
27. Cold Storage
28. Cycle & Carriage
29. Dato Keramat
30. DCB Holdings
31. DMIB
32. DNPP Holdings
33. DRB
34. Dutch Baby Milk
35. Eastern & Oriental
36. Esso Malaysia
37. Faber
38. FCW Holdings
39. Federal Flour
40. Fima Corp.
41. Gadek
42. General Corp.
43. Genting
44. George Kent
45. Glenealy Plantation
46. Gold Coin
47. Golden Hope
48. Golden Plus
49. Gopeng
50. Guiness
51. Guthrie Ropel
52. Hexza Corp.
53. Hicom
54. Highland & Lowland
55. Hong Leong Credit
56. Hong Leong Industries
57. Hong Leong Properties
58. Hume
59. Idris Hydraulic
60. Inchape Timuran
61. Innovest
62. IGB Corp.
63. IJM Corp
64. IOI
65. IOI Properties
66. Island & Peninsular
67. Jaya Tiasa
68. Johan Holdings
69. John Hancock
70. Keck Seng
71. Kelanamas
72. Kemayan
73. Kian Joo
74. Killinghall
75. KL Industrial Holdings
76. KL Kepong
77. Kong Guan
78. Kuala Sidim
79. Kulim
80. Kumpulan Emas

81. Land & Generals
82. Landmarks
83. Larut Consolidated
84. Lien Hoe Corp.
85. Lingui Development
86. Lion Corp.
87. Magnum
88. Malakoff
89. Malayan Cement
90. Malayan Flour
91. Malaysia Pacific Industries
92. Malaysian Aica
93. Malaysian Air
94. Malaysian Assurance
95. Malaysian General Investment
96. Malaysian Mining
97. Malaysian Mosaics
98. Malaysian Oxygen
99. Malaysian Plantation
100. Malaysian Resources
101. Malaysian Tobacco
102. Malaysian Utd Ind.
103. Malex Industries
104. Maruichi
105. Matsushita
106. MayBank
107. MBF Capital
108. MBF Holdings
109. Mechmar Corp.
110. Menang Corp.
111. Metroplex
112. Muda
113. MUI Properties
114. Mulpha International
115. Multipurpose Holdings
116. MWE Holdings
117. Mycom
118. NBT
119. NSTP
120. OYL Ind.
121. Pacific Chemicals
122. Palmco Holdings
123. Panglobal
124. Pan Malaysia Cement
125. Paramount
126. Pelangi
127. Perlis Plantation
128. Petaling Garden
129. Pilecon Engineering
130. PJ Development
131. *Promet*
132. Public Bank
133. Rahman Hydraulic
134. Renong
135. Rothmans
136. Samanda Holdings
137. Sanyo
138. Sateras
139. SCB Development
140. SEA Development
141. SEAL
142. Setron
143. Sime Darby
144. Sime UEP
145. Sin Heng Chan
146. Selangor Dredging
147. Selangor Property
148. Shell
149. Sitt Tatt
150. Sg Way
151. South Malaysia Industries
152. SPK Sentosa
153. Sri Hartamas
154. Tan Chong
155. TDM
156. Technology Resource Induntries
157. Time Engineering.
158. Tongkah Holdings
159. Tractors Malaysia
160. Tronoh
161. UAC
162. UMW Holdings
163. Uniphone
164. Westmont Land
165. Yeoh Hiap Seng
166. YTL Corp.

Appendix 2: Winners and Losers in each subperiods

Period 1: Winners

Company	Formation Period		Test Period	
	$CER_{86\text{-}88}$	$Beta_{86\text{-}88}$	$CER_{89\text{-}91}$	$Beta_{89\text{-}91}$
Tractors Malaysia	1.15015	0.40	0.58655	0.48
UMW Hldngs	0.93510	1.05	0.89085	1.29
M'sian Mining	0.83708	1.37	-0.30182	1.18
DNPP Hldgs.	0.75673	0.95	-0.72477	1.17
Amsteel	0.68612	1.25	0.08056	1.15
M'sian Air	0.62193	0.84	-0.33378	0.89
Jaya Tiasa	0.61864	0.58	-0.71872	0.91
Guiness	0.55072	0.85	-0.10372	0.69
Sime Darby	0.53800	1.08	0.01804	1.13
Federal Flour	0.53022	0.73	0.07511	0.27
Muda	0.52943	1.20	0.36315	1.11
Yeoh Hiap Seng	0.51021	0.68	-0.06011	0.62
M'sia Pacific Ind.	0.49527	1.10	0.42573	0.78
Perlis Plant.	0.48632	0.77	0.09454	0.40
KL Kepong	0.45417	0.91	-0.53884	0.74
Rothmans	0.42522	0.23	0.81638	0.44
Killinghall	0.39345	0.44	-0.71032	0.62
AVERAGE	0.61875	0.85	-0.00830	0.82

Period 1: Losers

Company	Formation Period		Test Period	
	$CER_{86\text{-}88}$	$Beta_{86\text{-}88}$	$CER_{89\text{-}91}$	$Beta_{89\text{-}91}$
Hong Leong Prop.	-1.37823	1.23	0.49882	1.53
M'sian Resources	-1.39564	1.23	-0.89809	1.43
KL Ind. Hldg.	-1.40257	1.37	-1.01160	1.59
Panglobal	-1.44269	0.81	-0.04008	1.00
Renong	-1.50431	1.12	1.53864	1.57
AP Land	-1.56885	0.97	0.25925	1.43
Tech Res. Ind.	-1.58112	1.29	0.11195	1.60
CASH	-1.74911	1.46	0.31358	1.74
Tongkah Hldgs.	-1.81849	1.05	-0.02391	1.63
M'sian Assurance	-1.83070	0.85	0.02466	1.61
MBF Hldgs.	-1.84723	1.11	0.54069	1.83
Lien Hoe Corp.	-2.01531	1.04	-0.09482	1.40
Landmarks	-2.04948	0.87	-0.12803	1.37
South M'sia Inds.	-2.07070	0.86	0.34462	1.80
Anson Perdana	-2.19989	0.95	-0.00328	1.47
DRB	-2.33052	1.31	-0.01492	1.78
Sri Hartamas	-2.40625	0.91	-0.14610	1.60
AVERAGE	-1.79948	1.08	0.07479	1.55

Period 2: Winners

Company	Formation Period		Test Period	
	$CER_{87\text{-}89}$	$Beta_{87\text{-}89}$	$CER_{90\text{-}92}$	$Beta_{90\text{-}92}$
UMW Hldngs	1.97172	0.92	0.08316	1.26
Muda	1.65846	1.24	-0.92213	1.21
M'sia Pacific Ind.	1.25839	1.12	-0.03244	0.69
Tan Chong	1.19957	1.44	-0.21055	1.51
Golden Plus	1.18974	1.54	-0.11367	1.54
Land & Gen	1.18505	1.54	-0.53278	1.11
CIMA	1.17490	1.06	-0.15138	0.90
Time Eng.	1.16932	1.09	-1.13558	1.45
IGB Corp.	1.03074	1.41	-0.39643	1.22
Pan M'sia Cement	0.97944	1.11	-0.67325	1.01
Amalg. Ind. Steel	0.87432	1.31	-0.63352	1.34
Cycle & Carriage	0.85559	1.05	-0.14010	1.38
Tractors Malaysia	0.84991	0.35	-0.17210	0.44
Maruichi	0.84816	1.03	-0.23464	0.69
Malayan Cement	0.84688	1.13	0.16867	0.84
Amsteel	0.83143	1.20	-0.81360	1.23
Setron	0.83116	1.12	-0.83446	1.55
AVERAGE	1.10322	1.16	-0.39675	1.14

Period 2: Losers

Company	Formation Period		Test Period	
	$CER_{87\text{-}89}$	$Beta_{87\text{-}89}$	$CER_{90\text{-}92}$	$Beta_{90\text{-}92}$
Tech Res. Ind.	-0.67483	1.27	0.32112	1.63
Lien Hoe Corp.	-0.71648	1.16	-0.53462	1.23
Tongkah Hldgs.	-0.72904	1.21	-0.32591	1.69
MBF Hldgs.	-0.78025	1.14	0.16459	1.78
Pacific Chemicals	-0.78648	0.28	1.39502	0.58
Best World Land	-0.85583	0.03	-0.00580	0.25
Sin Heng Chan	-0.85741	0.38	-0.10226	0.38
M'sian Resources	-0.87252	1.15	0.10675	1.43
John Hancock	-0.88142	0.91	-0.37636	0.64
Dutch Baby Milk	-0.91271	0.62	-0.05938	0.25
Ayer Hitam Tin	-1.01159	0.14	-0.02564	1.50
South M'sia Inds.	-1.02213	1.19	-0.02104	1.71
Anson Perdana	-1.06525	1.06	-0.16230	1.49
Sri Hartamas	-1.13005	1.05	-0.62966	1.59
Panglobal	-1.24805	1.05	-0.18180	0.83
M'sian Assurance	-1.89276	1.08	-0.11694	1.61
Aokam	-1.92508	0.53	1.69183	1.78
AVERAGE	-1.02129	0.84	0.06692	1.20

Period 3: Winners

Company	Formation Period		Test Period	
	CER_{88-90}	$Beta_{88-90}$	CER_{91-93}	$Beta_{91-93}$
UMW Hldngs	1.81269	1.50	-0.71192	1.07
CIMA	1.72053	1.03	-0.29125	0.91
Renong	1.47547	1.56	0.16927	1.25
Genting	1.13384	0.99	0.70707	1.14
M'sia Pacific Ind.	1.13196	0.86	-0.15218	0.74
Tractors Malaysia	1.04063	0.44	-0.60545	0.87
Malayan Cement	1.03585	1.10	-0.02738	0.81
Tan Chong	1.00905	1.54	-0.54890	1.30
Golden Plus	0.95569	1.67	1.47106	1.19
Carlsberg Brew.	0.92637	0.50	-0.33684	0.30
Rothmans	0.90389	0.48	-0.15977	0.55
Sg Way	0.88834	1.35	0.43127	0.90
Pan M'sia Cement	0.86446	1.13	-0.17058	1.03
Mycom	0.85400	1.20	0.27999	0.89
Pilecon Eng.	0.81246	1.60	0.40370	1.08
Palmco Hldgs.	0.78814	1.27	-0.19569	0.51
OYL Ind.	0.76794	0.60	0.96269	0.50
AVERAGE	1.06596	1.11	0.07206	0.88

Period 3: Losers

Company	Formation Period		Test Period	
	CER_{88-90}	$Beta_{88-90}$	CER_{91-93}	$Beta_{91-93}$
M'sian Assurance	-0.65370	1.49	0.55197	1.21
Cold Storage	-0.65923	0.72	0.21358	0.99
Berjuntai Tin	-0.66016	0.72	1.46353	0.77
Berjaya Group	-0.66805	1.27	0.38549	0.92
Dato Keramat	-0.67822	0.24	2.70778	1.06
KL Ind. Hldg.	-0.68488	1.64	-0.13524	1.25
M'sian Plantation	-0.70812	1.05	0.69691	1.34
John Hancock	-0.72555	0.75	0.60372	0.58
SEA Development	-0.75311	0.88	0.22338	0.59
Best World Land	-0.77983	0.03	0.34127	0.62
Pacific Chemicals	-0.79034	0.27	2.35649	0.51
Kuala Sidim	-0.80790	0.62	0.91446	0.72
Kelanamas	-0.82442	0.74	0.65675	1.17
Sin Heng Chan	-0.83611	0.48	1.55565	0.42
M'sian Resources	-0.98204	1.52	0.91303	1.20
Innovest	-1.08099	1.36	0.09047	1.12
Aokam	-1.42237	1.56	2.13709	0.98
AVERAGE	-0.80677	0.90	0.92214	0.91

Period 4: Winners

Company	Formation Period		Test Period	
	$CER_{89\text{-}91}$	$Beta_{89\text{-}91}$	$CER_{92\text{-}94}$	$Beta_{92\text{-}94}$
OYL Ind.	1.68763	0.57	0.44715	0.86
CIMA	1.64026	1.03	0.17519	0.80
Renong	1.53864	1.57	0.45327	1.27
Sanyo	1.42224	0.93	-0.20779	0.61
Magnum	1.29970	0.99	0.57862	1.14
Golden Plus	1.25508	1.66	1.29069	1.42
Genting	1.23286	1.03	0.55333	1.02
Kian Joo	1.22584	0.83	0.21385	0.80
Matsushita	0.95978	0.44	-0.41237	0.57
Mycom	0.92893	1.25	0.56909	0.99
FCW Hldgs.	0.91759	0.11	1.43266	0.58
UMW Hldngs	0.89085	1.29	0.05684	1.01
George Kent	0.87174	1.43	0.76116	0.56
Sg Way	0.85769	1.29	1.16180	0.79
Shell	0.85698	0.84	-0.30179	0.46
Rothmans	0.81638	0.44	-0.15265	0.52
Palmco Hldgs.	0.79580	0.85	-0.23366	1.29
AVERAGE	1.12929	0.97	0.37561	0.86

Period 4: Losers

Company	Formation Period		Test Period	
	$CER_{89\text{-}91}$	$Beta_{89\text{-}91}$	$CER_{92\text{-}94}$	$Beta_{92\text{-}94}$
Best World Land	-0.58901	0.11	0.21264	1.39
Sin Heng Chan	-0.59967	0.48	1.77799	1.05
Asiatic Dev.	-0.60743	0.86	0.68444	1.53
Golden Hope	-0.62807	0.82	0.20087	1.43
Malayan Flour	-0.63231	0.74	0.05041	1.37
Kuala Sidim	-0.67329	0.54	0.72975	1.43
Killinghall	-0.71032	0.62	0.28827	1.40
Innovest	-0.71152	1.27	-0.20374	1.39
Jaya Tiasa	-0.71872	0.91	1.27989	1.01
DNPP Hldgs.	-0.72477	1.17	0.38003	1.57
Rahman Hydraulic	-0.73936	0.43	0.87901	1.74
Cold Storage	-0.75836	0.88	0.29024	1.25
Berjuntai Tin	-0.76601	0.75	1.32424	1.68
M'sian Resources	-0.89809	1.43	1.02811	1.35
M'sian Plantation	-0.93191	1.07	0.38326	1.79
KL Ind. Hldg.	-1.01160	1.59	0.51842	1.46
Kelanamas	-1.30188	0.98	0.49591	1.35
AVERAGE	-0.76484	0.86	0.60704	1.42

Period 5: Winners

Company	Formation Period		Test Period	
	CER_{90-92}	$Beta_{90-92}$	CER_{93-95}	$Beta_{93-95}$
Magnum	2.04474	1.05	-0.07141	1.20
FCW Hldgs.	1.69955	0.11	0.62229	0.71
Aokam	1.69183	1.78	-0.74495	0.93
Pacific Chemicals	1.39502	0.58	0.31487	0.89
OYL Ind.	1.35143	0.44	0.49616	0.76
Sanyo	1.23846	1.09	-0.21104	0.70
Mycom	1.08086	1.31	0.24279	1.01
George Kent	1.02555	1.34	-0.19864	0.53
Genting	1.00061	1.04	0.41435	1.02
Hong Leong Credit	0.96057	1.18	0.55687	0.74
Berjaya Sports	0.93527	1.67	0.85878	1.04
Matsushita	0.91784	0.45	-0.49293	0.54
Dato Keramat	0.83668	0.67	1.34900	1.56
Kian Joo	0.69718	0.71	0.21933	0.76
YTL Corp.	0.61973	1.02	1.51813	0.83
MBF Capital	0.59767	1.55	0.36708	1.37
Renong	0.59455	1.41	0.80755	1.41
AVERAGE	1.09927	1.02	0.35578	0.94

Period 5: Losers

Company	Formation Period		Test Period	
	CER_{90-92}	$Beta_{90-92}$	CER_{93-95}	$Beta_{93-95}$
Cold Storage	-0.67852	1.09	0.27454	1.33
Berjaya Ind.	-0.69450	1.19	0.07775	1.36
Jaya Tiasa	-0.71074	0.87	1.49081	1.15
Menang Corp.	-0.71546	1.71	0.20281	1.85
TDM	-0.72749	1.78	0.52586	1.65
M'sian Air	-0.76238	0.91	0.03925	0.75
Rahman Hydraulic	-0.76801	0.48	0.75999	1.88
SEAL	-0.77263	0.97	0.95182	1.56
Amsteel	-0.81360	1.23	0.07631	1.34
Setron	-0.83446	1.55	0.56198	1.49
Innovest	-0.90883	1.16	0.31949	1.44
Muda	-0.92213	1.21	0.38116	1.48
KL Ind. Hldg.	-0.93297	1.52	0.15664	1.62
Larut Consolidated	-0.98293	1.70	0.79872	1.46
Berjuntai Tin	-1.01111	0.66	1.04140	1.79
Time Eng.	-1.13558	1.45	0.34975	1.28
DRB	-2.08429	1.69	1.16450	1.36
AVERAGE	-0.90915	1.25	0.53958	1.46

Period 6: Winners

Company	Formation Period		Test Period	
	CER_{91-93}	$Beta_{91-93}$	CER_{94-96}	$Beta_{94-96}$
Dato Keramat	2.70778	1.06	-0.81930	1.50
Pacific Chemicals	2.35649	0.51	-0.31441	1.06
Aokam	2.13709	0.98	-1.87924	1.07
Lingui Dev.	2.11646	1.24	-0.65089	1.37
Berjaya Sports	1.91223	1.33	0.72163	0.96
Hicom	1.82234	0.67	-1.13935	1.28
Kong Guan	1.69476	0.56	0.03011	1.14
Idris Hydraulic	1.66992	1.41	-0.93902	1.59
Sin Heng Chan	1.55565	0.42	0.24204	1.12
Magnum	1.50623	0.88	-0.02060	1.27
Mulpha Int'l.	1.50062	1.40	-0.70656	1.72
Golden Plus	1.47106	1.19	-1.00814	1.65
Berjuntai Tin	1.46353	0.77	-0.70842	1.89
Hong Leong Credit	1.38389	0.90	0.02168	0.79
Tech Res. Ind.	1.36664	1.18	-0.84615	1.16
Gopeng	1.36524	0.88	-0.16770	1.67
YTL Corp.	1.32169	0.82	0.96896	0.81
AVERAGE	1.72657	0.95	-0.42443	1.30

Period 6: Losers

Company	Formation Period		Test Period	
	CER_{91-93}	$Beta_{91-93}$	CER_{94-96}	$Beta_{94-96}$
CIMA	-0.29125	0.91	-0.08979	0.76
Esso M'sia	-0.29357	0.57	0.06969	0.55
Lion Corp.	-0.31269	0.97	0.25389	0.87
Amsteel	-0.32709	1.33	-0.20377	1.34
Carlsberg Brew.	-0.33684	0.30	0.83031	0.20
M'sian Tobacco	-0.34108	0.55	-0.08813	0.53
Antah	-0.34676	1.23	0.46107	1.50
UAC	-0.35474	0.79	-0.31407	0.99
KL Kepong	-0.36493	0.89	0.53139	0.95
Petaling Garden	-0.41484	1.13	0.05707	1.45
Perlis Plant.	-0.42729	0.37	-0.02655	0.62
M'sian Air	-0.45085	0.84	-0.18517	0.73
Tan Chong	-0.54890	1.30	0.14270	1.33
Tractors Malaysia	-0.60545	0.87	0.29745	0.70
UMW Hldngs	-0.71192	1.07	0.43369	0.96
Guiness	-0.73414	0.72	0.40115	0.78
DRB	-0.77042	1.03	0.02366	1.36
AVERAGE	-0.44899	0.87	0.15262	0.92

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