Does Climatic Seasonality Produce Seasonality in Stock Returns? Evidence from an Emerging Stock Market

Imad A. Moosa
Monash University

This paper investigates seasonality in the Kuwait stock market using monthly average data on the market index covering the period 1996-2005. While conventional regression analysis fails to detect seasonality, structural time series modelling reveals a significant June seasonal as well as the stochastic nature of seasonality. The main explanation put forward for this phenomenon is that harsh climatic conditions in the summer months of July and August forces a significant proportion of the Kuwaiti population (and hence stock traders) to leave the country for overseas holidays. Before leaving the country, traders accumulate stocks, putting upward pressure on prices and creating the June effect.

INTRODUCTION

The objective of this paper is to investigate seasonality in stock prices in the emerging stock market of Kuwait. A finding of seasonality in stock prices (or returns) may be used as the basis of a successful and profitable trading strategy. It also has implications for market efficiency, because the appearance of anomalies (such as seasonality) is taken to be an indication that the market is inefficient.

One of the most publicised and investigated seasonal patterns is the so-called "January effect": the tendency of stock prices to rise in January relative to December. Wachtel (1942) was the first economist to examine and document seasonality in the Dow Jones Industrial Average during the period 1927-1942. He observed frequent bullish tendencies from December to January in eleven of the fifteen years he studied. Over three decades later, Rozeff and Kinney (1976) conducted serious empirical research to examine seasonality in the U.S. stock market and found statistically significant differences in mean returns materialising in different months. Subsequent empirical research revealed strong January seasonality in stock returns and money market returns in the U.S. and other markets.[1] In a recent paper, however, Lindley et al (2004) demonstrated that many years during the period 1962-2000 did not have a significant January effect and that some years had a negative January effect.

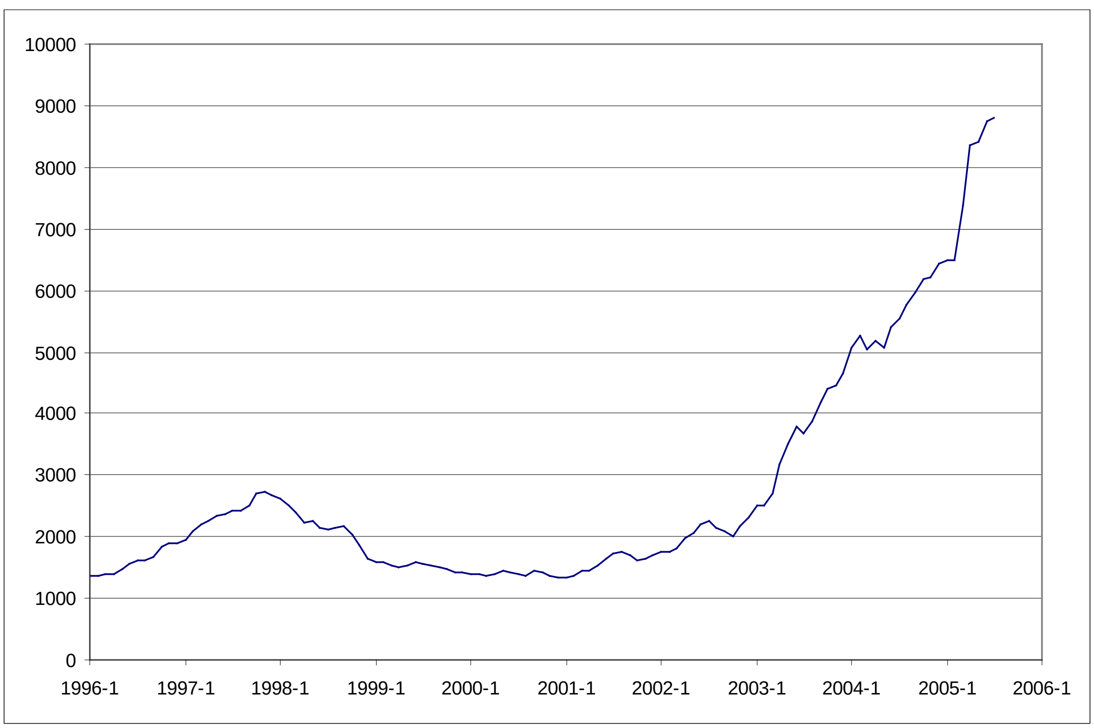
Several explanations for the January effect have been put forward, including the tax-loss selling hypothesis, the behaviour of portfolio managers who engage in window dressing at the end of the year, the relation between market capitalisation and seasonality, and the timing of information release. While the tax-loss selling hypothesis cannot be applicable to Kuwait because it is a tax-free country, the other explanations may have some validity. However, the tiny empirical evidence available indicates no support for the presence of the January effect in the Kuwait stock market (see, for example, Al-Saad and Moosa, 2005; Al-Deehani, 2006). Rather, there is some fragmented evidence on seasonal patterns involving the summer months and those preceding them.

In this paper, the issue of seasonality in the Kuwait stock market is re-examined using monthly averages of the daily closing prices rather than the month-end closing prices used in the previous studies. This is preferable because any monthly effect represented by the rise or fall of prices relative to the previous month is not only the result of activity in the last day of the month, but it rather emanates from the activity of market participants throughout the month. Furthermore, the use of monthly averages reduces the amount of noise embodied in month-end data. Conventional regression analysis as well as structural time series analysis are employed for the purpose of empirical analysis.[2]

AN INFORMAL EXAMINATION OF THE DATA

The statistical analysis presented in this paper is based on monthly average observations of the Kuwait Stock Exchange Index (KSEI) over the period January 1996 to July 2005. The data were obtained from the Kuwait Stock Exchange. Figure 1 is a time plot of the KSEI over the sample period, showing clearly the boom that commenced at the end of 2002. It is not possible to

FIGURE 1
THE KUWAIT STOCK EXCHANGE INDEX: MONTHLY AVERAGE OF DAILY CLOSING OBSERVATIONS



observe any seasonal behavoiur in this chart because the behavoiur of the index is dominated by a long-term upward trend.

Figure 2 displays the monthly percentage change in the KSEI, representing total monthly returns including any seasonal, cyclical and random behaviour, whereas Table 1 reports the means and standard deviations of the monthly return over the sample period. We can see that, on average, the monthly return in June is higher than in any other month. The evidence for the January effect seems to be very slim as the average monthly return in January is 1.63 per cent. Again, it is not possible to detect any seasonal behaviour from Figure 2 and Table 1. Indeed, the behaviour as depicted in Figure 2 looks random, and this is why the next step is the extraction of the seasonal factors embodied in the return series.

FIGURE 2
MONTHLY RETURN (%)

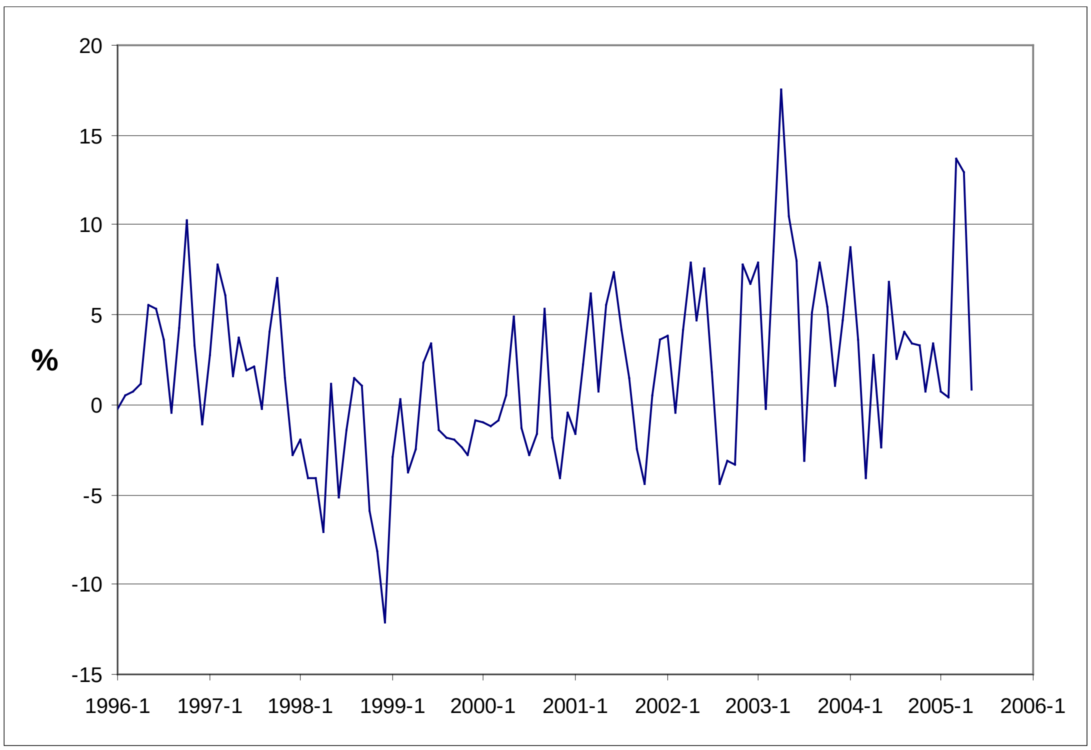


TABLE 1
MEANS AND STANDARD DEVIATIONS OF MONTHLY RETURNS (1996-2005)

Month	Mean	Standard Deviation
January	1.63	4.11
February	0.89	3.16
March	2.67	6.07
April	3.56	7.31
May	3.70	3.47
June	3.78	4.32

July	0.63	2.65
August	0.39	2.98
September	2.05	3.88
October	0.91	5.75
November	-0.01	4.58
December	0.12	5.59

EMPIRICAL RESULTS

To start with, the seasonal factors are estimated by using a conventional ARDL regression model containing 12 seasonal dummy variables, which in essence define the average seasonal factors (over the sample period) associated with each month. The model is specified as

$$r_t = \sum_{i=1}^{m} \alpha_i r_{t-i} + \sum_{i=1}^{12} \lambda_i D_t^i + \xi_t \qquad (1)$$

where $r_t \equiv \Delta \log P_t$ is the rate of return (measured as the first log difference of the general market index, P_t), D^i is a seasonal dummy assuming the value 1 in month *i* and zero otherwise, and *m* is the order of the autoregressive process, which is determined according to the Schwartz Bayesian criterion. A significant λ_i indicates that the seasonal factor corresponding to month *i* is significant.

The OLS estimation results of the λ_i's as they appear in equation (1) are reported in Table 2, showing no significant seasonal factor at all. Here, we must not jump to the conclusion that there is no seasonality in returns, because this model produces the average seasonal factors over the sample period. In other words, it implies that seasonality is deterministic rather than stochastic. If seasonality changes over time (that is, seasonality is stochastic), the average seasonal factors may turn out to be insignificant. For this reason, we resort to a technique whereby we can extract the seasonal component as it evolves over the whole of the sample period. This allows us to see changes in the seasonal behaviour as time goes by.

TABLE 2
MONTHLY SEASONAL FACTORS ESTIMATED FROM AN ARDL MODEL

Month	Seasonal Factor	t Statistic
January	1.649	1.19
February	-0.032	-0.02
March	2.601	1.87
April	2.026	1.52
May	2.017	1.49
June	1.907	1.40
July	-1.384	-1.01
August	0.023	0.01
September	1.419	0.99
October	-0.225	-0.16
November	-0.277	-0.20
December	-0.023	-0.02

The seasonal component is the part of the monthly return that is attributed to purely seasonal factors. The underlying assumption of the following analysis is that the return at any point in time consists of four components: a trend, a cycle, a seasonal component and a random component. What we are interested in is the seasonal component, which we can extract by using a version of Harvey's (1989, 1997) structural time series model that encompasses an autoregressive structure instead of the cycles.[3] The model may be written as

$$r_t = \mu_t + \alpha_t r_{t-1} + \gamma_t + \varepsilon_t \tag{2}$$

where μ_t is the trend component, γ_t is the seasonal component and ε_t is the random component, which is assumed to be white noise. The trend component, which represents the long-term movement in a series, is represented by

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{3}$$

$$\beta_t = \beta_{t-1} + \zeta_t \tag{4}$$

where $\eta_t \sim NID(0, \sigma^2_\eta)$, and $\zeta_t \sim NID(0, \sigma^2_\zeta)$. μ_t is a random walk with a drift factor, β_t, which follows a first order autoregressive process as represented by equation (4). This is a general representation of the trend, which encompasses all other possibilities (random walk with drift, random walk without drift, local level, etc).

There are a number of different specifications for the seasonal component (see Harvey, 1989, chapter 2). Harvey and Scott (1994) use a trigonometric specification that allows a smoother change in the seasonals. The problem with this specification, however, is that it does not lend itself to a straightforward interpretation.[4] For this reason, stochastic dummies are preferred, in which case the stochastic component is specified as

$$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j} + \kappa_t \tag{5}$$

where s is the number of seasons in one year (12 for monthly data) and $\kappa_t \sim NID(0, \sigma^2_\kappa)$. The interpretation is straightforward: γ_t is the seasonal factor corresponding to time (month) t, which is generated by the seasonals corresponding to times t-1, t-2, …., t-10, and as well as the random term κ_t.

Once it has been written in state space form, the model can be estimated by maximum likelihood, using the Kalman filter to update the state vector (whose elements are the time series components and the coefficient on r_{t-1}) as new observations become available. Related smoothing algorithms can be used to obtain the best estimate of the state vector at any point in time within the sample period. For details of the estimation method, see Harvey (1989, chapters 4 and 7) and Koopman et al. (1995, chapter 14).

Having estimated the model over the sample period, the seasonal components can be extracted and plotted over time, as shown in Figure 3. It can be seen from this chart that the seasonal behaviour changed around 2000 and established a new regular pattern in 2002. Figure 4 shows the seasonal factors (individual seasonals) corresponding to each month at the end of the sample period, obtained from the estimated final state vector. The only statistically significant seasonal factor is the one corresponding to June, which assumes the value of 3.74 per cent. This means that in June 2005, stock prices rose (relative to May) by more than three and a half percentage points for purely seasonal reasons. Therefore, there is a positive June effect, in the sense that stock prices tend to rise in June relative to May.

As we can see from Figure 3, the seasonal pattern has been changing. To examine this change further, consider the estimated seasonal factors reported in Table 3 for the whole sample period. We can see from this table conspicuous changes in the seasonal factors corresponding to some of the months, namely February, April, May, June and July. The seasonal factors corresponding to February, May and July are changing from being positive to being increasingly negative. On the contrary, the seasonal factor corresponding to April is changing from being negative to being increasingly positive. If this change continues, a significant April effect may emerge. The seasonal factor corresponding to June has always been positive, increasing in value progressively and creating the phenomenon of the June effect. Also conspicuous is the absence of the January effect.

FIGURE 3
THE SEASONAL COMPONENT OF MONTHLY RETURN (%)

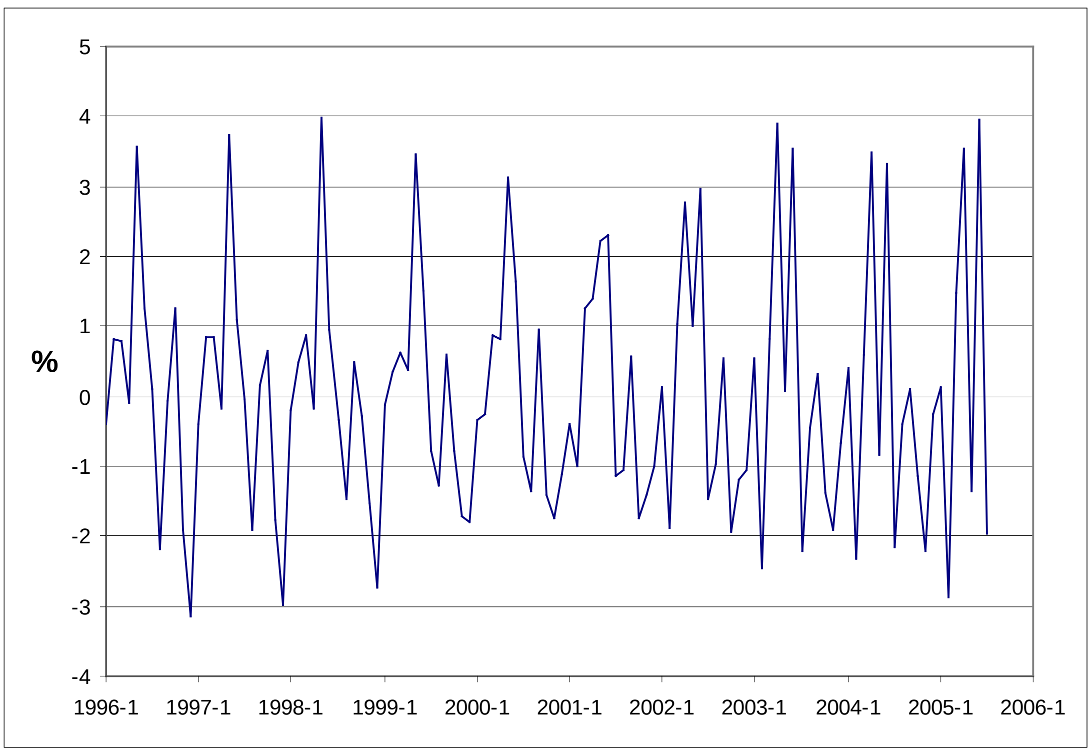
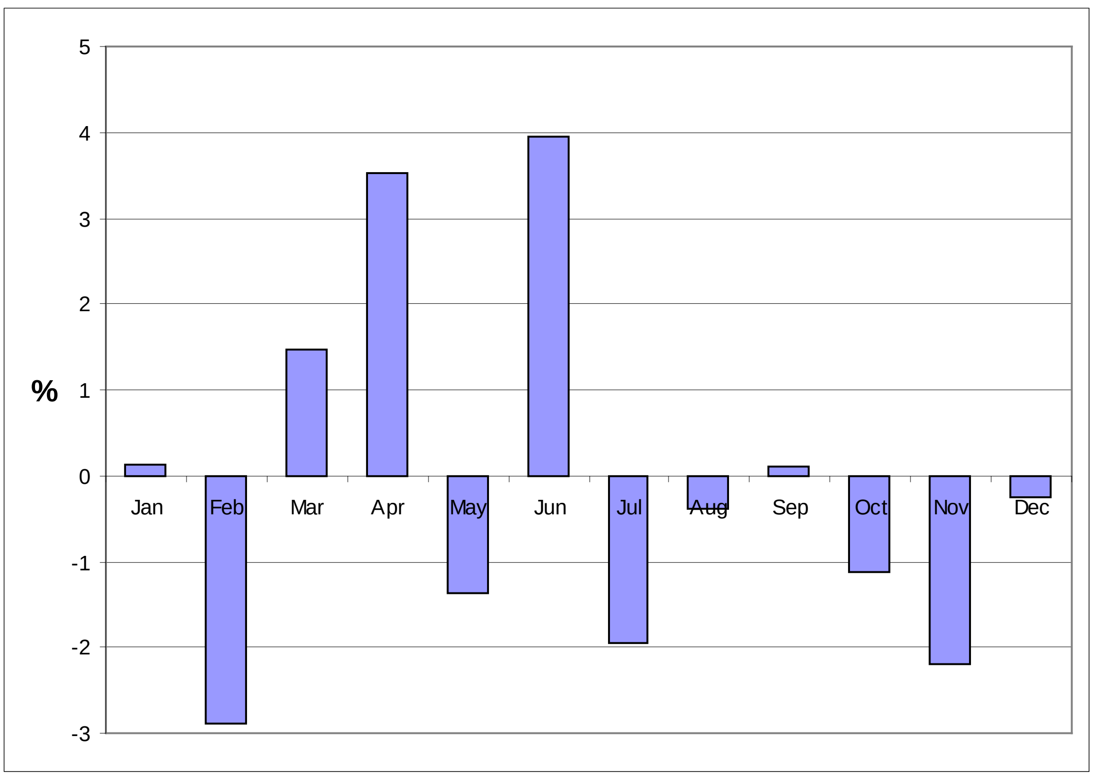


TABLE 3
MONTHLY SEASONAL FACTORS ESTIMATED FROM A STRUCTURAL TIME SERIES MODEL

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1996	-0.39	0.81	0.79	-0.10	3.58	1.25	0.09	-2.18	-0.06	1.24	-1.91	-3.14
1997	-0.39	0.83	0.83	-0.19	3.73	1.08	-0.03	-1.92	0.17	0.66	-1.77	-2.98
1998	-0.19	0.50	0.87	-0.19	3.99	0.94	-0.35	-1.46	0.49	-0.28	-1.52	-2.73
1999	-0.13	0.35	0.61	0.39	3.46	1.51	-0.78	-1.28	0.60	-0.78	-1.72	-1.79
2000	-0.35	-0.27	0.87	0.82	3.13	1.65	-0.87	-1.36	0.95	-1.41	-1.73	-1.12
2001	-0.39	-1.00	1.27	1.40	2.22	2.29	-1.13	-1.04	0.58	-1.75	-1.40	-1.01
2002	0.12	-1.87	1.05	2.78	1.00	2.95	-1.46	-0.97	0.54	-1.93	-1.20	-1.05
2003	0.53	-2.47	0.83	3.90	0.07	3.54	-2.22	-0.44	0.32	-1.40	-1.92	-0.66
2004	0.41	-2.33	0.61	3.51	-0.84	3.23	-2.17	-0.40	0.11	-1.13	-2.21	-0.25
2005	0.13	-2.88	1.47	3.54	-1.36	3.95	-1.95					

FIGURE 4
SEASONAL FACTORS AT THE END OF THE SAMPLE PERIOD (%)



DISCUSSION AND CONCLUDING REMARKS

The finding of a significant June effect requires an explanation. The most sensible explanation is that prices rise fast in June because of demand pressure arising from the desire of traders to accumulate stocks before going away on holiday to escape the harsh summer months. Since the market has been rising fast in the most recent period, this kind of behaviour is triggered by the fact that investors feel that they would be left out if they did not accumulate stocks while they are away. The second possible explanation is that June is the month in which the interim financial results are announced, which may trigger some demand pressure on the market.

The absence of the January effect has two explanations, the first of which is that Kuwait is a tax-free country. If the January effect is explained in terms of tax considerations, it will not appear in the tax-free environment of Kuwait. The second explanation is that even in the U.S. market, the January effect has disappeared and replaced by a July effect is attributed to the holiday factor. For one reason or another, the January effect seems to have vanished (see, for example, Moosa, 2007).

On the basis of the observation of a positive June effect, a sensible trading strategy would appear to be to buy in May and sell in June. But this will only be the case if the market is not dominated by a trend, because a strong trend may dominate the seasonal factor. Take, for example, the last 12 months of the sample period examined in this study. The return was positive in every month, even in those that had negative seasonal factors. Although a trader who bought in May and sold in June would have made profit, the profit would have been slightly bigger if he had sold in July. A trading strategy based on seasonal variation works best in a trendless or mildly declining market. The presence of a significant June effect means that profit can be made by buying in May and selling in June, even in a bear market.[5]

ENDNOTES

1. Jones and Wilson (1989) tested the January effect using seven assets from 1871 to 1986. Also, Musto (1997) tested the January effect in the commercial papers market.
2. For a survey of the applications of structural time series modelling in economics and finance, see Moosa (2006).
3. On the rationale of using this model, see Moosa (2006).
4. On the difficulty of interpreting trigonometric seasonals, see Koopman et al. (1995, p 226).
5. Provided, of course, that the seasonal variation is stronger than the downward trend. A caveat is warranted here. Heavy buying in June, as explained earlier, is motivated by the belief of market participants that failure to accumulate stocks prior to departure for holidays will deprive them of the potential profit to be realised from rising prices. This kind of belief becomes dominant in a bull market, which was the case in the latter part of the sample period. If and when the market turns bearish, it is likely that the desire to accumulate stocks in the pre-holiday months will dwindle and eventually vanish. It could be the case that the June effect revealed in this study is a phenomenon that is associated with bull markets only, and this is why it has been gaining strength. Time will tell if this proposition is sound.

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