DYNAMICS BETWEEN MALAYSIAN EQUITY MARKET AND MACROECONOMIC VARIABLES: AN APPLICATION OF KALMAN FILTER MODEL WITH HETEROSKEDASTIC ERROR

by

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LIST OF PUBLICATIONS

1 CHeah, L. H. and Arsad, Z. (2006). Estimating And Forecasting Volatility Of Malaysian Stock Market Using A Combination Of Kalman Filter And GARCH Models. *Capital Market Reviews*, 14, (1 & 2), 27-42.

DINAMIK ANTARA PASARAN EKUITI MALAYSIA DAN PEMBOLEHUBAH-PEMBOLEHUBAH MAKROEKONOMI: SATU APLIKASI MODEL PENAPIS KALMAN DENGAN RALAT HETEROSKEDASTIK

ABSTRAK

Sejak diperkenalkan oleh Kalman dan Bucy (1960), model penapis Kalman telah mendapat penggunaan yang luas dalam dalam program ruang angkasa dan bidang kejuteraan kawalan. Namun begitu, pengaplikasiannya dalam bidang siri masa kewangan masih jarang digunakan dan jauh ketinggalan. Model penapis Kalman adalah satu set persamaan yang membenarkan nilai anggaran dikemaskini sebaik sahaja satu cerapan baru diperolehi. Satu model untuk data bulanan Indeks Komposit Kuala Lumpur dari April 1986 hingga Februari 2005 dicadang dan dikaji. Model ini membenarkan aras berbalik purata bagi Index Komposit Kuala Lumpur dimodelkan secara stokastik. Perbandingan dilakukan menggunakan keputusan-keputusan di antara model ringkas penapis Kalman AR(1) dan penapis Kalman tulen yang dicadang. Model terbaik dipilih berdasarkan nilai log kebolehjadian maksimum, *Akaike Information Criterion* dan *Bayesian Information Criterion*.

Tesis ini juga menggunakan model penapis Kalman untuk menganalisa ruang keadaan dengan ralat bersifat ARCH seperti yang dicadangkan oleh Harvey, Ruiz and Sentana (1992). Analisis difokuskan terhadap model-model yang mana sebutan-sebutan ralat dalam persamaan pengukuran adalah heteroskedastik. Lima model dari jenis ARCH termasuk ARCH, GARCH, GARCH-M, EGARCH dan TARCH dipertimbangkan. Keputusan menunjukkan bahawa model-model dengan kombinasi penapis Kalman dan jenis ARCH memberikan ralat sampel dalaman dan ralat telahan sampel luaran yang lebih kecil daripada nilai-nilai yang dihitung daripada model penapis Kalman tulen.

Model penapis Kalman juga diaplikasikan untuk mengkaji dinamik di antara model bergabung bagi Index Komposit Kuala Lumpur, kadar tukaran wang *Pound Sterling* dan kontrak hadapan Indeks Komposit Kuala Lumpur. Bentuk ruang keadaan membenarkan satu siri tak tercerap diperkenalkan ke dalam struktur model tersebut. Siri tak tercerap ini dianggap sebagai kombinasi pembolehubah-pembolehubah lain yang tidak dipertimbangkan ke dalam model-model yang dikaji. Data bulanan dari Januari 1997 hingga Februari 2005 telah digunakan bagi analisis dan prosedur pemodelan. Bentuk ruang keadaan model penapis Kalman digunakan bagi mengkaji sekiranya kadar tukaran wang *Pound Sterling* dan kontrak hadapan Indeks Komposit Kuala Lumpur mempunyai kesan yang signifikan terhadap telatah Indeks Komposit Kuala Lumpur. Tambahan pula, matrik keadaan membolehkan kajian terhadap arah sesuatu hubungan yang wujud. Model-model yang diketengahkan seterusnya dibandingkan dengan model *Vector Autoregressive*.

Kajian secara keseluruhannya menunjukkan bahawa model penapis Kalman dengan ralat pengukuran sifar dan model penapis Kalman dengan ralat jenis EGARCH merupakan model terbaik daripada kategori model penapis Kalman tulen yang dicadangkan dan model degan kombinasi penapis Kalman dan jenis ARCH, masing-masing. Keputusan menunjukkan bahawa kedua-dua model penapis Kalman tulen dan *Vector Autoregressive* menunjukkan hubungan satu hala dari harga saham kepada kadar tukaran wang. Tambahan pula, didapati bahawa kedua-dua pembolehubah tersebut berkorelasi negatif. Walau bagaimanapun, telah didapati bahawa pasaran saham dan kontrak hadapan adalah tak sandar antara satu sama lain, yang bermaksud bahawa tiada terdapat hubungan yang signifikan antara dua pembolehubah tersebut. Bagi model-model dengan kombinasi penapis Kalman dan jenis ARCH , andaian varians berubah terhadap masa menghasilkan lebih banyak hubungan yang signifikan di kalangan pembolehubah yang dikaji. Keputusan menunjukkan hubungan satu hala di antara harga saham dan kadar tukaran wang. Di samping itu, didapati wujud hubungan dua hala di antara harga saham dan kontrak hadapan. Juga, keputusan-keputusan menunjukkan bahawa harga saham tidak dipengaruhi secara signifikan oleh siri tak tercerap bagi kedua-dua model penapis Kalman tulen dengan ralat pengukuran sifar dan model dengan kombinasi penapis Kalman dan jenis ARCH menandakan bahawa harga saham berkemungkinan tidak dipengaruhi secara signifikan oleh pembolehubah-pembolehubah lain.

Akhir sekali, analisis dan kajian yang serupa juga dilakukan dengan menggunakan model penapis Kalman dengan ralat pengukuran sifar dan model penapis Kalman dengan ralat jenis EGARCH bagi data harian untuk ketiga-tiga pembolehubah di atas. Data-data telah dibahagikan kepada tiga sub-sampel iaitu tempoh *World Recession* dari 2 Januari 2001 sehingga 21 Mei 2002 and dua sub-sampel *Recovery* dari 22 Mei 2002 sehingga 30 September 2004 hingga 1 Oktober 2004 hingga 28 Februari 2005 masing-masing. Bagi model penapis Kalman dengan ralat jenis EGARCH, didapati siri tak tercerap mempunyai kesan yang signifikan terhadap harga saham. Namun begitu, kejadian ini tidak dilihat bagi model penapis Kalman tulen. Kajian simulasi berdasarkan model penapis Kalman tulen dengan ralat pengukuran sifar dan model penapis Kalman dengan ralat jenis EGARCH bagi kedua-dua data bulanan dan harian, menunjukkan bahawa model terpilih berjaya menghasilkan realisasi yang baik bagi ketiga-tiga siri masa yang dicerap.

DYNAMICS BETWEEN MALAYSIAN EQUITY MARKET AND MACROECONOMIC VARIABLES: AN APPLICATION OF KALMAN FILTER MODEL WITH HETEROSKEDASTIC ERROR

ABSTRACT

Ever since the pioneering work of Kalman and Bucy (1960), Kalman filter model has become widely used in the space programme and control engineering. However, its applications in financial time series have been very few and far in between. Kalman filtering is a set of equations which allows an estimator to be updated once a new observation becomes available. A model for the monthly Kuala Lumpur Composite Index from April 1986 to February 2005 is proposed and investigated. The model allows the mean reversion level of Kuala Lumpur Composite Index to be modeled stochastically. Comparisons of results between the simpler Kalman filter AR(1) and the proposed models are made. The best models are chosen with reference to the value of maximum log likelihood, Akaike Information Criterion and Bayesian Information Criterion.

This thesis also makes use of Kalman filtering model to analyse state-space model with ARCH disturbances proposed by Harvey, Ruiz and Sentana (1992). The analyses are focused on models in which the disturbances terms of the measurement equations are heteroskedastic. Five ARCH-type models including ARCH, GARCH, GARCH-M, EGARCH and TARCH are considered. The results show that the Kalman filter and ARCH-type combination models give smaller both within sample and out-of-sample forecast errors than those calculated from the pure Kalman filter model.

The Kalman filter model is also applied to investigate the dynamics between a combined model for the Kuala Lumpur Composite Index, Pound Sterling exchange rates and Kuala Lumpur Composite Index Futures. The state-space form allows an unobserved series to be introduced into the structure of the model. This series is regarded as a combination of other variables which have not been taken into account to the models. Monthly data from January 1997 to February 2005 is used for the analyses and modeling procedures. The state-space form of the Kalman filter model is used to investigate whether Pound Sterling and Kuala Lumpur Composite Index Futures have any significant effect on the behaviour of the Kuala Lumpur Composite Index. In addition, the state matrix also enables us to investigate the direction of the relationship. The proposed models are then compared to the Vector Autoregressive model.

In general, the results show that Kalman filter with zero measurement error and Kalman filter-EGARCH models are the best from the categories of pure Kalman filter and Kalman filter-ARCH-type models respectively. The results indicate that both pure Kalman filter and Vector Autoregressive models show a uni-directional flowing from stock prices to exchange rates. In addition, it is found that the variables are negatively correlated. However, it is found that the stock market and financial futures are independent of each other, meaning that there is no significant relationship between them. For the Kalman filter-ARCH-type models, the assumption of time-varying variances produces more significant relationships among the variable analyzed. The result shows a uni-directional from the stock prices to exchange rates. Moreover, there is an existence of bi-directional relationship between stock prices and financial futures. In addition, the results show that stock prices is not significantly affected by the unobserved series in both Kalman filter with zero measurement error and Kalman filter-EGARCH models, indicting that the stock prices may not be significantly affected by other variables.

Finally, similar analyses and investigations are also carried out using Kalman filter with zero measurement error and Kalman filter-EGARCH models for daily data of the three variables above. The data is divided into three sub-samples: period of World Recession period from 2nd January 2001 to 21st May 2002 and two Recovery periods from 22th May 2002 to 30th September 2004 and 1st October 2004 to 28th February 2005 respectively. For the Kalman filter-EGARCH models, it is found that the unobserved series significantly affects the stock prices. However, this occurrence is not seen in the pure Kalman filter model. Simulation study based on the Kalman filter with zero measurement error and Kalman filter-EGARCH models using both monthly and daily data shows that the chosen best models successfully produce good realizations of the three observed series.

CHAPTER 1
INTRODUCTION

1.1 Overview of the Malaysian economy

The structure of Malaysian economy has gone through a remarkable transformation from an agro-based economy, exporting primary commodities to a country based on industry and exporting a variety of manufactured products. Nowadays, Malaysia is one of the economic miracles of East Asia. This strong economy growth has been almost completely driven by exports spurred on by high technology. In addition, political stability and attractive business environments, with high capita income and the efficient management of its natural resources which include oil and gas are all the strengths that makes Malaysia‘s economy grows steadily. The government of Malaysia also encourages massive foreign direct investment (FDI) in labor intensive manufacturing industries and this has resulted in lower rate of unemployment. Even more impressive is the fact that economic growth in Malaysia has been achieved within an environment of relatively low inflation.

According to Bank Negara Malaysia Annual Report (1991-2000) and Statistical Bulletin (1998-2005), Malaysia’s Gross Domestic Price (GDP) grew at an average rate of 5.1% and 7.8% in the 1960s and 1970s respectively. In the 1980s, the Malaysian economy continued to grow, although at a lower average rate of 5.9% due to the global recession during the 1985-1986 periods. The lower growth rate was also caused by the fact that the commodity prices were more favorable in the 1970s than in the 1980s. With the recovery of the world economy, the Malaysian economy grew steadily at an average rate of 8.7% from 1991 to 1997. However, the growth was disrupted by the East Asian financial crisis in 1998 and consequently it dropped rapidly with the rate of 7.4%. Fortunately, due to the government’s effort to resuscitate the economy, an average growth rate of 7.2% was achieved in 1999 and 2000. In the recent years, Malaysia expansions was influenced by several uncertainties that arise from international terrorism, political instability in Afghanistan, Iraq and some neighbouring ASEAN countries and the outbreak of the Severe Acute Respiratory Syndrome (SARS). In 2001, Malaysia achieved only 0.4% of GDP growth rate. As an oil and gas exporter, Malaysia has profited from higher world energy prices and thus growth increased to 7% and 5% in 2004 and 2005 respectively.

The 2005 World Competitiveness Report has placed Malaysia as the 10th most competitive nation among 30 countries with a population of more than 20 million. For sustainable economic growth and to achieve Vision 2020 eventually, the government of Malaysia seeks to make the leap to a knowledge-based economy. In other words, exploitation of knowledge plays an important role in the country development process. There will be intensive research and technology development with Information Communication Technology (ICT) as the enabling technology. In addition, Malaysia must be able to create products and technology that are recognized as our own through building on the creativity of our people. Equally important, the government must always be conscious of the need to ensure a balanced socio-economic environment whereby all Malaysians would benefit from the fast growth of the economy.

1.2 Bursa Malaysia

In Malaysia, Bursa Malaysia was first established in 1930 as the first formal organization in the securities business. It offers equity-related risk management instruments and access to portfolio management strategies which were not previously available. In this section, we will look back the history of Bursa Malaysia. When Bursa Malaysia was first established, it was named as Singapore Stockbrokers' Association and be re-registered as Malayan Stockbrokers' Association seven years later.

However, there was still no public trading of shares at that time. In 1960, the Malayan Stock Exchange was formed and public trading of shares began on 9th May of the same year.

In 1961, the Board system was introduced with two separate trading rooms for Singapore and Kuala Lumpur. The two trading rooms were linked by direct telephone lines into a single market with the same stocks and shares listed at a single set of prices on both boards. In 1964, the Stock Exchange of Malaysia was established. However, it was separated into The Kuala Lumpur Stock Exchange Bhd (KLSEB) and The Stock Exchange of Singapore (SES) in 1973. In the same year, Kuala Lumpur Stock Exchange took over the operation of KLSEB and it was renamed as Kuala Lumpur Stock Exchange in 1994. In 2004, Kuala Lumpur Stock Exchange was renamed Bursa Malaysia.

Figure 1.1 shows regulatory structure of Bursa Malaysia. Bursa Malaysia operates under the supervision of the Securities Commission which falls under the authority of the Ministry of Finance of Malaysia. This offers investors the security of trading on a regulated exchange with similar rules and regulations like other stock exchanges. Bursa Malaysia plays an important role as a central market place to manage people risk exposure and to offer a competitive market place for fund raising and investment. In addition, it is also a central market place for various types for securities transactions between buyers and sellers. Bursa Malaysia was fully computerized in 1992 with the introduction of System on Computerized Order Routing and Execution (SCORE) automated trading system.

Bursa Malaysia computes an index for each of the main sectors traded on the bourse but the most widely used performance index is by far the Kuala Lumpur Composite Index (KLCI). It was introduced in 1986 since then it serves as an accurate indicator of the performance of the Malaysian stock market and the economy. The companies that make up the KLCI are limited to 100 (although the actual number may change from time to time) and they are some of most heavily traded and the largest public corporations in Malaysia. The KLCI is presently calculated and disseminated on a minute by minute basis.

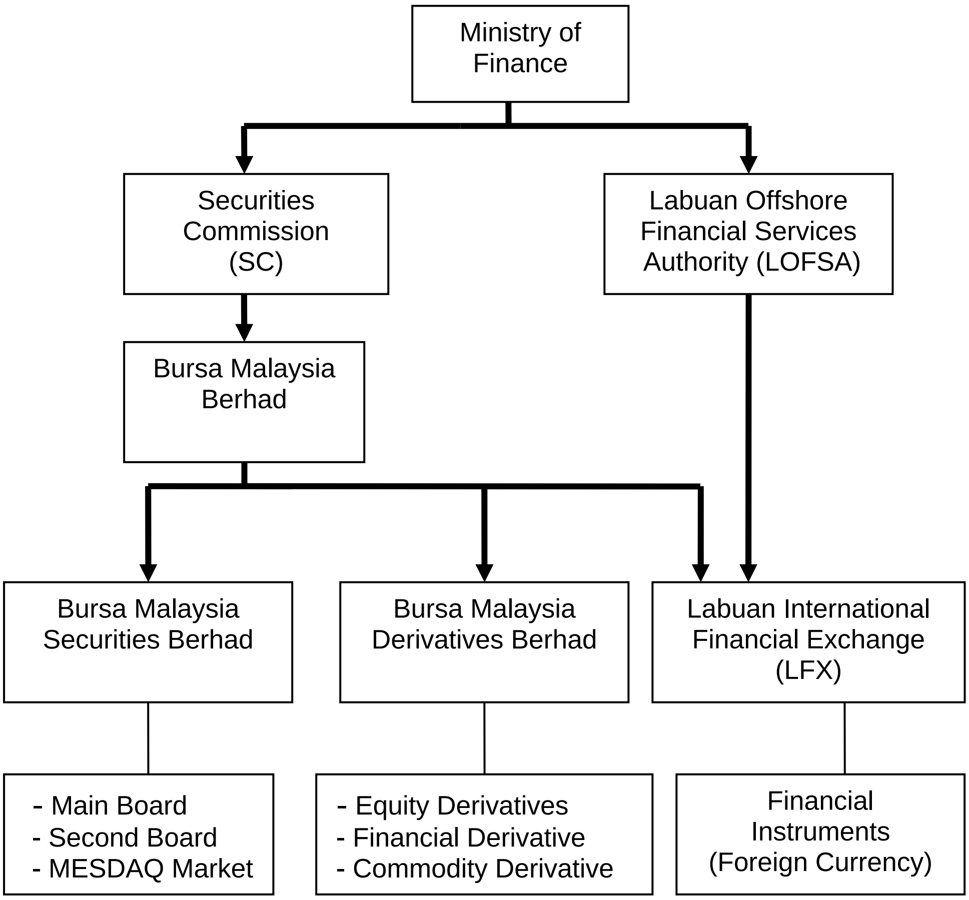
Ministry of Finance
Securities Commission (SC)
Labuan Offshore Financial Services Authority (LOFSA)
Bursa Malaysia Berhad
Bursa Malaysia Securities Berhad
Bursa Malaysia Derivatives Berhad
Labuan International Financial Exchange (LFX)
- Main Board
- Second Board
- MESDAQ Market
- Equity Derivatives
- Financial Derivative
- Commodity Derivative
Financial Instruments (Foreign Currency)

Figure 1.1: The regulatory structure diagram (Reproduced from Bursa Malaysia)

The futures industry plays a significant role in the transformation towards a more dynamics capital market and financial industry. Futures are contract that are legally binding agreement between two parties to buy or sell the underlying instrument at a certain date in the future. The Kuala Lumpur Composite Index Futures (FKLI) contract traded on Bursa Malaysia Derivatives Berhad is an alternative trading instrument compared to stocks on Bursa Malaysia. Note that the first futures exchange in Southeast Asia, Kuala Lumpur Commodity Exchange (KLCE) was establishment in July 1980. This is then followed by the establishment of Kuala Lumpur Options and Financial Futures Exchange (KLOFFE) which introduces the Kuala Lumpur Composite Index Futures (FKLI) in 1995. With the introduction of FKLI, Malaysia became the third Asian economy after Hong Kong and Japan to offer domestic equity derivatives products. In June 2001, KLOFFE merged with the Commodity and Monetary Exchange of Malaysia (COMMEX) and become Malaysian Derivative Exchange Berhad (MDEX).

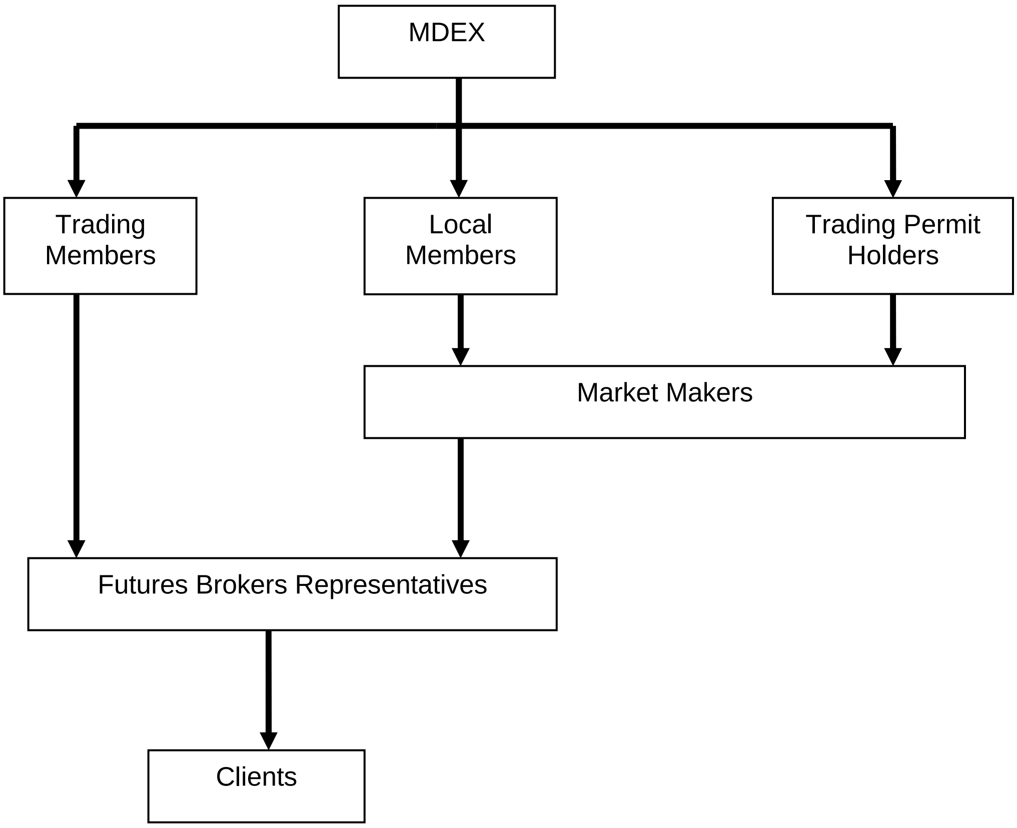
MDEX
Trading Members
Local Members
Trading Permit Holders
Market Makers
Futures Brokers Representatives
Clients

Figure 1.2: Derivatives market structure in Malaysia (Reproduced from Bursa Malaysia)

MDEX is an organization which provides a variety of products to the market and offers various types of financial and commodities futures. It was established as a result of the provisions of the Futures Industry Act 1993 (FIA). The FIA was amended to provide a more efficient and effective regulation of the financial futures and options industry. The derivative market structure is illustrated in Figure 1.2. The Malaysian Securities Commission was empowered by the Ministry of Finance to regulate and monitor the securities and futures industries. In addition, it is responsible to provide licensing of participants in the market including futures brokers, futures trading advisers, futures fund managers and their representatives.

1.3 Literature Review

1.3.1 Relationship between stock prices and stock index futures prices

This section reviews a few related papers on the relationship between stock prices and stock index futures prices. At present, investment in stock market is widely regarded as a more popular type of investment compared to property, unit trust and a few others. Due to the streaming news or information in this internet era, making the right trading decisions quickly and consistently is a big deal. Therefore in many economic models, public's expectations of the future have important consequences. This is necessary in the stock market in order to help investors making better investment decisions and to help in reducing loss in the future.

When making decisions, traders incorporate information pertaining to price movements and volatility in the asset they are trading. Investors, regulators and brokers have all expressed concern over the level of stock market volatility. Information and knowledge of the behaviour of return volatility is important due to the fact that changes in the volatility would affect share prices. For example, large increases in the volatility will generally produce a negative effect to share prices. The stock market crash in October 1987 and drop in stock price in 1989 left many people wondering whether stock prices have not become too volatile. Fama (1965) concluded that the movements of stock price are best characterized by a random walk process. Thus, it will be useless to investigate the stock volatility if all information has been incorporated into prices.

Although stock and futures prices may wander widely, the two series may share the same stochastic trend since stock is the underlying asset for the futures. If so, the series are cointegrated and are not expected to drift too far apart. The relationship between stock index and stock index futures prices is critical because it has implications regarding predominant financial theory, including market efficiency. Many studies have examined how price movements are correlated across asset and derivative security markets. In the last couple of decades, the relationship between stock index and stock index futures markets has been the interest to academicians, regulators and practitioners. Therefore, a number of studies have been conducted ranging from developed markets to less developed markets. Nonetheless, the sensitiveness of the relationship varies depending on the period of studies and the occurrence of economic crisis or structural change in the data period.

Brooks *et*. *al*. (2001) showed that the return on a spot market index and associated futures contract should be perfectly and contemporaneously correlated if the respective markets are perfectly efficient. According to the efficient market hypothesis, any mispricing in the market would be adjusted to eliminate any arbitrage opportunities. Hence, the stock prices and futures will simultaneously reflect new information in the market and no arbitrage profit can be made from the markets.

The theoretical relationship between a stock index and futures prices and its underlying asset is presented by:

$$F_t = S_t \exp\left[(r-d)(MD-t)\right] = S_t e^{(r-d)(MD-t)}$$

where:

F_t = stock index futures prices quoted at time *t*

S_t = value of the underlying stock index at time *t*

r = rate of return

d = continuously compounded dividend yields

MD = maturity date for futures contract

The model above can be transformed into a model of log-returns as follows:

$$f_t = s_t + \left(r - d\right)$$

where $f_t = \ln(F_t / F_{t-1})$ and $s_t = \ln(S_t / S_{t-1})$.

According to Brooks *et*. *al*. (2001), market sentiment and arbitrage trading are the major determinants of lead-lag relationship between stock market index futures and it underlying asset. Note that the movements in futures prices should reflect expected futures movements of the underlying cash price. Thus, it will quickly reflect all available information and response quickly to new information. Besides, it is believed that stock index should response in a similar pattern as in the stock index futures. Since most stocks are not traded constantly, say every 5 or 10 minute, it has leaded to lag respond of the new information. Hence, lead-lag relationship frequently observed in the spot and futures market.

In their paper, a number of techniques drawn from time series econometrics are employed. The models used are cointegration and error correction model (ECM), cost of carry error correction model, Autoregressive Moving Average (ARMA) and Vector Autoregressive (VAR) models. The data used is the 10 minutes observations for all trading days of the London Financial Time Index (FT-SE 100) from June 1996 to 1997. The results show that futures returns lead the spot returns. Also, cost of carry error correction model is found the best to be used for forecasting purposes.

Wahab and Lashgari (1993) investigated the daily price-change in stock index and stock index futures markets using cointegration and causality analysis. The data employed in the study are daily closing spot and futures price for both the New York Standard and Poor 500 index (S&P) and London FT-SE 100 index started from 4th January 1988 to 30th May 992. The results show that cash and futures are cointegrated. Morever, spot and futures price appear to be mostly simultaneously related on a daily basis and this is generally consistent with the notion of market efficiency. They also found that significant feedback exists between the cash and futures for both the S&P 500 and London FT-SE 100 indexes. However, the spot-to-futures lead appears to be more pronounced across days relative to the futures-to-spot lead. In addition, it is known that futures prices exhibit stronger subsequent response to disequilibrium in the spot prices and conversely, this does not apply to the spot prices towards last period's futures equilibrium error.

Ghosh (1993) investigated the relationship between spot and futures price using Dickey-Fuller cointegration test and error correction model. There are two data set used in the study: Standard and Poor's (S&P) 500 spot index and intra-day futures price as well as daily closing prices of Commodity Research Bureau (CRB) spot index and near term delivery of futures covering the time period from January 1988 to December 1988 and 12th June 1986 to 31st December 1989 respectively. The results show that both systems are cointegrated and therefore exhibit stable long-run equilibrium relationship. The error correction models are shown to be statistically significant in most cases. It is found that the disequilibrium in one period is corrected in the next period. For the S&P index, log of current spot price depends to a great extent on futures prices. However, the opposite occurrence is seen for the CRB index. The forecasting performance from error correction model outperforms the naïve model using the Ordinary Least Squared (OLS) regression. The result suggests that this modeling strategy offers potential for forecasting prices changes.

Iihara *et*. *al.* (1996) examined time series properties of intraday returns for stock index and stock index futures in Japan. The data set contains the time of transaction and the price for every futures transaction as well as the Tokyo Nikkei Stock Average (NSA) index from March 1989 to February 1991. There are three distinct time periods in the sample. The first period includes the year 1989 (bull market), the second year includes the year 1990 until the introduction of the stricter measures (bear market) while the third year begins after the introduction of the stricter measures and continues to March 1991 (bear market). The reason for this partition is due to the change in stock market condition. During the first period of bull market, the stock prices generally increase and achieve its highest value while during the second period of bear market, the stock prices generally decrease.

Lead-lag relationship between the intraday returns is investigated using regression technique. The results show that the introduction of stricter measures increase the volatility of both index and futures prices. At the same time, the speed of information dissemination in the futures markets is reduced. This suggests that futures returns strongly leads cash returns for all three periods. In term of volatility, there is no bi-directional information flows between the cash and futures markets. However, it is found that the futures market shocks significantly affect the conditional volatility of the cash market before the stricter measures are introduced. In other words, the stricter measures appear to reduce the information flow from the futures to the cash market. In addition, results show that the inter-market dependence of conditional volatilities is insignificant. Past conditional volatility affects only the current conditional volatility of its own market.

Marie and Lucy (1998) adopted the multivariate Generalized Autoregressive Heteroscedasticity (GARCH-M) model to examine relationship between stock indices and the associated futures prices. The study also provides evidence concerning day-ofweek and holiday effects on price movement and volatility. There are three series used in the paper including the New York Stock Exchange Composite, S&P 500 and Toronto 35. The data consists of daily observations for the three indices and their futures prices from January 1998 to March 1993.

The paper suggested that the GARCH-M model provides useful information concerning the movement of asset prices over time. The paper jointly models first and second moments of the price processes across markets. At the same time, seasonal effects are allowed in the model. The results show that seasonal effects are not consistently reflected in price movement and volatility. In general, the results provide significant evidence of time variation in price volatility and correlation in volatility across stock and futures markets. It is shown that the time-varying volatilities are significantly and positively correlated for the North American markets. This is mostly due to the fact that Canada and United States share similar market structures and regulatory environment. As expected, the volatility correlations decrease over time.

Wong and Meera (2001) studied the market efficiency in Malaysia stock index, KLCI and futures market, FKLI. Methodologies employed in the paper are Granger causality and error correction approach. The data are divided into two sub-samples: before financial crisis, from January 1996 to March 1997 and during the financial crisis, from April 1997 to September 1998. The results show that KLCI price lead FKLI before the economic crisis but not vice versa. In addition, there is no long run equilibrium relationship between both markets.

Chan and Karim (2004) analyse the lead lag relationship between spot and futures market of the KLCI. They used cointegration and error-correction model in their analysis. Daily closing price from January 1996 to December 2002 is used. It is suggested that KLCI prices and the corresponding futures markets are cointegrated.

Also, it is proven that futures prices can be a good indicator on predicting spot prices due to the stronger impacts of futures prices on cash markets compared to that from cash market to futures market. There are many other studies that have investigated the lead-lag relationship between futures market and cash market. These includes Lim (1992) who found that there is no lead-lag relationship between the Tokyo Nikkei Stock Average (NSA) stock and futures markets. Tang *et*. *al*. (1992) suggested that Hang Seng Index Futures cause the spot index prices to change during the pre-crash period but not vice-versa. However, there is a bi-directional relationship between the two variables during the post-cash period.

1.3.2 Relationship between stock prices and foreign exchange rates

Since stock market provides an ideal investment opportunity for local company as well as for foreign company, there is a strong correlation between a country's stock market and its currency. A currency is a unit of exchange, facilitating the transfer of goods and services. A currency zone is a country or region in which a specific currency is the dominant medium of exchange. To facilitate trade between currency zones, there are exchange rates i.e. prices at which currencies (and the goods and services of individual currency zones) can be exchanged against each other. Modern currencies can be classified as either floating currencies or fixed currencies based on their exchange rate regime.

Changes in the international and regional financial as well as the economic environment have made it important for Malaysia to have a stable exchange rate. To achieve stability of exchange rate, our government has to maintain the value of Ringgit against the currencies of its major trading partners. The United Kingdom has the fifth largest economy in the world in terms of market exchange rates. Its currency, Pound Sterling is one of the highest valued currencies among the major currency units in the world. Therefore it is believed that the UK's economy is associated with many other capitalist economies in the world and thus Pound Sterling has a close relationship with most of the world stock markets including Malaysia. When the currency is bought, its value will rise. On the other hand, the currency will fall when it is sold.

Fluctuations in the currency can affect the values of firms and the structure of financial markets. Besides, it also affects people's investment and financial decisions. Consequently, it brings a huge impact to a country's stock market and thus the economy development. Studies show that, in the long run, exchange rates are determined by current and future economic fundamentals. These fundamentals include interest rates, inflation and money supplies. However, in the short run, exchange rates are also affected by other factors such as political stability and changes of policy.

Exchange rates play the role of balancing the demand for and supply of assets. An increase in domestic stock prices lead individuals to demand more domestic assets. To buy more domestic assets local investors would sell foreign assets (they are relatively less attractive now), causing local currency appreciation. In addition, a blooming stock market would attract capital flows in from foreign investors, which may cause an increase in the demand for a country's currency. As a result, rising (declining) stock prices would lead to an appreciation (depreciation) in exchange rates.

The issue regarding relationship between stock price and exchange rates has received considerable attention especially after the East Asian crisis. If these two macroeconomic variables are related then investors can predict the behaviour of one variable based on the information of another variable. If the causation runs from exchange rates to stock prices then crises in the stock markets can be prevented by controlling the exchange rates. Similarly, if the causation runs from stock prices to exchange rates then authorities can focus on domestic economic policies to stabilize the stock market.

For the past few decades, many works have been carried out to examine the relationship between stock prices and exchange rate. However, most of the attention has been focused on developed countries. The results of these studies are inconclusive as some studies have found a significant positive relationship between stock prices and exchange rates while others have reported a significant negative relationship between the two variables. On the other hand, there are some studies that have found very weak or no association between stock prices and exchange rates. In general, there is clearly neither a theoretical nor empirical consensus on the relationship between exchange rates and stock prices.

Baharumshah *et. al.* (2002) presented and tested an augmented monetary model that includes the effect of stock prices on the bilateral exchange rates. The model is given as follows:

$$e_t = \beta_0 + \beta_1(m_t - m_t^*) + \beta_2(y_t - y_t^*) + \beta_3(i_t - i_t^*) + \beta_4(s_t - s_t^*) + u_t$$

where $\beta_1 > 0$, $\beta_2 < 0$ and $\beta_3 > 0$. Note that e_t is the log of the exchange rate (defined as the domestic price of foreign currency), m is the nominal demand for money, y is the real income level, i is the nominal rate of interest, s is the real level of the stock market and u_t is a random error term. The asterisk (*) denotes the corresponding foreign variables.

In Baharumshah *et. al.* (2002), the exchange rates and the macroeconomic variables from the first quarter in 1976 to the forth quarter in 1996 are used. By defining Malaysia (RM) as the home country whereas US (US) and Japan (JY) as the foreign countries, the RM/US and the RM/JY exchange rates are used. The income variable is measured by real gross domestic product, money supply is represented by M1 (a measure of money supply including all coins, notes and personal money in current accounts) and the stock market is represented by the main stock index. Besides, short-run interest rate of 3-month Treasury bill is also used in the analysis.

The analysis is carried out by using Johansen method of cointegration and a restricted VAR model by Sims (1990). The initial results show that the monetary variable is cointegrated but it is subjected to parameter instability. The time-varying parameter is found affecting at least a particular subset of the variables in the system including the stock prices. The analysis is then continued by using VAR model which imposes exogeneity restrictions on the first order integrated, $I(1)$ variables. The result shows existence of cointegration and parameter stability. It suggests that the equity market significantly affect the exchange rate and hence models of equilibrium exchange rate should be extended to include equity markets in addition to bond markets. The study also indicates that factors affecting the equity price are likely to influence the movement of exchange rates.

Granger *et. al.* (2000) applied unit root test and cointegration model to investigate the relationship between stock prices and exchange rates. Since the Augmented Dickey Fuller (ADF) test is suspected when sample period includes structural breaks or major events such as great depression and stock market crash, the authors introduced a dummy variable into the original ADF formula as suggested by Perron and Vogelsang (1992):

$$\Delta y_t = \alpha + \beta t + (\rho - 1)y_{t-1} + \gamma DU_t(\lambda) + \sum_{i=1}^{k-1} \theta_i \Delta y_{t-i} + a_t$$

where $\Delta = 1 - L$, y_t is a macroeconomic variable, t is a trend variable and a_t is a white noise term. For $t > N\lambda$, $DU_t(\lambda) = 1$, otherwise $DU_t(\lambda) = 0$, $\lambda = T_B / N$ is the location where the structural break lies, N is sample size and T_B is the date when structural break occurred.

Data used in the study are exchange rates and stock prices from some Asian countries, namely Hong Kong, Indonesia, Japan, South Korea, Malaysia, the Philippines, Singapore, Thailand and Taiwan. Daily data from 3rd January 1996 to 16th June 1998 are taken and are divided into three sub-samples i.e. crash, after crash and the Asian flu period.

Before the crash period (1986-1987), there is little interaction between currency and stock markets except for Singapore where changes in the exchange rates lead the stock price. In the period after crash, there is no definite pattern of interaction between the two markets. However, seven of the nine nations including Malaysia suggest significant relations between the two markets during the Asian flu period. The impulse response analysis lends further support to the importance of stock market as the leader or the existence of feedback interaction during the Asian flu period.

Nieh and Lee (2001) investigated the dynamic relationship between stock prices and exchange rates for G-7 countries. Data consists of daily closing stock market indices and foreign exchange rate from 1st October 1993 to 15th February 1996. The analysis is carried out using Engle-Granger (1987) two steps method and the Johansen maximum likelihood cointegration test. The appropriate framework of Vector Error Correction model (VECM) is further applied to assess both the short-run inter-temporal co-movement between the two variables and their long-run equilibrium relationship. The paper also incorporates Johansen’s (1988, 1990 and 1994) five VECM models to consider the determinant of cointegrating ranks in the presence of a linear trend and a quadratic trend.

The results reject most of the previous studies that suggest a significant relationship between stock prices and exchange rates. Their result is similar to that suggested by Bahmani-Oskooee and Sohrabian (1992) finding where there is no long-run significant relationship between stock prices and exchange rates for each G-7 countries. Additionally, result from the VECM estimation suggests that the two lead-lagged length of one financial variable has little power in predicting the other. The result shows that these two financial variables do not show predictive capabilities for more than two consecutive trading days. In other words, only one day's short run significant relationship has been found in certain G-7 countries. Another finding from the study is that the US fails to show any significant correlation and thus the value of dollar cannot be used to predict the future in the US.

Phylaktis and Ravazzolo (2005) examined both the long-run and short-run link between stock prices and exchange rates in a group of Pacific Basin countries including Hong Kong, Malaysia, Singapore, Thailand and the Philippines. The main concern of the study is to investigate whether any relationship is affected by the existence of foreign exchange controls and by the Asian financial crisis in the middle of 1997. The sample period covered from 1980 to 1998 and it varies for each country depending on the availability of data. By using cointegration and multivariate Granger causality tests, the study suggests that stock and foreign exchange markets are positively related and that the US stock market acts as a medium for these links. Furthermore, the relationship between stock and foreign exchange markets are found not to be affected by foreign exchange restrictions. Besides, it is shown that the financial crisis had a temporary effect on the long-run co-movement of these markets.

Wu (2001) analyses the symmetric asset-price movements in Singapore by using a monetary approach. The relative magnitudes of the exchange rate elasticity of real money demand and that of real money supply determine the relations between stock prices and exchange rates. The results show that if the demand for real money balances is relatively exchange-rate elastic, exchange rate and stock prices are negatively related, and if the overall price level and thus real money supply is relatively exchange-rate elastic, the opposite holds. The results also reveal that the interest rate is positively related to stock prices when the demand for real money balances is more exchange-rate elastic than the real money supply, and vice versa.

In addition, the distributed lag model and the VAR model are used to analyse the Straits Times Industrial Index's macroeconomic exposure (STII) both before and during the 1997 Asian financial crisis periods. It is suggested that fiscal revenues and fiscal expenditures exert positive influences on stock prices for both the investigated periods. Morever, a positive interest rate shock tends to boost the stock prices during the crisis period. It is also found that the Singapore dollar has bi-directional relationship with currencies of developed countries, except Singapore dollar-Malaysian Ringgit are negatively related with the STII both before and during the 1997 Asian financial crisis. Finally, the results imply that the real money demand is relatively exchange-rate elastic with respect to the rich country's currencies but relatively inelastic with respect to the Malaysian Ringgit when compared to the real money supply.

Ibrahim (2003a) applied cointegration and VAR modeling to evaluate the long-run relationship and dynamic interactions between the Malaysian equity market, various economic variables and major equity markets of the US and Japan. The stock indices used are KLCI, S&P 500 and Nikkei 225 Index from January 1977 to August 1998. The variance decompositions and impulse-response functions generated from the VAR suggest dominant influence of nominal variables on Malaysian equity prices. It is noted that KLCI positively related to money supply, consumer price index and industrial production index but it is negatively linked to the exchange rate. At the same time, variations in equity prices do contain some information on such nominal variable, implying bi-directional causality between them. Besides, it is found that the nature of long-run relationships in the Malaysian and Japan equity market are similar but they are different from that of the US market. The possible explanation is that Malaysia and

Japan are considered as one East Asian market whereas the US market is an alternative market.

1.3.3 Application of Kalman filter technique (KF) and Generalized Autoregressive Conditional Heteroskedaticity (GARCH)

Ever since its development by Kalman and Bucy in early 1960s, the Kalman filter technique has played an important role in the space programme and has become an important tool for many analyses in control engineering. This may be due to difficulty in understanding different terminology in control engineering, statistics and economy. However, its applications in statistics and economics have been very few and far in between. The Kalman filter is useful for parameter estimation and inference about unobserved variables in linear dynamic systems. It is a basic technique relates to the state-space model. The following section discusses the applications of the Kalman filter technique in econometrics and time series analysis.

Arsad (2002) makes use of Kalman filtering technique to analyse state-space model extensions of the Wilkie stochastic asset model. A model for the United Kingdom Retail Price Index (RPI) is proposed and investigated. The rate of inflation and its mean reversion level are allowed to be modeled stochastically. The proposed model is compared to the simpler Wilkie Autoregressive, AR(1).

In addition, the Kalman filter technique is applied to a combined series of price inflation, equity dividend yields and dividend growth rates. The dynamics between equity dividend yields and dividend growth rates with the future rate of inflation are investigated respectively. Through the state-space form of the Kalman filter, an unobserved series is introduced into the structure of the model.

The proposed model assumed that the difference between the logarithms of the Retail Price Index (RPI) could be modeled as a first-order autoregressive series, denoted as an AR(1) model as given by:

$$Q_t = Q_{t-1}\exp\left(I_t\right)$$

$$I_t = \mu_i + \alpha_i\left(I_{t-1} - \mu_i\right) + S_i\varepsilon_t^i \qquad (1.1)$$

where Q_t is the value of a Retail Price Index at time *t*, I_t is the rate of inflation over the year from *t*-1 to *t* and μ_i is the mean for the inflation rate of time *t*.

The model for the equity dividend yields, Y_t is given as:

$$\log\left(Y_t\right) = \omega_y I_t + \log\left(\mu_y\right) + \alpha_y YN_t \qquad (1.2)$$

where YN_t follows an AR(1) model:

$$YN_t = \alpha_y YN_{t-1} + S_y\varepsilon_t^{dy}$$

Finally, the model for equity dividend is given as follows:

$$K_t = \log D_t - \log D_{t-1}$$

$$K_t = \omega_{k1}D_t^m + \omega_{k2}I_t + \mu_k + \eta_k S_y\varepsilon_{t-1}^{dy} + \beta_k S_k\varepsilon_{t-1}^k + S_k\varepsilon_t^k \qquad (1.3)$$

where D_t and K_t are the values of a dividend index and force of equity dividend growth respectively at time *t*. The three series ε_t^i, ε_t^{dy} and ε_t^k are series of independent, identically distributed unit normal variates and they are assumed to be independent of each other. In addition, the unobserved series, U_t follows an AR(1) process as given by:

$$U_t = \mu_u + \alpha_u \left(U_{t-1} - \mu_u\right) + S_u \varepsilon_t^u \, . \tag{1.4}$$

where μ_u is the mean of the unobserved series.

The four equations above are then rewritten in the state-space form as given by:

$$y_t = A\theta_t + \mu$$

$$\theta_t = \Omega\theta_{t-1} + S\varepsilon_t^\theta$$

where:

$$y_t = \begin{pmatrix} I_t \\ \log Y_t \\ K_t \end{pmatrix} \quad A = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad \mu = \begin{pmatrix} \mu_i \\ \log\mu_y + \omega_y \mu_i \\ \mu_k + \mu_i \end{pmatrix}$$

$$\theta_t = \begin{pmatrix} I_t - \mu_i \\ \log Y_t - \left(\log\mu_y + \omega_y \mu_i\right) \\ K_t - \left(\mu_k + \mu_i\right) \\ \varepsilon_t^{dy} \\ \varepsilon_{t-1}^{dy} \\ \varepsilon_t^k \\ \varepsilon_{t-1}^k \\ U_t - \mu_u \end{pmatrix} \qquad S = \begin{pmatrix} S_i & 0 & 0 & 0 \\ \omega_y S_i & S_y & 0 & 0 \\ \left(1 - \omega_k \alpha_k\right) S_i & 0 & S_k & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & S_u \end{pmatrix}$$

$$Cov\left(\varepsilon_t^y\right) = C = \begin{pmatrix} C_{11}^2 & 0 & 0 \\ 0 & C_{22}^2 & 0 \\ 0 & 0 & C_{33}^2 \end{pmatrix}$$

and

$$\Omega = \begin{pmatrix} \alpha_i & \delta_{\mathrm{y}} & \delta_k & 0 & 0 & 0 & 0 & \psi_{\mathrm{i}} \\ \omega_{\mathrm{y}}\left(\alpha_i - \alpha_y\right) & \alpha_y & 0 & 0 & 0 & 0 & 0 & \psi_{\mathrm{y}} \\ \alpha_{31}^{*} & 0 & \alpha_k & \eta_k S_y & -\alpha_k \eta_k S_y & \left(\beta_k - \alpha_k\right) \mathrm{S}_k & -\alpha_k \beta_k \mathrm{S}_k & \psi_k \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha_u \end{pmatrix}$$

The results suggest that in many cases, the feedback effect from last year’s dividend yield on the current rate of inflation is not significant. However, it is found that the feedback effect from last year’s dividend growth on the current rate of inflation is significant. In addition, one of the major findings in this study is that the Kalman filter model gives a significant improvement with respect to the dividend yield and dividend growth over the Wilkie model. The results also show that residuals for the rate of inflation and dividend growth give significant improvement on the normality assumption.

Kato *et. al.* (1995) investigated the relationship between Japanese output and prices using the Kalman filter technique. The data used are the quarterly index of industrial production (IIP) and the wholesale price index (WPI) using the 1985 average as a base of 100. The sample period is from the first quarter of 1967 to the forth quarter of 1989. The author fitted several models with and without a seasonal component. These models are compared to independent 2-series univariate models and the AIC is used to select the best fitted model. In general, the results show that influence of the fluctuation of WPI around its trend on the fluctuation of IIP is greater than the influence of IIP on WPI. In addition, the model with seasonal component is found significantly better than both the model without seasonal component and the model with two independent univariate series.

Brooks *et. al*. (1998) investigated three different approaches using multivariate GARCH, a market model suggested by Schwert and Seguin (1990) and the Kalman filter technique. The approaches are applied to a sample of returns on Australian industry portfolios from 1974 to 1996 to estimate the time-varying parameters of industry risk (conditional time-dependent beta series).

The Kalman filter model used to estimate the time-varying beta (β_{it}^{K}) is given as follows:

$$R_{it} = \alpha_t + \beta_{it}^{K} R_{Mt} + \varepsilon_t, \quad \varepsilon_{\mathrm{t}} \sim \mathrm{N}(0,\Omega)$$

$$\beta_t^{K} = T \times \beta_{t-1}^{K} + \eta_t, \quad \eta_{\mathrm{t}} \sim \mathrm{N}(0,Q)$$

given the initial value:

$$\beta_0^{K} \sim \mathrm{N}(\beta_0^{K}, P_0)\ .$$

where R_{it} is the returns to industry i , R_{Mt} is the market returns and β_{it}^{K} is the systematic risk for industry i .

The Kalman filter technique used the first two observations to establish the prior conditions and then recursively estimates the entire series to provide the conditional estimates of β_{it}^{K} . Using measures of forecasting errors of MAE (mean absolute forecasting error) and MSE (mean squared forecasting error) , performance of the three approaches are compared. The results provide evidence that the Kalman filter technique outperforms the other two approaches. When out-of-sample forecasts are considered, the improvement of both GARCH and Schwert and Seguin models are quite marked. However, the results again find in favour of the Kalman filter technique.

Morris and Pfeffermann (1984) applied the Kalman filter technique to monthly time series which are affected by moving festivals. The model used to forecast festivals which do not fall on the same date in the Gregorian calendar from year to year. Examples of these festivals are the Passover in Israel, Easter weekend and the Chinese New Year.

The model is applied to three different series including Taiwan traffic volume (1963-1976), Israel work seekers (1962-1981) and Israel tourist arrivals (1960-1982). Below is the proposed model:

$$\begin{aligned} y_t &= A_t\theta_t + \varepsilon_t \\ &= \mu_\mathrm{t} + \rho_t^{(\ell)} + F_t\varphi_t + \varepsilon_t^y \end{aligned}$$

$$\theta_t = \Omega\theta_{t\text{-}1} + \varepsilon_t^\theta$$

where

$$\theta_t^T = \begin{pmatrix} \mu_t & \beta_\mathrm{t} & p_t^{(12)} & p_t^{(11)} & \ldots & p_t^{(1)} & \varphi_\mathrm{t} \end{pmatrix}$$

$$A_t = \begin{pmatrix} 1 & 0 & 0 & \ldots & 0 & 0 & 1 & F_t \end{pmatrix}$$

$$\varepsilon_t^\theta \sim \mathrm{N}(0,R_t), \quad \varepsilon_t^y \sim \mathrm{N}(0,C_t)$$

μ_t and β_t are the levels and slope of the process at time month *t* respectively, F_t is the festival coefficient for month *t*, φ_t is the festival parameter for month *t* and $\rho_t^{(\ell)}$ is the seasonal effect associated with calendar month $(\ell+1)$ prior to the current month.

For the first series, it is assumed that the New Year affects a ten day period starting three days before the festival and that the extra traffic is distributed evenly throughout this period. The results show that there is a considerable increase in traffic volume around the date of the Chinese New Year from 21st January to 17th February.

In addition, both Passover (26th March to 25th April) and the Jewish New Year (6th September to 5th October) are believed to significantly affect the second and third series respectively. It is also assumed that the Passover affects a twenty-three day period starting seventeen days before the festival and that the New Year affects a thirty day period starting five days before the festival.