Impact of capital control measures on the Malaysian stock market

A multiresolution analysis

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Abstract

Purpose – The purpose of this paper is to examine the extent to which the capital control measures implemented by the Malaysian central bank in late 1998 had an influence on segmenting the Malaysian equity market from other major equity markets.

Design/methodology/approach – The S&P 500, the Nikkei 225 Index, the STI Index and the KLSE Composite Index are considered. The discrete wavelet transform technique – "Haar" is employed to decompose the series into various time scales during the pre- and post-capital control periods in Malaysia. The decomposed series are then used to estimate the interdependence between KLSE Composite Index with the other three markets at various time scales.

Findings – The empirical findings support three conclusions. First, in the pre-capital control period, Singapore is the most influential market followed by the US across all time scales in transmitting news into Malaysia. Second, after the imposition of capital controls, the spillover effects from Singapore to Malaysia have declined substantially, suggesting a reduced integration between these two markets. Finally, in the post-capital control period, all three markets appear to be imparting a similar but moderate level of influence on the Malaysian market.

Research limitations/implications – To explore the return and volatility spillovers, the use of return and volatility series at different time scales provided a greater level of insight into the dynamics than the standard approaches which employ only one series in the time domain.

Originality/value – The results from this paper will have potential implications for asset allocation, the pricing of domestic securities, the implementation of global hedging and trading strategies and the evaluation of regulatory proposals to restrict international capital flows.

Keywords Financial markets, Malaysia, Time series analysis, Capital instruments

Paper type Research paper

1. Introduction

In mid 1997, along with its Southeast East Asian neighbours, Malaysia experienced the devastating East Asian financial crisis, which lashed the region and caused a huge turmoil in these economies. The volatile short-term capital flows and the excessive volatility of the Ringgit made it impossible for the Malaysian central bank, Bank Negara Malaysia (BNM) to embark on the desired expansionary policy to overcome the contraction in the economy. To stabilize the depreciating exchange rate, in September 1998, Malaysia made a controversial decision to implement exchange rate and selective capital control measures. The exchange rate was fixed at RM3.80 per US dollar while the short-term capital flows were restricted. The main aim of these measures was to insulate the domestic financial markets from volatile portfolio capital flows and

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speculative activities. These measures were also imposed to provide BNM with the required breathing space to restructure the financial and corporate sectors.

The implementation of this incongruous policy measure in a highly liberalized world makes the Malaysian stock market an interesting case study. It provides an ideal laboratory to investigate the impact of capital controls on return and volatility spillovers between equity markets. In a highly integrated global financial market, it is vital to analyse the return and volatility spillover effects between stock markets. If information originating in one market is "pertinent" to investors in another market and there is market efficiency with respect to information in the second market, there will be spillover effects showing up in the second market's stock prices (e.g. Kim and Rogers, 1995). The results from this paper will therefore have potential implications for asset allocation, the pricing of domestic securities, the implementation of global hedging and trading strategies and the evaluation of regulatory proposals to restrict international capital flows (e.g. Koutmos and Booth, 1995).

As mentioned in Muller *et al.* (1997), Ramsay and Zhang (1997) and Gencay *et al.* (2005), the traders in stock markets form a heterogeneous group creating multiple layers of investment horizon or time scale which ranges from long view traders i.e. about a year or more to extremely short view traders, usually less than a day. Therefore market activity is heterogeneous with each trading horizon dynamically providing feedback across all classes of traders. According to Muller *et al.* (1997), these different categories of traders would perceive and react to news or shocks differently, causing different types of price and volatility movements in the market[1]. Despite this, the vast amount of empirical research examining spillover effects between equity markets typically employs data at one time domain only[2].

Since traders' response to news or shocks in the market can vary widely, a wavelet transform that decomposes the stock market returns and volatility into different time scales is appealing as it has the ability to unveil the underlying structure at different time horizons. This involves the separation of local dynamics from the global dynamics and the transitory from the permanent dynamics. Wavelet analysis can also be seen as a powerful tool for signal processing. In particular, the discrete wavelet transform allows a time series to be viewed in multiple resolutions as it has the ability to decompose a time series data into orthogonal time scale components with different frequencies. The stock market returns and volatility can be analysed separately in a succession of time scales i.e. on daily, weekly or monthly basis. This will provide a greater level of insight into the dynamics than the standard approaches which employ one series in the time domain.

Recent application of wavelet analysis to examine the return and spill over effects between stock markets can be found in Lee (2004), Sharkasi *et al.* (2004) and Fernandez (2005). These three studies tested the return and or volatility spill over effects by running a sequence of simple linear regressions using different time scales series obtained via a multi-resolution decomposition. By exploring the spill over effects between the US and Korean stock markets, Lee (2004) upheld the stylised fact that only news from the developed market influences the emerging market but not vice versa. Sharkasi *et al.* (2004) explored spillover effects between the Irish, Portuguese, UK and US stock markets. They concluded that there are significant bi-directional spillovers between the two emerging markets with the UK, while no strong interdependence can be found with the US market. Fernandez (2005) on the other hand found bi-directional interrelationships between the developed markets such as North America with the developing markets such as Latin America[3].

In this paper, the Malaysian market represents as an emerging market, while the USA is the world's major market, Japan is Asia's largest market and Singapore is Southeast Asia's leading market[4]. Wavelet analysis is used to decompose the stock market returns and squared returns into different timescales. By examining the causal link at each time scale separately we investigate more explicitly the interdependence between the Malaysian stock market with the three major markets at different resolutions. This investigation will provide new evidence about the extent to which the Malaysian market is integrated globally and how vulnerable it is to shocks originating from major foreign stock markets.

To study whether the capital control measures have segmented or strengthened the relationship between the Malaysian market with the other major markets, the sample period is divided into pre- (11 March 1994 to 31 August 1998) and post- (1 September 1998 to 20 September 2007) capital control periods. These two sub-periods are considered primarily to assess the importance of the break owing to the capital control measures and the succeeding changes in the behaviour of the traders[5].

The paper is organized as follows: Section 2 reviews the wavelet methodology, while in Section 3 the data and the related issues of the four stock markets are discussed. Section 4 reports the empirical results and finally Section 5 concludes.

2. Wavelet analysis

This section provides a brief description of the wavelet methodology, which closely follows Gencay *et al.* (2002), Percival and Walden (2000) and Ramsay and Lampart (1998a). The series of stock price reactions to variations in information and the financial needs of the participating traders in the market can be regarded as a sequence of signals of various types and of varying duration. Wavelet analysis decomposes a given series into orthogonal components according to time scale rather than of frequencies as in Fourier analysis. Therefore, it can be seen as a powerful tool for signal processing as it provides a natural platform to deal with time varying characteristics found in financial time series.

Applications of wavelet analysis commonly make use of discrete wavelet transform (DWT) which calculates the coefficients of the wavelet representations in discrete signals of finite extent. Wavelet filters can separate a signal into multiresolution component i.e. fine and coarse resolution components. Each step of the wavelet transform produces a set of averages known as scaling or smoothing coefficients and a set of differences referred as the wavelet coefficients[6]. The wavelet filter has the following properties:

$$\int \phi(t)dt = 1 \tag{1}$$

$$\int \psi(t)dt = 0. \tag{2}$$

Expression (1) integrates to one and is useful in revealing the smooth and low-frequency components of a signal. Expression (2) integrates to zero, describing the detailed high frequency components of a signal and is used to represent the deviations from the trend.

In wavelet analysis, a signal is represented as a linear combination of wavelet functions. The orthogonal wavelet series approximation to a signal *f(t)* is given by:

$$f(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k} \quad (3)$$

where J is the number of multi-resolution components or scales and k ranges from 1 to the number of coefficients in the specified components. The approximating wavelet functions $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ are generated as follows:

$$\phi_{j,k}(t) = 2^{-j/2}\phi\left(\frac{t-2^jk}{2^j}\right) \quad \psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^jk}{2^j}\right) \quad (4)$$

where $j = 1, 2, \ldots, J$ in a J-level wavelets decomposition.

The coefficients $s_{J,k}, d_{J,k}, \ldots d_{1,k}$ in (3) are the wavelet transform coefficients and can be approximated by the following integrals:

$$s_{J,k} = \int \phi_{J,k}(t)f(t)dt \qquad d_{j,k} = \int \psi_{j,k}(t)f(t)dt, j-1,2,\ldots J. \quad (5)$$

These coefficients are a measure of the contribution of the corresponding wavelet function to the total signal and are generated through the chosen family of wavelets. For the approximation in (3), the DWT calculates "N" wavelet coefficients that contains $s_{J,k}$ and $d_{j,k}$. The coefficients $s_{J,k}$, known as the smooth coefficients represent the underlying smooth behavior of the signal at the coarse scale 2^J. These coefficients reflect the long-term variations that are similar to the trend of the original time series. The coefficients $d_{j,k}$ known as the detailed coefficients, represent the deviations from the smooth behaviour where $d_{J,k}$ describe the coarse scale deviations and $d_{J-1,k}, \ldots, d_{1,k}$ provide progressively finer scale deviations.

If a time series of length N is divisible by 2^J, there will be J number of dyadic scales available. For the scale 2^j there will be $N/2^j$ detail coefficients while at the coarsest scale 2^J there will be $N/2^J$ detail and smooth coefficients respectively. Therefore, in total there will be "N" coefficients as shown in equation (6):

$$N = N\left(\sum_{i=1}^{J}\frac{1}{2^i} + \frac{1}{2^J}\right). \quad (6)$$

The number of coefficients at a given scale is related to the width of the wavelet function. At scale 2^j, the translation steps are t (where $1 \leq t \leq N$) times and $N/2^j$ terms are required for the functions to cover the length of N[7]. The wavelet coefficients at scale 2^j are associated with frequencies in the interval $[1/2^{(j+1)}, 1/2^{(j)}]$. As index j gets larger, the scale factor gets larger and consequently the approximating function gets shorter while their translating steps gets larger[8]. These coefficients are fully equivalent to the information contained in the original series and the time series can be perfectly reconstructed from its DWT coefficients. The long time scales give more low frequency information about the series, while the short time scales give more high frequency information about the time series.

The multiresolution decomposition of a signal can now be defined as follows:

$$S_J(t) = \sum_k s_{J,k}\phi_{J,k}(t) \tag{7}$$

$$D_j(t) = \sum_k d_{j,k}\psi_{j,k}(t) \text{ for } j = 1, 2 \ldots, J. \tag{8}$$

The functions (7) and (8) are called the smooth and detail signals respectively. These signals are orthogonal components at different scales. The wavelet representation in (3) can now be expressed in terms of these signals:

$$f(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \ldots + D_1(t). \tag{9}$$

Each term in (9) represents components of the signal $f(t)$ at different resolution.

An appealing characteristic of the DWT is that it is an energy (variance) preserving transform i.e. the energy in all of the DWT coefficients are equal to the energy in the original time series. Specifically, the variance of the original time series is perfectly captured by the variance of the coefficients from the DWT and thus the total variance of a time series can be portioned using the DWT wavelet and scaling coefficient vectors. With reference to equation (10), the structure of the wavelet coefficients, $||X||^2$ is composed on a scale-by-scale basis as follows:

$$||X||^2 = ||S_J||^2 + \sum_{j=1}^{J} ||D_j||^2 \tag{10}$$

where $||D_j||^2$ is the energy (proportional to variance) of *f(t)* due to changes at scale 2^j and $||S_J||^2$ is the information due to changes at scales 2^J [9].

A variety of families of wavelets have been developed for use as the fundamental wavelet. Amongst them, the most commonly used wavelets are the orthogonal ones such as Haar, Daublets, Symmelets and Coiflets. The Haar wavelet is a square wave with compact support and it is the only orthogonal wavelet that is symmetric and discrete. By contrast, the Daublets are continuous with compact support, but they are quite asymmetric. The Symmelets also have compact support, but are constructed to be as symmetric as possible. Finally, the Coiflets are also constructed to be symmetric with additional properties that both scaling (ϕ) and detail (ψ) components have vanishing moments.

As in Lee (2004) we focus on two major features of wavelet analysis i.e. discrete wavelet transform (DWT) and multiresolution analysis (MRA). Given that the stock returns have discrete changes, the DWT technique Haar was found to be useful as a basic wavelet function to decompose the return and the squared return series into an orthogonal set of components with different resolutions. The stock market return series is used to examine the return spillover effects while the squared return series is used as a volatility proxy to test the volatility spillover effects between the stock markets.

3. Description of the data

The data employed in this study are the daily adjusted closing stock market indices of the USA (the Standard & Poor's 500 Index), Japan (the Nikkei 225 Index), Singapore (the Straits Time Index) and Malaysia (the KLSE Composite Index). The data were obtained from "Yahoo.Finance" and are in terms of local currency units. The daily stock return for each country is computed as $R_t = (\ln P_t - \ln P_{t-1})^{*}100$, where P_t is the stock price index.

As for missing data due to different public holidays in each stock market, some daily observations were deleted. After matching the daily observations between the four markets there were 3072 observations. The sample period from 11 March 1994 to 20 September 2007 was divided into pre- (11 March 1994 to 31 August 1998) and post- (1 September 1998 to 20 September 2007) capital control periods. The first sub-period consists of 1,024 observations, while the remaining 2,048 observations represent the period after the imposition of the control measures.

An MRA ($J = 6$) was performed on the return and squared return series for each stock market[10]. The six wavelet details with the corresponding oscillation period are listed in Table I.

Tables II and III provide the proportion of energy in the original return and squared return series respectively that are accounted in each wavelet details and wavelet

Scale	Wavelet details	Oscillation period (days)
1	D1	2-4
2	D2	4-8
3	D3	8-16
4	D4	16-32
5	D5	32-64
6	D6	64-128

Note: As the time scales gets larger, the wavelet series cover longer oscillation period to capture more low frequency information about the time series

Table I. Wavelet details and timescales

	S&P 500		NIKKEI		STI		KLSE	
Series	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Original	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
D1	0.43	0.53	0.56	0.53	0.45	0.47	0.43	0.48
D2	0.31	0.24	0.24	0.24	0.23	0.25	0.29	0.24
D3	0.14	0.13	0.10	0.11	0.14	0.13	0.16	0.11
D4	0.06	0.06	0.05	0.07	0.07	0.07	0.05	0.08
D5	0.02	0.03	0.01	0.03	0.08	0.04	0.03	0.03
D6	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.02
S6	0.03	0.01	0.01	0.01	0.02	0.03	0.03	0.03

Notes: The figures represent the proportion of energy in the original return series accounted for by each wavelet series. The proportion of energy is calculated separately for both the pre- and post-capital periods

Table II. Return series – proportion of energy retained by each wavelet series

Series	S&P 500 Pre	S&P 500 Post	NIKKEI Pre	NIKKEI Post	STI Pre	STI Post	KLSE Pre	KLSE Post
Original	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
D1	0.37	0.33	0.36	0.36	0.32	0.40	0.43	0.25
D2	0.27	0.16	0.16	0.17	0.20	0.19	0.20	0.20
D3	0.14	0.09	0.10	0.09	0.11	0.08	0.12	0.18
D4	0.06	0.05	0.07	0.04	0.10	0.07	0.04	0.06
D5	0.03	0.04	0.03	0.03	0.02	0.03	0.03	0.11
D6	0.02	0.04	0.03	0.03	0.05	0.03	0.01	0.07
S6	0.10	0.29	0.25	0.28	0.21	0.18	0.16	0.14

Notes: The figures represent the proportion of energy in the original squared return series accounted for by each wavelet series. The proportion of energy is calculated separately for both the pre- and post-capital periods

Table III.
Squared return series – proportion of energy retained by each wavelet series

smooth. The results in Table II clearly shows that in all four stock markets and in both sub-periods, more than 80 per cent of the energy in the stock returns is concentrated in the first three wavelet series namely the D1, D2 and D3. This implies that the sharpest fluctuations in the stock returns take place in the short run that is within two to 16 days. Since the movements in stock returns are mainly caused by short term fluctuations, as expected the stock returns cannot be predicted in advance.

Table III reveals that more than 60 per cent of the energy in the volatility series is concentrated in the first three finest wavelet series while about 10-30 per cent of the energy is retained in the low frequency smooth component S6. According to Lee (2004), this can be associated with the volatility clustering phenomenon commonly discussed in the financial literature. Since the first three timescale components of the return and the squared return series together account for large proportion of the energy of the original series across all time, in the next section, these series are used to examine the presence of return and volatility spillovers between the stock markets at different timescales.

4. Mean and volatility spillover effects

Spillovers are concerned with the effects of new developments or shocks in one stock market on other markets. In this section, we examine the international transmission mechanism of such shocks between the Malaysian stock market with the three major stock markets. In order to investigate international stock market spillovers, we need to obtain the innovations from each stock market. As in Lee (2004), the orthogonal high frequency time scale series obtained through the multiresolution decomposition approach are used to represent the stock market innovations.

Since the stock markets operate on a variety of time-scales simultaneously, we investigate the relationships between various pairs of the orthogonal high frequency rescaled data to analyse the spillover effects between the markets. Following Lee (2004), Sharkasi *et al.* (2004) and Fernandez (2005), a simple linear regression model is used to measure the relative importance of the contemporaneous relationships between pairs of orthogonal stock market returns and squared returns series between the Malaysian market and each of the three major markets. The original return series and the three high frequency wavelet series, D1, D2 and D3 are used to investigate the extent of market interdependence between the markets:

$$(R_{KLCI,j})_t = \alpha + \beta(R_{i,j})_t + \varepsilon_t \tag{4}$$

where "i" represents either S&P 500, Nikkei 225 or STI indexes while "j" represents either the original return series, D1, D2 or D3[11]. The presence of spillover effects were examined by testing the significance of the contemporaneous coefficient β across different time scales. Because of the time differences between the US and Malaysian markets, we regress the return of the Malaysian market on the lagged return of the US market. The regressions for the other two markets are performed using the same trading days.

4.1 Mean spillover effects

Table IV reports the coefficient estimates from a sequence of least squares regressions using different scales for the return series. The empirical results were productive and informative. The result reveals substantial positive interactions between the Malaysian and Singapore stock markets during the pre-capital control periods. This outcome reflects the close proximity and economic ties between these two economies and that news from Singapore has a stronger influence on the Malaysian market. Though, these two-way effects also prevail during the post-capital control period, the responses of Malaysian traders to Singapore news seems to be less in magnitude compared to the first sub period.

The response of the Malaysian market to the US and Japanese markets reveals several interesting insights. Prior to the capital controls, Malaysia only reacted significantly to US news, while no interactions could be detected between Malaysia and Japan. The empirical results also revealed that during the first sub period, spillovers from the USA are rapidly transmitted to the Malaysian market at the oscillation period

Scales	MS on US	US on MS	MS on JP	JP on MS	MS on SG	SG on MS
Regression of stock returns during pre capital control period						
Original	0.388	0.077	0.060	0.031	0.871	0.449
	(0.000)	(0.000)	(0.164)	(0.164)	(0.000)	(0.000)
D1	0.163	0.029	0.009	0.005	0.870	0.401
	(0.014)	(0.043)	(0.822)	(0.821)	(0.000)	(0.000)
D2	0.399	0.106	0.019	0.016	0.820	0.429
	(0.000)	(0.000)	(0.049)	(0.048)	(0.000)	(0.000)
D3	0.636	0.109	0.005	0.001	0.938	0.540
	(0.000)	(0.000)	(0.928)	(0.926)	(0.000)	(0.000)
Regression of stock returns during post capital control period						
Original	0.268	0.004	0.233	0.287	0.343	0.379
	(0.000)	(0.826)	(0.000)	(0.000)	(0.000)	(0.000)
D1	0.223	-0.124	0.197	0.258	0.320	0.348
	(0.000)	(0.043)	(0.000)	(0.000)	(0.000)	(0.000)
D2	0.233	0.030	0.249	0.338	0.343	0.426
	(0.000)	(0.145)	(0.000)	(0.000)	(0.000)	(0.000)
D3	0.289	0.127	0.277	0.322	0.284	0.320
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: The figures represent the coefficient estimates from the sequence of least squares between the Malaysian market with the other three markets and the figures in the parentheses denote the p-value of the coefficients

Table IV. Simple regression of the Malaysian stock returns with the US, Japan and Singapore stock returns at different scales before and after the imposition of Malaysian capital control of eight to 16 days. A very mild positive spillover effect is also detected going from the Malaysian market to the USA. Hence, this finding appears to be contradicting the stylized fact that only innovations from the major markets are transmitted to the emerging markets but not the other way around. During the crisis period, the Asian countries namely Singapore, Thailand, South Korea, Indonesia and Malaysia were affected either directly or indirectly. These countries generally have a strong trade connection with USA. As such, when the whole region was under turmoil, it is plausible to assume that US stock market might have felt the impact and it is reflected in the stock return series. During the second sub period, we observe a positive and significant bi-directional spillover effects taking place between the Malaysian and Japanese markets. Meanwhile, the US shocks remain significant in explaining the movements in the Malaysian stock prices.

Overall, there seem to be some changes in the influences of international markets on the Malaysian market during the two sub periods. In the first sub period, Singapore was the most influential market followed by the USA. During this period, the regional market developments appear to be an important force in driving the dynamics of the Malaysian market. In the capital control era, all three markets appear to be transmitting similar moderate size influence into the Malaysian market. These results demonstrate that the regional, continent and global developments seem to have a similar impact on the Malaysian market.

4.2 Volatility spillover effects

The changes in the level of volatility of the stock market returns may reflect the arrival of "new" information. An increasing attention has also been given in the recent financial literature on volatility spillovers, i.e. to what extent a stock market responds to new information. Based on the similar approach as the previous subsection, the original and the three finest wavelet details, D_1, D_2 and D_3 of the squared return series were used to examine the presence of volatility spillovers between the stock markets at different time periods. Tables V reports the coefficient estimates from a sequence of least squares regressions using different scales for the squared return series.

Surprisingly, in both sub periods, clear volatility spillover effects from the US to Malaysian market were only detected at the third wavelet series D3. The Japanese market did not impart much influence onto the Malaysian market in the first sub period while a moderate spillover effects were observed in the second period at D2 and D3 series. In general, the volatility movements in these two markets did not convey strong information to the Malaysian market in both sub periods.

An obvious difference in the volatility spillover effects were observed between the Malaysia and Singapore. In the first sub period, a very strong interdependence between these two markets is observed at all time scales. In the second sub period, though significant, the magnitude of integration has dropped to almost one-third of the size observed in the first period. The capital control measures to some extent seemed to have reduced the volatility integration between these two markets.

5. Conclusion

This paper investigates the interdependence between the Malaysian stock market and the US, Japanese and Singapore markets at various time scales during the pre- and post-capital control periods. The empirical results support three conclusions. First, in

Scales	MS on US	US on MS	MS on JP	JP on MS	MS on SG	SG on MS
Regression of squared returns during pre- capital control period						
Original	0.639	0.044	0.209	0.014	1.455	0.289
	(0.000)	(0.000)	(0.083)	(0.083)	(0.000)	(0.000)
D1	− 0.627	0.042	0.013	0.001	1.936	0.292
	(0.035)	(0.000)	(0.915)	(0.915)	(0.000)	(0.000)
D2	0.192	0.044	0.113	0.007	1.770	0.254
	(0.223)	(0.000)	(0.347)	(0.347)	(0.000)	(0.000)
D3	0.506	0.018	− 0.148	− 0.029	1.003	0.221
	(0.001)	(0.006)	(0.328)	(0.325)	(0.000)	(0.000)
Regression of squared returns during post capital control period						
Original	0.419	0.035	0.269	0.056	0.402	0.172
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D1	0.263	0.025	0.025	0.007	0.102	0.056
	(0.000)	(0.002)	(0.530)	(0.530)	(0.000)	(0.000)
D2	0.082	0.052	0.233	0.081	0.366	0.282
	(0.126)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D3	0.435	0.034	0.221	0.035	0.436	0.144
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: The figures represent the coefficient estimates from the sequence of least squares between the Malaysian market with the other three markets and the figures in the parentheses denote the *p*-value of the coefficients

Table V. Simple regression of the Malaysian squared returns with the US, Japan and Singapore squared returns at different scales before and after the imposition of Malaysian capital control

the pre-capital control period, Singapore is the most influential market in transmitting news to Malaysia followed by the USA. Second, in the post-capital control period, the size of the spillover effects from Singapore to Malaysia declined, suggesting a reduced integration between these two markets. Finally, in the post-capital control period, all three markets appear to be imparting a moderate level of influence on the Malaysian market at various time scales. This indicates that the imposition of capital control measures by the Malaysian government in 1998 has not led to a complete segmentation of its stock market from major international equity markets. It is also worth highlighting that while the capital control facilitated a better management of the currency and interest rates, its overall impact on the mean and volatility spillovers into the Malaysian equity market was marginal.

Notes

1. Short-term traders evaluate the market at higher frequency and thus they tend to execute transactions at higher frequency, while long-term traders would watch the market less frequently and are usually more interested in large price movement.
2. See for example Eun and Shim (1989); Arshanapalli and Doukas (1993); Hamao *et al.* (1991); Kim and Rogers (1995); Koutmos and Booth (1995); Liu and Pan (1997); Ng (2000) and Worthington and Higgs (2003).
3. Wavelet analysis is also increasingly being used in other areas of economics and finance. In two related papers by Ramsay and Lampart (1998a) and Ramsay and Lampart (1998b), the decomposed wavelet series were used to study the relationship between two economic variables i.e. income-consumption relationship and the money income relationship across different time scale. Dalkir (2004), on the other hand, used the wavelet timescale series to

study the causality relationships between two monetary aggregates with income. Norsworthy *et al.* (2000) and Gencay *et al.* (2005) used the different wavelet series to estimate the systematic risk of an asset at different time scales of the market returns. Norsworthy *et al.* (2000) focused on an individual asset returns while Gencay *et al.* (2005) focused on portfolio returns.

4. Based on Malaysian External Trade Development Corporations (MATRADE) 2006 report, Malaysia's three largest trading partners are the USA, Japan and Singapore. The trade link between Malaysia and these three economies remain strong during the pre- and post-capital control periods.
5. Using the wavelet technique, Fernandez (2005) also detected volatility shifts over 1997-1998 periods in the North American, Europe and Emerging Asian markets.
6. The averages from the previous step become the input for the next step and a new set of averages and differences will be obtained. The process continues until one average and one coefficient are left.
7. For example if a time series of length $2{,}048 = 2^{11}$ were employed, there will be maximum of 11 dyadic scales available ranging from $2^1, 2^2, \ldots, 2^{11}$ and at these scales there are 1,024, $512, \ldots, 1$ wavelet coefficients respectively.
8. Since in this study the time series under consideration consists of daily data, for the scale 2^1, the wavelet coefficients are associated with frequencies in the interval [1/4, 1/2] and it captures the behavior of the time series within a two-to-four-day period while at the scale 2^2, the coefficients are associated with frequencies in the interval [1/8, 1/4] thus captures the behavior of the time series within a four-to-eight-day period and so on.
9. The energy is calculated as the sum of squares of all of its elements over the sum of squares of all observations in the original time series.
10. The wavelet details and the wavelet smooth of the return and squared return series for each market was generated using the MATLAB 7.0 software.
11. A reverse regression was also estimated, where the Malaysian market is the independent market while the other market is the dependent market.

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