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26 September 2014

Online at https://mpra.ub.uni-muenchen.de/58909/
MPRA Paper No. 58909, posted 27 Sep 2014 03:50 UTC

Portfolio diversification strategy for Malaysia: International and sectoral perspectives

Idwan Hakim[1] and Mansur Masih[2]

The focus of this paper is to investigate the potential for portfolio diversification strategies based on investing across international markets or economic sectors, using Malaysia as a case study. Analysing the comovement and correlation between returns and volatilities of the different markets or assets, therefore, is the key to gauge the potential benefits from diversification. Two important features of the comovement are their dynamic fluctuations across time period and time horizon or scales. Thus, the paper applies recent techniques of multivariate volatility modelling and wavelet transform, which can analyse time series over both the time and frequency domain. Our findings suggest that there are potential for gains from portfolio diversification strategies into both international markets, as well as sectors of the domestic stock market. There are international stock markets and domestic sectors which have low correlations and comovement with the Kuala Lumpur Composite Index. The low correlation makes it ideal to diversify the portfolio and reduce the overall investment risks. However, the findings also noted that the correlations vary across time and scales. Hence, fund managers need to be aware of the dynamics which may change at any particular point in time, which may affect the portfolio risks.

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1. Introduction

Portfolio diversification forms an important part of any investors' strategy. The gains from portfolio diversification in reducing volatility and subsequently investment risks have been widely accepted ever since the seminal work by Markowitz (1952 and 1959). Today, many globally successful investors share a common component of investment strategy – a diversified investment portfolio.

There are many ways to achieve a diversified investment portfolio, for example, by investing in various asset classes, different international markets or across diverse sectors or industries (RBC Direct Investing, 2012). Grubel's (1968) seminal work on international diversification of investment was the start of the focus in finance to find the best possible combination of markets around the world that can provide the most optimal gains from investment. Diversification across economic sectors or industries is also a possibility due to the potential differences in performances within each economic cycle or market conditions. For this reason, a company or a particular sector cannot consistently be the top or worst performer all the time.

The key to the diversification, therefore, is the correlation or comovement between stocks. A portfolio with stocks that have low or negative correlation among themselves tends to benefit from reduced risk. Recent studies have pointed out the nature of the correlation which may not be stable over time. The time-varying feature of stock markets' relationships may affect the actual risks of every portfolio at different points in time. Hence, many studies have analysed the correlation and comovement of stock markets over different time periods, including the recent crisis periods faced by countries worldwide.

More recently, studies have also focused on another feature of correlation between markets – the different time scales and heterogeneous time horizons of the investors involved. Some investors are interested in short-term gains, while some are more interested in the longer-term profits. Hence, the former will be more interested in the short-term fluctuations and correlations, while the latter are more concerned about long-term comovements and fluctuations. These studies have utilised a new and promising analytical tool of wavelet transform, which is able to decompose and analyse the series within the time and frequency domain.

This paper attempts to analyse the potential investment diversification strategies based on international markets and different economic sectors for the case of Malaysia. The key questions to answer are whether there are any opportunities for investors in Malaysia to diversify their investment across markets and sectors, and whether the correlations with these markets and sectors have been stable or varying across time.

There have been many papers that looked at international stock market comovements in terms of volatility and returns. Most of these studies analysed from the point of view of grouped market indices or between different regions in the world. For example, studies have compared the comovements of stock markets in the developed economies against the emerging markets, or among regions, including Asia Pacific, Middle East and North Africa (MENA) and Euro area. This paper will analyse based on a single country basis, focusing on some of Malaysia's major external trade partners from around the world, given the highly open economy that Malaysia has developed into. Secondly, the paper will also attempt to analyse potential diversification into different sectors within the local domestic stock market.

Finally, the paper uses modern econometric techniques to analyse the issues. The first technique is the dynamic conditional correlation of multivariate generalised autoregressive conditional heteroskedasticity (MGARCH-DCC) model proposed by Engle (2002), which is used to analyse the time-varying nature of volatility and correlation across markets and sectors. The second technique is wavelet coherency, which is used to look at the heterogeneous time scale effect and evolving correlation between the international markets, and also between the selected economic sectors.

The structure of the remainder of the paper is as follows. The next section will provide a short review of some of the selected recent literature relevant to the issues, while Section 3 will give a brief description of the methodology and data. The empirical results will be presented and discussed in Section 4. The final section will conclude the paper and provide some suggested improvements for future research.

2. Overview and literature review

"…I thank my fortune for it,

My ventures are not in one bottom trusted,

Nor to one place; nor is my whole estate

Upon the fortune of this present year…"

In *The Merchant of Venice, Act 1, Scene 1.*

William Shakespeare (1596-1598).

Rubinstein (2002) termed the ground-breaking article by Markowitz in 1952 as a significant landmark. It marked the birth of financial economics, and Markowitz, together with Merton Miller (Miller-Modigliani Theorem) and William Sharpe (Capital Asset Pricing Model), won the 1990 Nobel Prize in Economics for their pioneering contribution to financial economics. Markowitz himself, however, said that investment diversification has been practiced long before his famous article was published. In his historical review of portfolio theory, Markowitz (1999) pointed out that diversification of investment was already a well-established practice. William Shakespeare knew about the diversification concept, as reflected by the above quotes by his key actor in *The*

Merchant of Venice, Antonio, who believed that his investment is well-diversified across ships, places and time.

Markowitz's portfolio selection strategy stands on the fact that diversification helps to reduce risks, but not eliminate the risks in totality (Rubinstein, 2002). It is not the stock's own risk or variance, but rather its covariance with the other stocks in the portfolio that is important to an investor's diversification strategy. Diversifying the stocks within a portfolio can help to reduce the risks, without changing the expected portfolio returns. Hence, portfolio returns and risk management is one of the key learning topics in finance.

The analysis of comovement of the returns of different stocks is important to assess the risks of the investment portfolios (Rua and Nunes, 2009). Understanding comovement of asset returns, as measured by the correlation coefficient, and their volatility within each portfolio is vital to achieve the gains from portfolio diversification. A higher positive comovement among the stocks implies lower gains in terms of risk management from portfolio diversification. Hence, investors generally look for combination of stocks with low or negative correlation to derive the full benefits from diversification (Kabir et al., 2013).

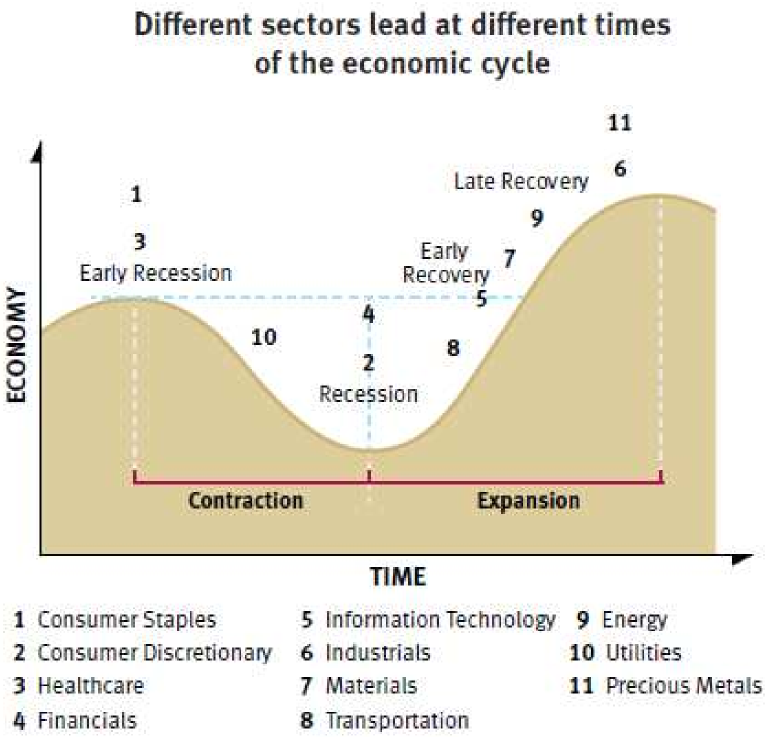
There are different ways of diversifying the investment portfolio. The most well-known is perhaps through international diversification of several stock markets in the world. Since Grubel's seminal work in 1968, which extended upon Markowitz's earlier ideas, many studies have flourished in analysing diversification into cross-border markets. Earlier studies discussed the issue by looking at the long run relationships among international stock markets, and based on different methodologies, including estimated correlation matrices, cointegration theory, error correction framework, Granger causality and principal components analysis. Results of these studies are surveyed by Madaleno and Pinho (2010). In general, the existence, or non-existence, of long run cointegration between the stock markets will impact the portfolio diversification strategy.

More recent articles have recognised the time-varying nature of the correlation between stocks, especially in light of the few crises periods that the world has faced over the last two decades. These crises potentially could provide structural breaks in the long run relationships established in the earlier studies. The correlations do not remain constant over time, depending, among others, on the current conditions of the markets (lower correlation during bull market, higher correlation during bear markets), and the degree of international equity market integration. Hence, the research focus changed towards identifying the changing patterns of comovement across time.

Kabir et al. (2013) provides a recent summary of some of the studies that found time-varying returns among stocks. They noted that there has been an increase in studies of multivariate volatility modelling, particularly related to the family of generalised autoregressive conditional heteroskedasticity (GARCH) models developed mainly by Robert Engle and Tim Bollerslev from the mid-1980s. Kabir et al. (2013) quoted several studies which used dynamic conditional correlation of the multivariate GARCH (MGARCH-DCC) models to analyse comovement of stock markets, in addition to other issues involving time-varying volatility relationships, across major developed and emerging countries.

Another way to diversify the investment portfolio is through economic sectors or industries within individual stock markets. One of the reasons for proposing the sectoral diversification is the assumption that not every sector performs similarly at any given point in time or during each economic cycle. Figure 1 below shows an example of sectors of the economy that have historically performed well at specific points in the economic cycle (RBC Direct Investing, 2012). It is noted that different sectors may perform differently at various points of the market conditions. No one particular sector or industry tends to be consistently the top or worst performer.

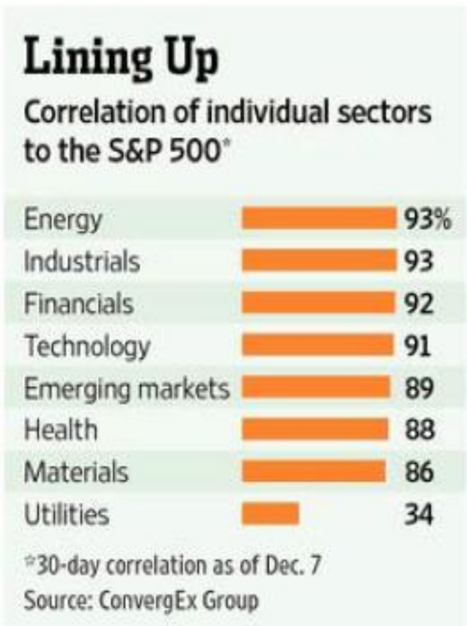
Figure 1



Source: RBC Direct Investing

Nonetheless, there are evidences that suggests comovement of sectoral indices have been high especially since the recent Global Financial Crisis in 2007/08. Figure 2 shows the correlation of sectoral indices in Standard & Poor's stock market over a month in Nov-Dec 2012 (The Wall Street Journal, 27th Dec 2012).

Figure 2



It is noted form the chart, though, that the Utilities sector shows a fairly low correlation of 34%. Hence, there is still a possibility of diversification within the individual sectors of the S&P 500. Furthermore, the article mentioned that the sectoral correlation has been increasing after the crisis, which is in line with the time-varying nature of stock market correlations. Hence, further analysis can still be done to see time-varying correlation trends, including in the recent turbulent and uncertain periods.

Source: The Wall Street Journal

Compared to the vast amount of literature available on the international portfolio diversification of stock markets, studies on sectoral portfolio diversification are limited, suggesting the small amount of research in this area. Among the recent articles are Balli et al. (2013), Ahmed (2011), Aslanidis and Savva (2011), Poldauf (2011), Rua and Nunes (2009), Phylaktis and Xia (2009), Mohamad et al. (2006) and Ehling and Ramos (2005).

Balli et al. (2013) examined the spillover effects of local and global shocks on Gulf Cooperation Council (GCC)-wide sector equity returns using data from 2005-2012. In terms of portfolio diversification strategy, they found that portfolios diversified across GCC-wide sectors perform better than portfolios diversified across GCC national equity markets. Furthermore, portfolios diversified with a mix of GCC-wide sector and national equities produce higher returns compared with portfolios made up of pure GCC national equity indices or GCC-wide sector indices.

Aslanidis and Savva (2011) looked at the impact of the integration of the European Union (EU) on portfolio diversification benefits, particularly for the three newest EU members – Hungary, the Czech Republic and Poland. The results showed that there are potential diversification benefits at the sectoral indices of the Eastern European markets due to its low but increasing correlation, compared with the higher correlation at the country markets levels.

Poldauf (2011) examined the co-movements among international equity returns at the market and industry level over the period 2000-2010, analysing daily data from major markets in Australia, Brazil, Canada, China, Germany, Japan, Russia, South Africa, the UK, and the USA using GARCH family of models. He found that the sectoral indices, including the financial sector, were significantly less correlated than the market indices over the whole period.

Rua and Nunes (2009) undertook time and frequency domain analysis using wavelet to study the stock market comovement between Germany, Japan, the UK and the USA at the aggregate and sectoral level. The data covered monthly frequency from

1973 to 2007. They found that the strength of comovement across markets is higher at lower frequencies, suggesting lower portfolio diversification benefits in the long term. In terms of sectoral comovement across the different markets, there are sectors which correlate highly but they still differ across frequencies and across time.

Phylaktis and Xia (2009) studied the equity market comovement and contagion at the sector level between 1990 and 2004 across the regions of Europe, Asia, and Latin America. Their results confirmed the sector heterogeneity of contagion, implying that there are still potential for achieving the benefits of international diversification during crises despite the prevailing contagion at the market level.

On country-specific studies, Ahmed (2011) examined the long and short run aspects of the inter-sectoral linkages in the Egyptian stock market using daily data between 2007 and 2010. He found a single cointegraing equation and limited short run causal relationships, suggesting potential benefits from diversifying in the short run, but not in the long run investment.

Mohamad et al. (2006) analysed the opportunities for diversification across sectoral indices in Malaysia using cross correlation measures, stability tests and the Sharpe ratio to measure the risk-return performance. The findings indicate that there are high but unstable correlations between the indices. This presents limited diversification benefits unless over the short term.

Finally, Ehling and Ramos (2005) used a mean-variance efficiency test to compare the performance of portfolio diversification strategies based on countries against that based on industries. The data covered weekly indices of new European Monetary Union (EMU) entrants over 1991-2003. Without any constraints, the two strategies are equal, which is against the conventional wisdom that the country diversification strategy should outperform industry diversification. If short-selling constraints are introduced, then the country diversification strategy outperforms industry diversification strategy slightly.

Among all the various studies reviewed above, there have been an increasing number of articles in recent periods utilising wavelet analysis to examine the time and frequency domain perspectives of the related issues. This is because, in addition to the time-varying nature of the correlation, the distinction between short- and long-term investors should not be ignored as it also affects the degree of comovement among stocks. The short-term investors are naturally more interested in the movement of stock returns at short-term fluctuations, i.e. at the higher frequencies. On the other hand, the long-term investors would be more interested at the longer-term fluctuations, i.e. at the lower frequencies (Madaleno and Pinho, 2012; Rua and Nunes, 2009).

While there are methodologies that can address frequency domain analysis such as Fourier transform or spectral analysis, wavelet analysis is able to analyse the frequency domain perspective without losing the time domain analysis. Hence, the time-evolving nature of the frequency relationships can also be analysed. Aloui and Hkiri (2014) provides a survey of the recent articles that have utilised wavelet tools to analyse the comovement of stock markets in the time and frequency domain.

After going through the related literature above, this paper largely follows the work of Najeeb and Masih (2014) albeit at a smaller scale, and attempts to fill specific gaps and enhance understanding on the following three areas:

1. Country-specific comovement between Malaysia and selected trading partners
2. Potential for sectoral diversification
3. Extend the methodologies involved by using MGARCH-DCC and wavelet

3. Empirical Methodology and Data

3.1. Methodology

3.1.1 Dynamic Conditional Correlation model of Multivariate Generalised Autoregressive Conditional Heteroskedasticity (MGARCH-DCC)

Nobel Laureate, Robert F. Engle introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model in his seminal work in 1982. The ARCH model relates the time-varying conditional variances based on past information. In 1986, Tim

Bollerslev extended it to a more general form known as Generalised ARCH (GARCH) model, which takes into account the past error terms and conditional variances simultaneously. Bollerslev extended it further into a multivariate form, which means that the conditional variances depend not only on its own past, but also on the past innovations and conditional variances of the other variables. However, in his Constant Conditional Correlation or MGARCH-CCC model, he made the assumption that the conditional correlations among the variables are constant across time. Engle (2002) then proposed a time-varying conditional correlations model known as MGARCH-DCC. The main merit of the DCC model is its ability to pinpoint changes in the relationships between time series variable, in terms of the timing (when) and nature (how) of their changes (Kabir et al., 2013).

In practice, the DCC model is estimated in two stages. The first step involves estimating univariate volatility parameters through a GARCH model of each of the variable. The second stage uses the standardised residuals from the first stage as inputs to estimate a time varying correlation matrix.

Following Pesaran and Pesaran (2009), let $\boldsymbol{r}_t=(r_{1t},\dots,r_{mt})'$ be an m x 1 vector of asset returns at time t, with conditional mean and variance as follows:

$$\boldsymbol{\mu}_{t-1} = E(\boldsymbol{r}_t|\Omega_{t-1})$$

$$\boldsymbol{\Sigma}_{t-1} = Cov(\boldsymbol{r}_t|\Omega_{t-1})$$

where Ω_{t-1} is the information set available at close of day $t-1$. The conditional covariance matrix can be decomposed as follows:

$$\boldsymbol{\Sigma}_{t-1} = \mathbf{D}_{t-1}\mathbf{R}_{t-1}\mathbf{D}_{t-1}$$

where $\mathbf{D}_{t-1}$=m x m diagonal matrix of conditional volatilities of the asset returns, $\sigma_{i,t-1}$ (all the off-diagonal elements are 0)

$\mathbf{R}_{t-1}$=m x m symmetric matrix of pairwise conditional correlations, $\rho_{ij,t-1}$, (all the diagonal elements are 1)

The conditional volatility of the asset return is defined as:

$$\sigma^2_{i,t-1} = Var(r_{it}|\Omega_{t-1})$$

while the conditional pairwise correlation between the *i*th and the *j*th asset is defined as:

$$\rho_{ij,t-1} = \rho_{ji,t-1} = \frac{Cov(r_{it}, r_{jt}|\Omega_{t-1})}{\sigma_{i,t-1}\sigma_{j,t-1}}$$

The conditional volatility $\sigma_{i,t-1}^2$ can be estimated in the following GARCH(1,1) model:

$$\sigma_{i,t-1}^2 = \bar{\sigma}_i^2(1 - \lambda_{1i} - \lambda_{2i}) + \lambda_{1i}\sigma_{i,t-2}^2 + \lambda_{2i}r_{i,t-2}^2$$

where $\bar{\sigma}_i^2$ is the unconditional variance of the *i*th asset return. Under the restriction for the individual asset volatilities, $\lambda_{1i} + \lambda_{2i} = 1$, then the unconditional variance does not exist. This implies a non-mean reverting process, and any shock to the variance is permanent.

For the cross-correlations, the conditional correlation between the *i*th and *j*th asset is estimated as follows:

$$\tilde{\rho}_{ij,t-1}(\phi) = \frac{q_{ij,t-1}}{\sqrt{q_{ii,t-1}q_{jj,t-1}}}$$

where $q_{ij,t-1}$ are given by:

$$q_{ij,t-1} = \bar{\rho}_{ij}(1 - \phi_1 - \phi_2) + \phi_1 q_{ij,t-2} + \phi_2 \tilde{r}_{i,t-1}\tilde{r}_{j,t-1}$$

where $\bar{\rho}_{ij}$ is the (i, j)th unconditional correlation;

ϕ_1, ϕ_2 are parameters such that $\phi_1 + \phi_2 < 1$

$\tilde{r}_{i,t-1}$ are the standardised asset returns

3.1.2 Wavelet Transform

Time domain analysis is generally the most widespread approach in economics literature to study time series variables. There is also another approach which focuses on the frequency domain. The large number of investors who participate in the stock market consist of a diverse group of decision makers – intraday traders, hedging strategists, international portfolio managers, commercial banks, corporations, and central banks (In and Kim, 2013). These parties operate on different time scales and horizons. The frequency domain analysis is able to analyse the patterns at the different scales. Wavelet analysis combines both the time and frequency domain, and is able to analyse the trends at the different horizons across the time series. Economics applications of wavelets, nonetheless, have been quite limited, compared with other fields like physics and medical sciences.

Following In and Kim (2013), Rua (2012), Rua and Nunes (2009), the wavelet transform decomposes a time series into specific wavelet functions, $\psi_{\tau,s}(t)$, sometimes referred to as the daughter wavelets. These wavelets result from the mother wavelet, $\psi(t)$. The wavelets can be expressed as a function of the time position, τ (translation parameter) and the scale, s (dilation parameter), which is related to the frequency.

The daughter wavelet can be defined as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

where $\frac{1}{\sqrt{s}}$ is a normalisation factor to ensure comparability of the wavelet transforms over time and scales. The continuous wavelet transform (CWT) of a time series $x(t)$ with respect to the mother wavelet, $\psi(t)$, is given as follows:

$$W_x(\tau,s) = \int_{-\infty}^{+\infty} x(t)\,\psi_{\tau,s}^{*} dt = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\,\psi^{*}\left(\frac{t-\tau}{s}\right) dt$$

where * denotes the complex conjugate.

The most commonly used mother wavelet is the Morlet wavelet, which is defined as:

$$\psi(t) = \pi^{-\frac{1}{4}}\left(e^{i\omega_0 t} - e^{-\frac{\omega_0^2}{2}}\right)e^{\frac{-t^2}{2}}$$

Since the term $e^{-\frac{\omega_0^2}{2}}$ becomes negligible for an appropriate ω_0, the Morlet wavelet is simply defined as:

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{\frac{-t^2}{2}}$$

Given two time series, $x(t)$ and $y(t)$, with wavelet transforms $W_x(\tau, s)$ and $W_y(\tau, s)$, then across wavelet spectrum can be defined as $W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s)$. The wavelet squared coherency, $R^2(\tau, s)$, can then be defined as the absolute value squared of the smoothed cross wavelet spectrum, normalised by the smoothed wavelet power spectra.

$$R^2(\tau, s) = \frac{\left|S(s^{-1} W_{xy}(\tau, s))\right|^2}{S(s^{-1}|W_x(\tau, s)|^2)\, S(s^{-1}\left|W_y(\tau, s)\right|^2)}$$

where *S(.)* denotes smoothing in both time and scale.

The wavelet squared coherency, or sometimes referred to as the wavelet transform coherency (wtc), is analogous to the squared correlation coefficient, as it is essentially the ratio of the squared cross wavelet spectrum to the product of the two wavelet spectra. Hence, the wavelet coherency can be used to measure the extent to which a pair of time series variables comove over time and across frequencies. Similar to the normal correlation coefficient, $R^2(\tau, s)$ is between 0 and 1, with a number closer to 1 indicating a high comovement between the variables.

3.2. Data

Daily data for the stock market indices have been sourced mainly from Bloomberg. The baseline index used for Malaysia is Bursa Malaysia's Kuala Lumpur Composite Index (KLCI). For country-specific analysis, the indices selected are for Dow Jones (DOWJ), London's FTSE 100 (LOND), Japan's Nikkei (JAPAN) and Shanghai's Composite Index (CHINA). These countries have consistently been among the top ten major trading partners in Malaysia.

For sectoral analysis, the study obtained data for the following sectors that are categorised and maintained by Bursa Malaysia - Financial (KLFIN), Industrial Products (KLIPROD), Property (KLPROP), Trading Services (KLTRAD), Technology (KLTECH), Mining (KLMINI), Plantation (KLPLANT), Consumer Goods (KLCONS) and Construction (KLCONST).

The study focuses on daily returns of the stock indices compared with the previous trading day, which is defined as the log first differenced of each index, $Ln(p_t - p_{t-1})$. The overall sample period to be analysed covers 2,616 observations from 2nd January 2004 until 31st December 2013. The analysis is done in Microfit 5.1 and R programming software [1].

4. Empirical Results and Analysis

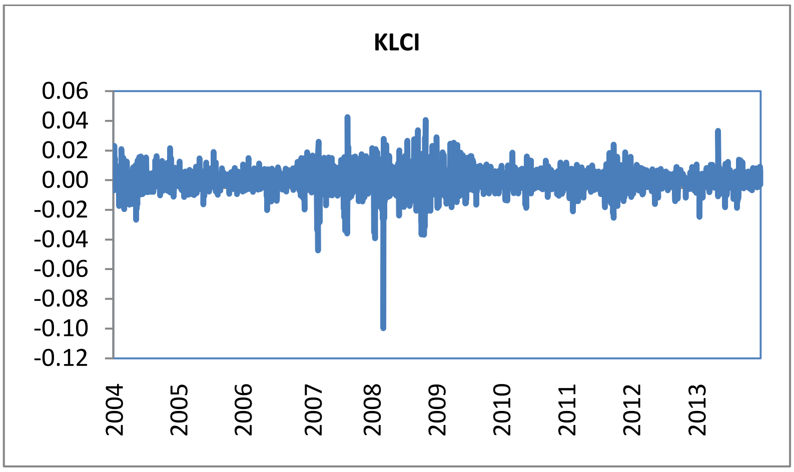
4.1. Initial observations

Figure 3 shows daily returns of KLCI and DOWJ stock indices [2]. Table 1 lists some of the key descriptive statistics for all the return series.

Figure 3

Daily returns of selected stock indices

[1] The wavelet coherence was done with the "biwavelet" package in R, similar to "wtc" package in Matlab.
[2] Appendix 1 contains the charts of the daily returns for all country-specific indices, while Appendix 2 contains the charts of the daily returns for all sector-specific indices from KL stock market.



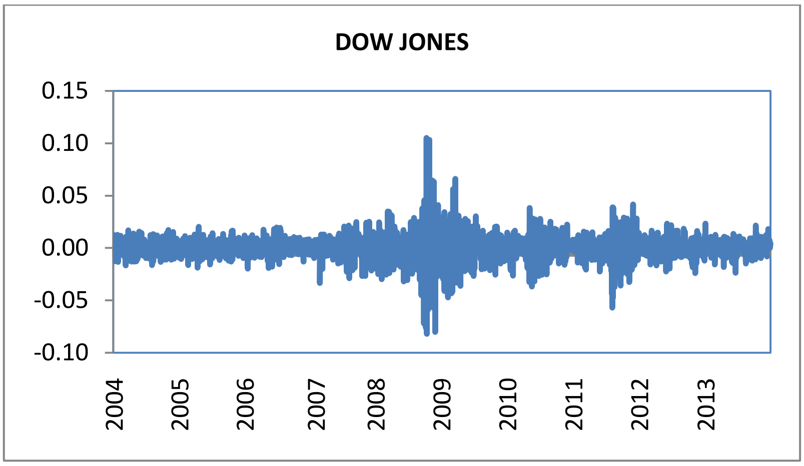


Table 1

Key descriptive statistics

Variable	Mean	Std. Deviation	Skewness	Kurtosis
Country-specific				
KLCI	0.00033	0.00757	-1.1644	15.4180
DOWJ	0.00018	0.01156	-0.0726	11.6305
CHINA	0.00013	0.01628	-0.2800	3.8872
JAPAN	0.00016	0.01518	-0.6010	9.2657
LOND	0.00016	0.01191	-0.1569	9.0758
Sector				
KLPROP	0.00021	0.01044	-0.6552	9.6045
KLTECH	-0.00053	0.01258	-0.0353	5.6881
KLPLANT	0.00053	0.01138	-0.3416	14.9315

KLMINI	0.00013	0.03018	1.6421	60.7198
KLFIN	0.00037	0.00874	-0.5536	7.4958
KLCONS	0.00038	0.00611	-0.7573	5.7788
KLCONST	0.00015	0.01224	-1.3883	21.1230
KLIPROD	0.00021	0.00792	-0.9096	9.5452
KLTRAD	0.00028	0.00769	-1.0670	15.2333

Based on Table 1, among the country-specific indices, KLCI has the highest mean returns which almost doubled that of DOWJ, while the lowest is CHINA. At the same time, KLCI also has the lowest variance and risk, while the highest risk is CHINA. This means that among the selected indices, KLCI has the best combination of low risk, high return. On the other hand, CHINA has the opposite of higher risk, low return.

Among the sectoral indices, the highest return is KLPLANT, or the plantation index, with a mean return of 0.00053. The lowest return is KLTECH, or the technology index, with a negative return of 0.00053. In fact, KLTECH is the only index with a negative mean return compared with the other indices. In terms of risk and variability, the sector with the lowest variance is KLCONS, or consumer products index, with a variance of 0.00611. On the other hand, the mining sector index has the highest variance of 0.03018.

In terms of skewness and kurtosis, the statistics (especially kurtosis) seem to suggest that the distributions of most if not all of the series are possibly not normal, as can be expected from a financial time series data.

4.2. MGARCH-DCC analysis

First, we look at the results of the analysis on the country-specific indices. We ran an MGARCH-DCC model on all the five indices (KLCI, CHINA, JAPAN, DOWJ, LONDON). The results for the estimates of the individual asset volatility, λ_{1i} and λ_{2i}, as well as the unconditional volatility and correlation between the indices are listed in Table 2 below.

Table 2

MGARCH-DCC estimation results for country-specific indices (using t-distribution)[3]

Parameters	Estimate	Std. Error	T-ratio (p-value)
Lambda1_KLCI	0.9067	0.0144	62.85 (0.000)
Lambda1_CHINA	0.9523	0.0097	97.94 (0.000)
Lambda1_JAPAN	0.9209	0.0102	90.31 (0.000)
Lambda1_DOWJ	0.9129	0.0095	96.50 (0.000)
Lambda1_LOND	0.9197	0.0106	86.69 (0.000)
Lambda2_KLCI	0.0790	0.0112	7.03 (0.000)
Lambda2_CHINA	0.0414	0.0075	5.48 (0.000)
Lambda2_JAPAN	0.0631	0.0075	8.40 (0.000)
Lambda2_DOWJ	0.0770	0.0079	9.72 (0.000)
Lambda2_LOND	0.0659	0.0079	8.35 (0.000)
Delta1	0.9926	0.0016	632.01 (0.000)
Delta2	0.0054	0.0008	6.45 (0.000)
df	9.3531	0.5770	16.210 (0.000)
Maximised log-likelihood = 42,559.4			

Estimated Unconditional Volatility Matrix

	KLCI	CHINA	JAPAN	DOWJ	LOND
KLCI	**0.0076**				
CHINA	0.2662	**0.0163**			
JAPAN	0.4344	0.2633	**0.0152**		
DOWJ	0.1035	0.0574	0.1204	**0.0116**	
LOND	0.2959	0.1478	0.3322	0.5770	**0.0120**

* Unconditional volatilities on the diagonal; unconditional correlations on the off-diagonal elements.

The estimates are all statistically significant, as shown by the large t-ratios and low p-values. Based on the lower panel of Table 2, KLCI has the lowest unconditional volatility (0.0076), while the highest volatility is CHINA (0.0163). In terms of portfolio diversification strategy, investors can potentially benefit by diversifying KLCI with DOWJ, since the correlation in returns is low (0.1035). On the other hand, the correlation with JAPAN is fairly strong (0.4344), and may not provide major benefits in terms of portfolio diversification.

We now move to analysing the conditional volatility and correlation estimates. Figure 4 provides the time-varying or dynamic conditional volatilities of the indices, while Figure 5 shows the dynamic conditional correlations of the indices.

Figure 4

[3] The estimates for t-distribution were used as the Maximum Log Likelihood (42,559.4) was larger than the Log likelihood for the estimates under Normal distribution (42,287.3).

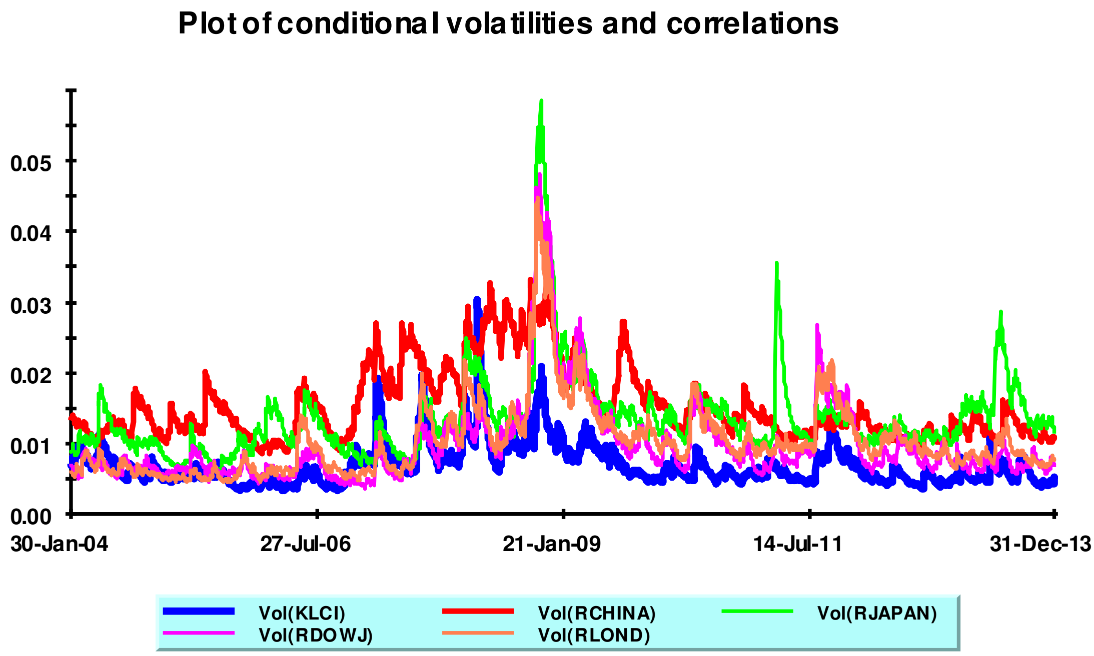
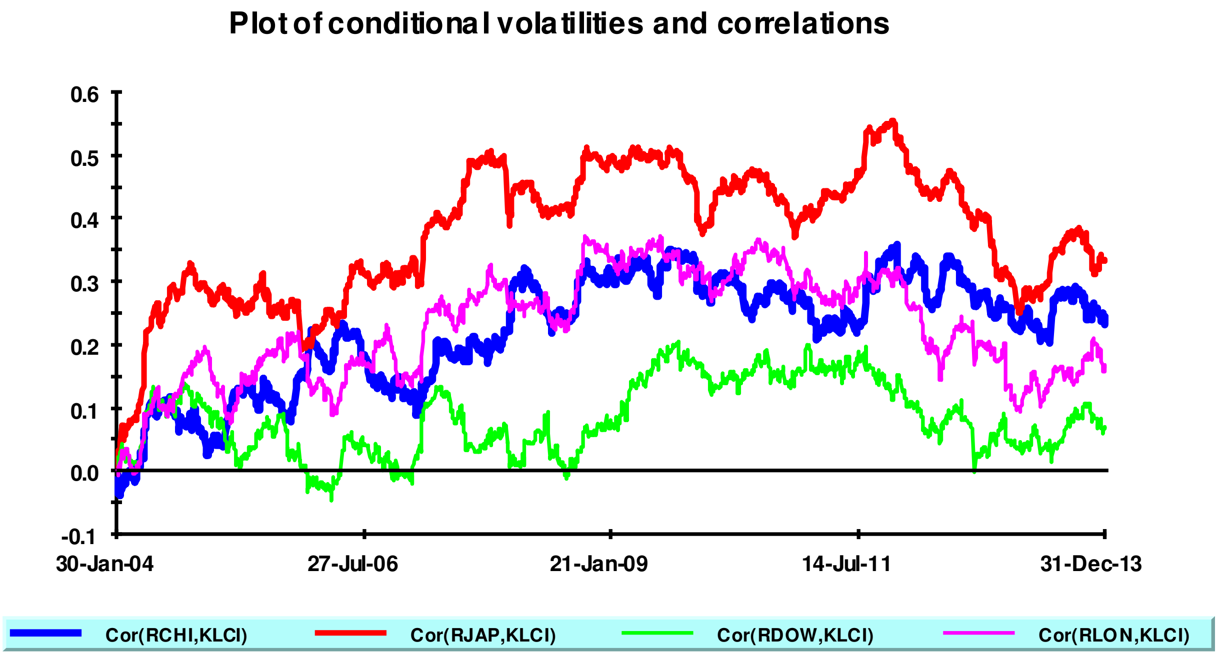


Figure 4 confirms the time-varying nature of the volatilities. Volatilities increased during the Global Financial Crisis in 2008/09, although not so much for KLCI as compared to the others. Furthermore, there seems to be some asymmetric behaviour before and after the crisis. The volatilities seem to comove better after the crisis than before the crisis. Figure 5 confirms this observation, as the conditional correlations between KLCI and the major markets were generally higher after the crisis. In the last couple of years, however, the comovement has been trending downwards, especially with JAPAN, LOND and DOWJ.

Figure 5



In terms of portfolio diversification, again, it is better to diversify KLCI together with DOWJ as shown with the relatively low correlation throughout the period (maximum 0.2). JAPAN should be avoided, as the correlation tends to move fairly high, reaching above 50% a few times in recent years.

Despite the time-varying and dynamic nature of the volatilities, the processes tend to be mean-reverting. Table 3 summarises the tests for the restriction under the null hypothesis that $\lambda_{1i} + \lambda_{2i} = 1$, or there is no unconditional variance. Any shock to the system is permanent. At 5% critical value, the null hypothesis is rejected for all variables.

Table 3

Tests for mean reversion (H_0: no mean reversion)

Parameters	Estimate	Std. Error	T-ratio (p-value)
1 - λ_1_KLCI - λ_2 _KLCI	0.0143	0.0040	4.55 (0.000)
1 - λ_1_CHINA - λ_2 _CHINA	0.0064	0.0028	2.29 (0.022)
1 - λ_1_JAPAN - λ_2 _JAPAN	0.0160	0.0043	3.75 (0.000)
1 - λ_1_DOWJ - λ_2 _DOWJ	0.0101	0.0025	3.98 (0.000)
1 - λ_1_LOND - λ_2 _LOND	0.0145	0.0040	3.62 (0.000)

We now move to sector-specific indices [4]. Table 4 lists the unconditional volatilities of each sectoral index, and also its unconditional correlation with KLCI.

Table 4

Summary results of various MGARCH-DCC estimates of the sectoral indices

Sectoral Index	Uncond. volatilities	Uncond. Correlation with KLCI
KLPROP	0.0105	0.7440
KLTECH	0.0126	0.4818
KLPLANT	0.0114	0.7410
KLMINI	0.0302	0.2144
KLFIN	0.0087	0.8979
KLCONS	0.0061	0.7482
KLCONST	0.0123	0.7908
KLIPROD	0.0079	0.7998
KLTRAD	0.0077	0.9464

From Table 4, the highest unconditional volatility in returns is within the Mining Index (0.0302), while the least volatile is the Consumer Goods index (0.0061). In terms of unconditional correlation with KLCI, most of the indices seem to have high comovement with KLCI. This is similar to the observation earlier in the S&P500, although not as high as theirs. The highest in the KL stock market is KLTRAD or the Trading Services sector, with a correlation of almost 95%. KLFIN is also high, with a correlation of almost 90%. Most of the sectoral indices have a correlation of about 75%. Only KLMINI or the Mining sector, and KLTECH or the Technology sector, have a correlation of below 50%. In particular, KLMINI has an unconditional correlation of 21%. This implies that there are still possible portfolio diversification benefits within the sectoral indices of KL stock market.

Figures 6 and 7 show the time-varying conditional volatilities and correlations of the returns of four of the sectoral indices which had the lowest unconditional correlation with KLCI based on Table 4 (KLMINI, KLTECH, KLPLANT, KLPROP).

[4] Achieving convergence for the MGARCH-DCC estimates was a difficult process for the sector-specific indices. We had to test different combination of variables within different model specifications until we had a better understanding about the time-varying correlation and volatility of the specific index. Only the key results are presented in the main text. Appendix 4 lists all the various specifications and results.

Figure 6a

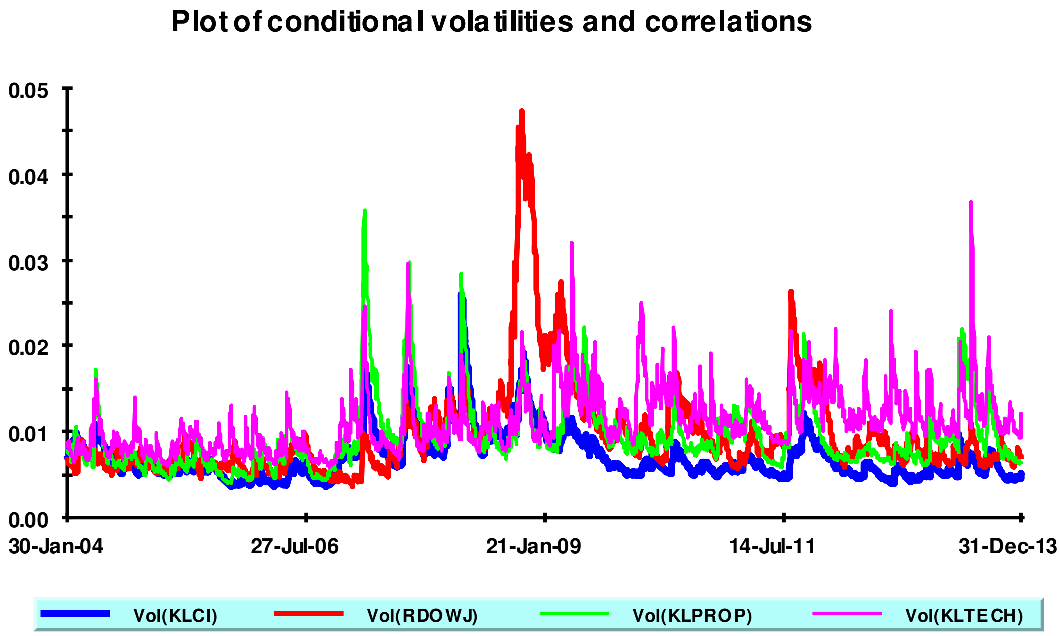
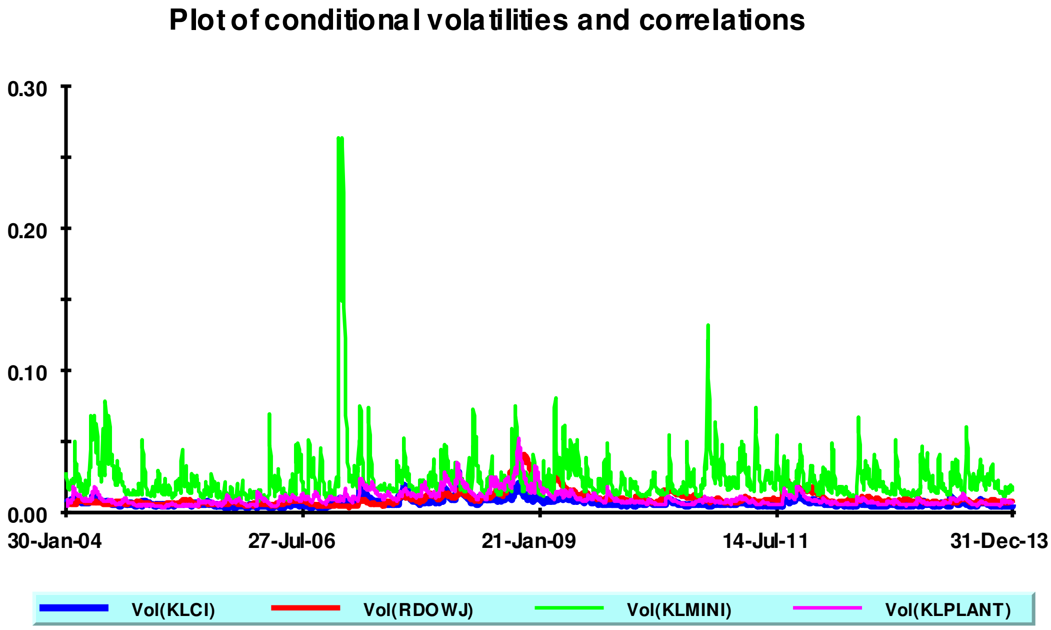


Figure 6b



The conditional volatilities are time-varying but generally stable, despite the occasional large spikes, especially for KLMINI. As observed in Table 4, KLMINI has the highest unconditional volatility among all the sectoral indices.

Figure 7a

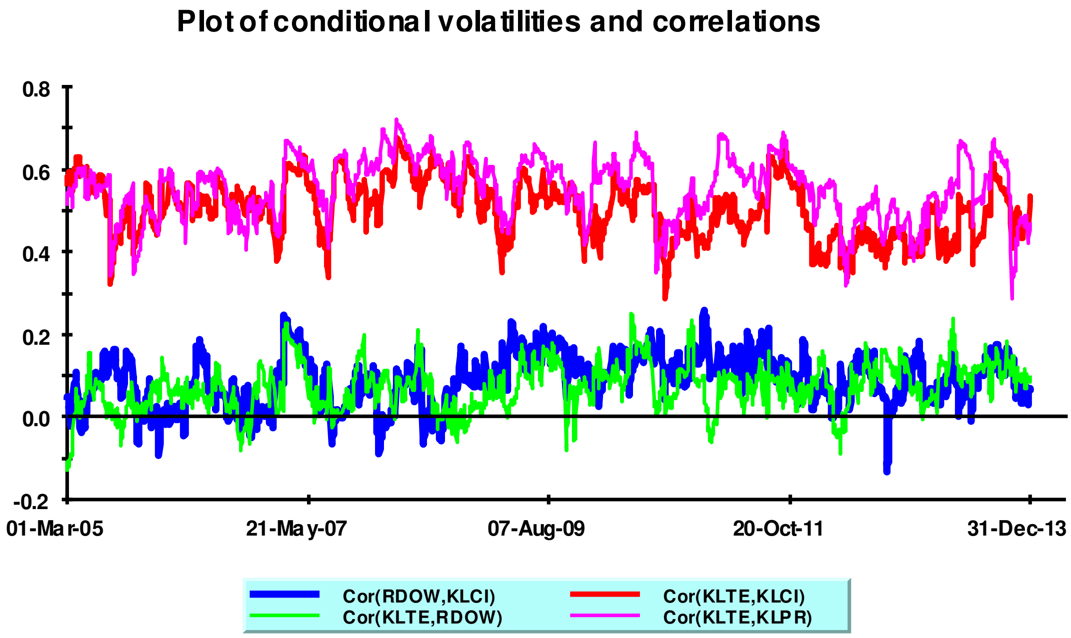


Figure 7b

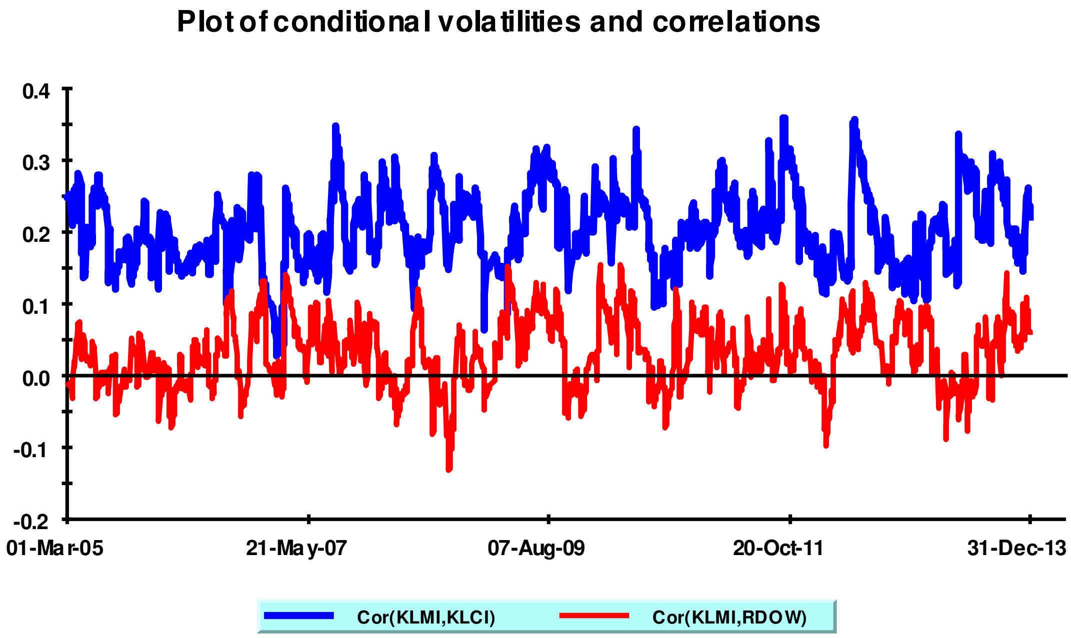


Figure 7a and 7b give an indication that only the correlation between KLMINI and KLCI is fairly low compared to other sectoral indices. Even KLTECH seems to have periods where the correlation touches almost 70%.

The broad summary from the MGARCH-DCC analysis on the sectoral indices seem to point towards availability of potential portfolio diversification benefits, but more limited compared with international stock market diversification. In terms of international diversification, there are potential portfolio gains from diversifying into the US market. Finally, the MGARCH-DCC analysis confirmed the time-varying nature of the correlations and volatilities of the returns.

Now, we move to analyse the presence of scale effects of different types of investors, and how these effects evolve over time.

4.3. Wavelet analysis

The wavelet squared coherence, or wavelet transform coherence, provides a similar analysis like the correlation coefficient, but across time and frequency. Figure 8a-8d shows the wavelet coherence between KLCI and the selected country-specific indices [5].

Figure 8a

Wavelet coherence: KLCI vs. DOWJ

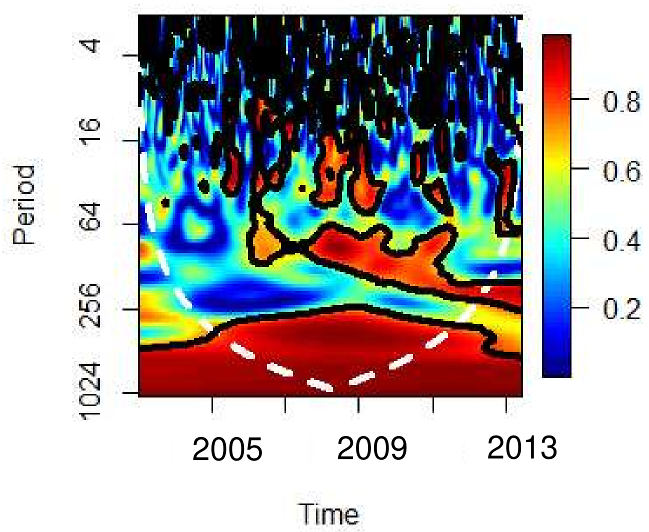


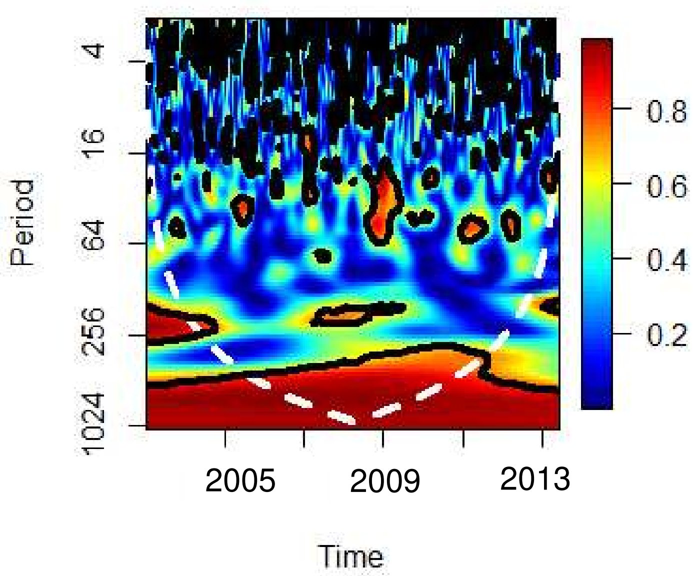
Figure 8a shows the time-varying feature of the comovement, as well as the different correlations at the different time scales. There is a strong comovement between KLCI and DOWJ at the higher scale of more than 256 days (low frequency or

[5] The wavelet coherence was done with the "biwavelet" package in R, written by Gouhier and Grinsted, which is similar to the "wtc" package for Matlab originally written by Grinsted et al. (2004).

longer term) throughout the whole time period. In the medium scale of 64-128 days, there has been a strong correlation which developed since 2006. At the shorter scale, there have been patches of strong correlation. If an investor was to diversify into DOWWJ, then the review of the strategy has to be done on a more frequent basis, e.g. every month or so.

Figure 8b

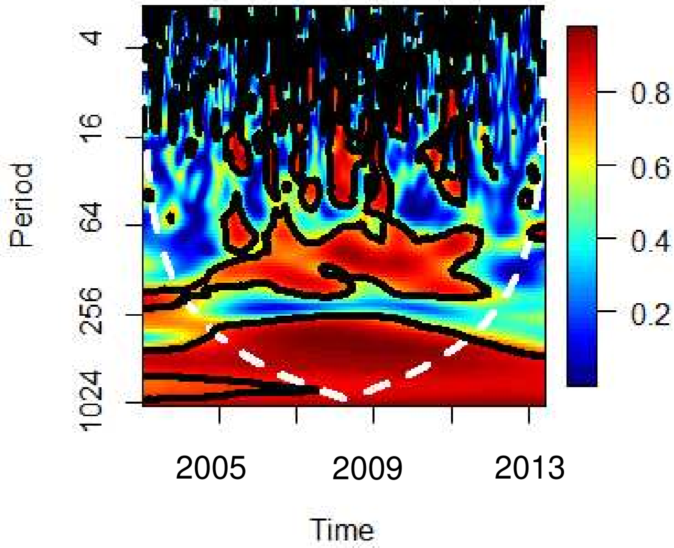
Wavelet coherence: KLCI vs. CHINA



CHINA, on the other hand, represents a good opportunity to diversify. Figure 8b shows only a strong comovement at the higher scale of more than 256 days (low frequency or longer term). The short to medium term scales occasionally see some strong comovement, especially during the Global Financial Crisis in 2008/09. But, in general, there is relatively low correlation (more blue area than red) across most of the short-to-medium scales. Thus, there could potentially be gains from portfolio diversification into CHINA, compared with the other countries.

Figure 8c

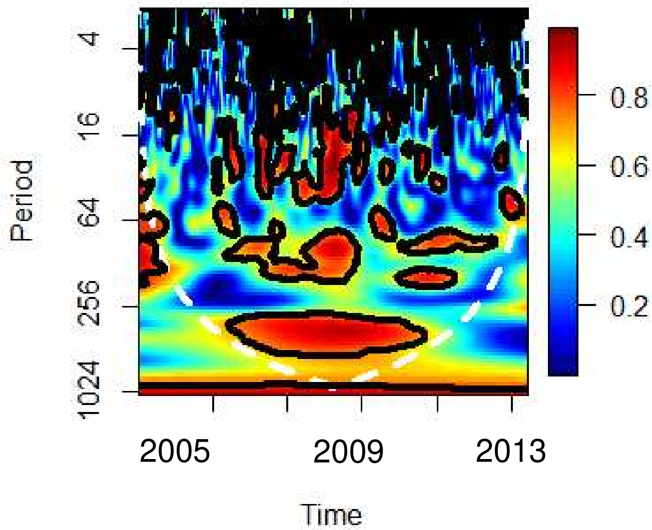
Wavelet coherence: KLCI vs. LOND



Historically, LOND had strong comovement at the medium scales of 64-256 days, and also occasionally at the 16-64 days especially during the Global Financial Crisis period. The long-term comovement is also present throughout. Recently, however, there has been lack of strong comovement between KLCI and LOND, which may open up opportunities to diversify ones' investment.

Figure 8d

Wavelet coherence: KLCI vs. JAPAN



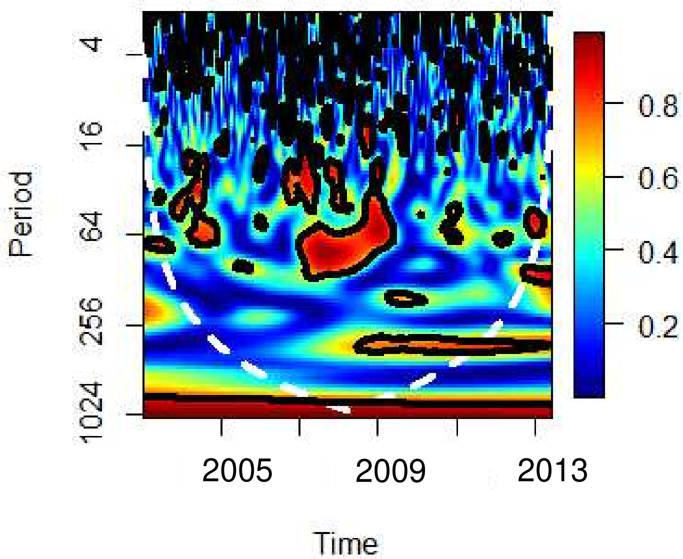
Despite the strong unconditional correlation identified by the DCC estimates, Figure 8d does not suggest such a strong comovement between KLCI and JAPAN. A caveat, though, may be applicable in the sense that there are many black areas in the very short end of the scales (<8 days), which may be areas of high strong correlation. However, these areas are not continuous (like the island at 256-512 days).

As a summary, the wavelet coherence analysis on country-specific indices indeed showed that the degree of correlation and comovement across the markets varies across time and scales. There are opportunities to achieve gains from international portfolio diversification, but the fund managers have to frequently review their markets to see the dynamics of the latest comovement, especially those that have strong correlations at the medium-to higher-scales (medium- to long-term).

The next Figures 9a-9d provides the wavelet coherence diagrams only for selected sectoral indices against KLCI. These indices were selected as they had the lowest unconditional correlations from the DCC estimates in Table 4.

Figure 9a

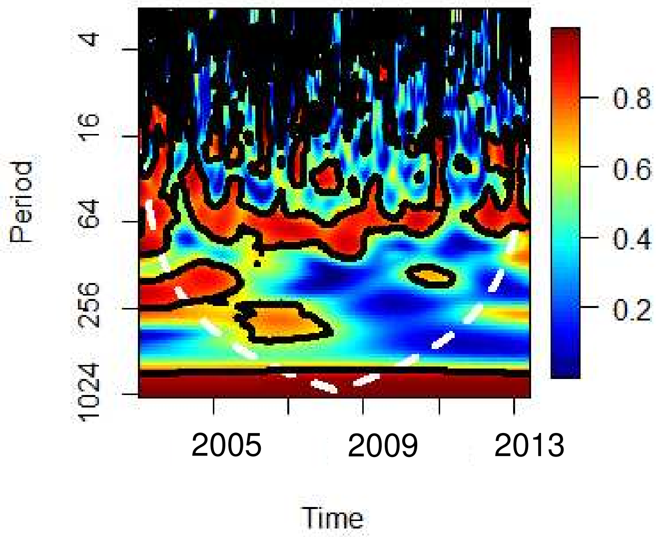
Wavelet coherence: KLCI vs. KLMINI



As suggested by the DCC estimates, KLMINI seems to have low correlation with KLCI in most of the time scales and period. The strong correlation occurred at the 64-days scale during the GFC, and at the higher scale of 256-days since the crisis period.

Figure 9b

Wavelet coherence: KLCI vs. KLTECH



The comovement of KLTECH and KLCI occurs mostly at the medium scale of 64 days. Interestingly, the correlation seems to be low at the higher scale (long term) since the start of the GFC crisis. This sector may benefit portfolios of longer-term investors.

Figure 9c

Wavelet coherence: KLCI vs. KLPLANT

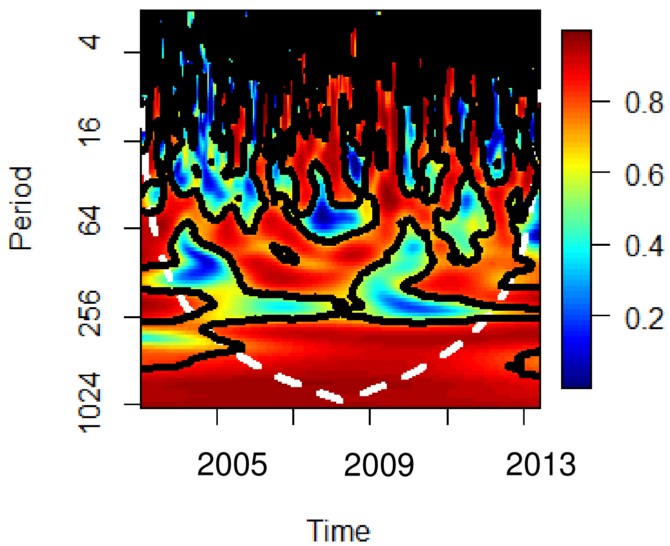
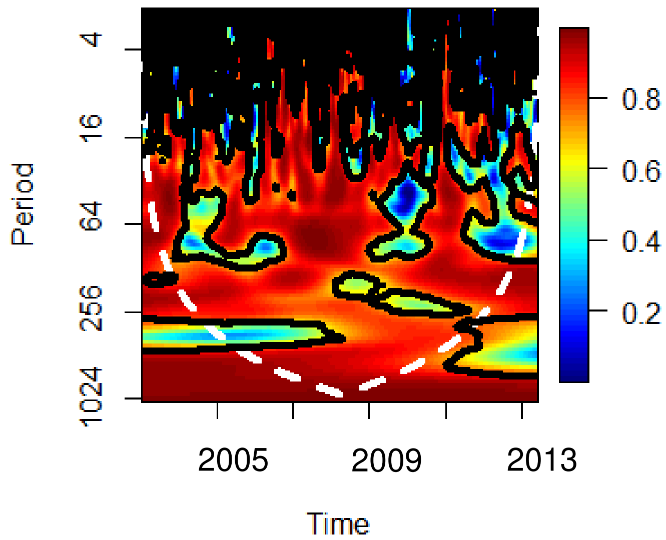


Figure 9d

Wavelet coherence: KLCI vs. KLPROP



The DCC estimates of the unconditional correlations of KLPLANT and KLPROP with KLCI were close to 75%. The wavelet coherence diagrams of Figures 9c and 9d also suggest that the correlation between these two sectors and KLCI is high. More importantly, the high correlation occurs almost throughout all the different scales (more red area than blue).

To summarise, the wavelet analysis of the selected sectoral indices also confirmed that the nature of correlation among the stock returns varies across time and scales. Different types of investors led to varying degrees of comovements. In terms of diversifying ones' portfolio, there are sectors with low correlation to be considered, but perhaps, the choices may not be as large as the international markets.

5. Summary and Conclusion

The focus of this paper is to investigate the potential for portfolio diversification strategies based on investing across international markets or economic sectors, using Malaysia as a case study. The key question to address is whether there exists opportunities for diversifying the investment portfolio across markets or sectors that can help to reduce risks. Analysing the comovement and correlation between returns and volatilities of the different markets or assets, therefore, is the key to gauge the potential benefits from diversification.

Two important features of the comovement are their dynamic fluctuations across time period and time horizon or scales. Thus, the paper applies recent techniques of multivariate volatility modelling and wavelet transform, which can analyse time series over both the time and frequency domain.

Our findings suggest that there are potential for gains from portfolio diversification strategies into both international markets, as well as sectors of the domestic stock market. There are international stock markets and domestic sectors which have low correlations and comovement with the Kuala Lumpur Composite Index. The low correlation makes it ideal to diversify the portfolio and reduce the overall investment risks.

However, the findings also noted that the correlations vary across time and scales. Hence, fund managers need to be aware of the dynamics which may change at any particular point in time, which may affect the portfolio risks. Hence, there is a need for periodic review of the stocks within the portfolio, depending on the dynamics of the stocks that moves across markets and sectors, and also across frequencies and time scales.

Notwithstanding these results, there are areas for further improvements to the study. First, we only covered selected individual markets based on important trading partners of Malaysia. More countries could be added from other regions of the world, for example, Latin America. Second, we did not analyse the direction of causality or the lead and lag periods between the different stock markets and sectors. This would enhance the understanding of the linkages between the markets and sectors, and may lead to a more efficient risk management strategy. Thirdly, we did not study in detail what causes specific trends of comovements, for example, impact of rising financial integration or liberalisation of cross border investments. Finally, the study can be extended to include more countries with sectoral indices. But, a more universal sector classification across the countries' stock markets is needed. Then, we can see which sectors tend to have low correlation with the main index, and contribute towards achieving the benefits of reducing the risks by diversifying the investment portfolio.

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