Co-integration and Causality in different Time Scales between SENSEX and SHARIAH 50 Indices in Indian Stock Markets

Irfan ul Haq[1]
Chanderashekara Rao[2]

Abstract

In this paper, we test for Co integration and Causality between the SENSEX and SHARIAH 50 of Bombay Stock Exchange (BSE).Co integration was checked using Engle Granger Co integration and Causality by Granger Causality in different time scales by decomposing the series using wavelet analysis. The results suggest that both the indices are co integrated in the long run and there is feedback relationship i.e. bidirectional flow of information between the indices in 2-4 days, as we go on increasing the time scale no causality is found.

JEL Classification: C12, C32, E44

Keywords: Co integration, Granger Causality, Wavelet Analysis.

1. Introduction

One of the important sectors of any economy that relay on information is the stock exchange. Researchers have discussed a lot in the information transmission from one market to another (Antoniou et al. 2003), Baur and Jung (2006), and Caporale, Pittis and Spagnolo (2006). According to Koutmos (1996) studies investigating the information, transmission in the first moment and second moment can be done based on returns and volatility respectively. Most of the earlier studies on the information transmission focused on the developed market especially US and Europe such as Koutoms (1996), Kasibhtla et al. (2006), Antoniou et al. (2003), Koutoms et al. (1993) and Baur et al. (2006). Few studies focused on the emerging markets such as Daly (2003), Lamba et al. (2001), Shachmurove (2005 and 2006), and Soydemir (2000).

Islamic investments are investments that follow Shariah or tenets of Islam. The concept of Islamic banking and finance has been introduced to get away with conventional banking and finance based upon interest. Many financial developments have been made in different fields like banking, capital markets, money markets, insurance which are all Shariah complaint. One of these developments is the initiation of Islamic indices in many Muslim populace and non-Muslim populace countries alike. In US, Dow Jones Islamic Market Index (DJIMI) was introduced in 1999, and Kuala Lumpur Syariah Index (KLSI) introduced in 1999. However it was replaced by FTSE Bursa Malaysia Hijrah Shariah index in May 2007. Bombay Stock Exchange in collaboration with Taqwaa Advisory and Shariah Investment Solutions (TASIS) launched SHARIAH 50 a Shariah Complaint Index in January 2010. This paper investigates the cointegration of this newly introduced Shariah Complaint Index (Shariah 50) with already established Indian index (SENSEX) and the flow of information between the two in different time scales using the Wavelet Analysis.

2. Literature Review

Several recent studies have examined whether or not two or more indexes of stock prices are co integrated (see Epps 1979; Cerchi and Havenner 1988; Takala and Perre 1991; Bachman et al. 1996; Choudhry 1997; Crowder and Wohar 1998; Chan and Lai 1993; Ahlgren and Antell 2002).

Fahim et al. investigated the transmission of information (at return and volatility level) as well as the correlation between Kuala Lumpur Syariah and Jakarta Islamic Indices. They found significant unidirectional return and volatility transmissions from Kuala Lumpur Syariah and the Jakarta Islamic Indices. Christos Floros (2011) examine the dynamic relationships between Middle East stock markets and found that the Egyptian market plays a price discovery role, implying that CMA prices contain useful information about TASE-100 prices. Shabri et al. studied the co integration between different Islamic stock markets and found that Malaysian and Indonesian markets are closely integrated with each other, while those of US, UK and Japan are closely integrated with themselves.

Evidence of co integration (or co-movement) among several indexes of stock prices suggests that these series have a tendency to move together in the long-run even if experiencing short-term deviations from their common equilibrium path. Should two indexes of stock prices be co integrated, their relationship can be represented by an Error Correction Model (ECM) on the basis of which movements in any one of them

[1] Corresponding Author, Research Scholar Department of Banking Technology, School of Management, Pondicherry University-605014. Fanpin20@gmail.com, 9487609707

[2] Dean School of Management Pondicherry University-605014.

can be used to predict movements in the other. Accordingly, the ECM associated with co integrated stock price indexes provides investors and policy makers with valuable information regarding their investment decisions and for economic policy. Furthermore, as pointed out by Granger (1986, 1988) and Engle and Granger (1987), knowledge of co integration is also important in view of the fact that if two economic time series are co integrated, there must be a causal relationship at least in one direction.

Several applications of wavelet analysis to economics and finance have been documented in recent literature which include examination of foreign exchange data using waveform dictionaries (Ramsey and Zhang 1997), analysis of commodity price behavior (Davidson, Labys, and Lesourd 1998), decomposition of economic relationships of expenditure and income (Ramsey and Lampart 1998a, 1998b), stock market inefficiency (Pan and Wang 1998), scaling properties of foreign exchange volatility (Gencay, Selcuk, and Whitcher 2001), and systematic risk (the beta of an asset) in a capital asset pricing model (Gencay et al. 2003). Francis and Kim (2006) examined the lead lags in US markets using wavelets, and found the feedback relationship contemporaneously as well as in various time scales.

3. Data and Methodology

We have used the daily closing prices of SENSEX and SHARIAH 50. The data is collected from CMIE (Centre for Monitoring Indian Economy) Prowess. The data period of the study is from 01-03-2008 to 31-12-2012. We computed the daily returns for both the indices. The daily changes of both indices are calculated by log (P_t) - log (P_{t-1}).

3.1 Co integration

According to Engle and Granger (1987), if two time series variables, p_t and q_t, are both non-stationary in levels but stationary in first-differences, i.e., both are I(1), then there could be a linear combination of p_t and q_t, which is stationary, i.e., the linear combination of the two variables is I(0). The two time series variables that satisfy this requirement are deemed to be co integrated. The existence of co integration implies that the two co integrated time series variables must be drifting together at roughly the same rate (i.e., they are linked in a common long-run equilibrium). A necessary condition for co integration is that they are integrated of the same order (Granger 1986; Engle and Granger 1987).

To check whether or not two or more variables are co integrated, it is necessary to first verify the order of integration of each variable by performing unit root tests. Two of the most commonly used techniques for unit root testing are the ADF and PP tests.

In both cases, the null hypothesis of a unit root is tested against a stationary alternative. The ADF test is performed by testing $\delta_0 = 0$ against the one sided alternative $\delta_0<0$ in the regression:

$$\Delta p_t = \beta_0 + \beta_1 t + \delta_0 p_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta p_{i-1} + e_t \qquad t=1, 2,\ldots\ldots\ldots, T \quad (1)$$

Where e_t is the error term and Δ denotes the first-difference operator, i.e. ($\Delta p_t = p_t - p_{t-1}$)... The term $\beta_1 t$ is usually included to produce a test that is similar in the presence of an unknown drift. In the present paper, the optimal lag length l for the ADF test is determined using an appropriate model selection criterion (e.g., the Akaike information criterion, the Schwarz's Bayesian Information Criterion (BIC), etc.). It has been observed by Banerjee et al. (1993) that the results provided by the ADF test are more robust than those provided by any other unit root tests in the presence of autoregressive errors, since the autoregressive terms are captured precisely.

The PP test, which has been shown to be robust to a wide range of serial correlation and time dependent heteroscedasticity in the error term, is performed by testing $\delta_0 = 0$ against the alternative that the series is stationary in the regression:

$$\Delta p_t = \beta_0 + \beta_1 (t - T/2) + \delta_0 p_{t-1} + e_t \qquad t = 1, 2\ldots\ldots\ldots, T \quad (2)$$

Where the term (t - T/2) denotes the time trend. If the series has a constant term β_0 but no time trend, the term β_0 (t - T/2) is omitted from equation (2).

If the ADF or PP test accepts the relevant null hypothesis for the series in level but rejects the null hypothesis for the series in first difference, then the series is deemed to have a unit root. The difference between the ADF and PP unit root test is that the former has in general better size properties and the latter has better power. Also, the PP test adjusts nonparametrically for possible autocorrelation and heteroscedasticity of the long-run covariance.

If two time series variables, p_t and q_t, are both I (1), then the possible co integration relationship between these two variables can be tested in two steps. The first step entails running the co integration regression

$$p_t = \theta_0 + \theta_1 q_t + u_t \qquad (3)$$

Where θ_0 is a constant, $\theta 1$ is a coefficient for qt, and u_t is the ordinary least squares (OLS) residuals. In the second step, the unit root test is performed on the OLS residuals of the co integration regression equation (3), i.e. $\hat{u}_t = p_t - \hat{\theta}_0 - \hat{\theta}_1 q_t$ $\hat{u}_t = p_t - \hat{\theta}_0 - \hat{\theta}_1 q_t$ where $\hat{\theta}_0$ and $\hat{\theta}_1$ are OLS estimates θ_0 and θ_1 respectively, in the co integrating regression (3), and $\hat{u}_t$ is the OLS residual from the same co integrating regression. If the result of the unit root test confirms $\hat{u}_t$ is I (0) (i.e., $\hat{u}_t$ is stationary), we conclude that p_t and q_t are co integrated.

3.2 Error Correction Mechanism

Following Granger (1986) a time series model of a co integrated series may be rewritten in error correction form. Such a transformation renders the series stationary, and allows for standard hypothesis testing. A prototypical ECM useful for testing the short-run relationship between spot and futures prices may be specified as

$$\Delta S_t = -\rho u_{t-1} + \beta \Delta F_{t-1} + \sum_{i=2}^{m} \beta \Delta F_{t-1} + \sum_{j=1}^{k} \psi \Delta S_{t-j} + v_t \qquad (4)$$

Where Δ is a first difference operator such that $\Delta S_t = S_t - S_{t-1}$; u_{t-1} is the error correction term, the coefficient of which indicates the speed of adjustment of any disequilibrium towards the long-run equilibrium state.

3.3 Wavelets and Wavelet Analysis

A natural concept in financial time series is the notion of multiscale features. That is, an observed time series may contain several structures, each occurring on a different time scale. Wavelet techniques possess an inherent ability to decompose this kind of time series into several sub-series which may be associated with a particular time scale. Processes at these different time scales, which otherwise could not be distinguished, can be separated using wavelet methods and then subsequently analyzed with ordinary time series methods. Wavelet methods present a lens to the researcher, which can be used to zoom in on the details and draw an overall picture of a time series in the same time. Gençay et al. (2002a) argue that wavelet methods provide insight into the dynamics of economic/financial time series beyond that of standard time series methodologies. Also wavelets work naturally in the area of non-stationary time series, unlike Fourier methods which are crippled by the necessity of stationarity. In recent years the interest for wavelet methods has increased in economics and finance. This recent interest has focused on multiple research areas in economics and finance like exploratory analysis, density estimation, analysis of local in homogeneities, time scale decomposition of relationships and forecasting (Crowley 2005).By decomposing a time series on different scales, one may expect to obtain a better understanding of the data generating process as well as dynamic market mechanisms behind the time series. Investigation methods applied to a financial time series over the last decades can now be implemented to multiple time series presenting different scales (frequencies) of the original time series. Therefore efficient discretization of the time-frequency space allows isolation of many interesting structures and features of economic and financial time series which are not visible in the ordinary time-space analysis or in the ordinary Fourier analysis.

A wavelet is a 'small wave' which has its energy concentrated in a short interval of time. The wavelet analysis allows researchers to decompose signals into a parsimoniously countable set of basic functions at different time locations and resolution levels. Due to the Compact support property of wavelets, the wavelet analysis is capable of capturing short lived, transient components of data in shorter time intervals, as well as capturing trends and patterns in longer time intervals.

Basic wavelets are characterized into father and mother wavelets, f(t) and w(t), respectively. These wavelets are functions of time only. A father wavelet represents the smooth baseline trend, and mother wavelets are used to describe all deviations from trends Any time series, for example f(t), can be decomposed by wavelet transformations, which can be given by

$$f(t) \approx \sum_k S_{j,k}\Phi_{j,k}(t) + \sum_k d_{j,k}\Psi_{j,k}(t) + \sum_k d_{j-1,k}\Psi_{j-1,k}(t) + \dots\dots\dots + \sum_k d_{1,k}\Psi_{1,k} \qquad (5)$$

Where J is the number of scales and *k* ranges from one to the number of coefficients in the specified component. The coefficients are $S_{j,k}$, $d_{j,k}$,…,$d_{1,k}$ are the wavelet transform coefficients. The functions $\Phi_{j,k}(t)$ and $\Psi_{j,k}(t)$, where j= 1,……., j-1, j, are the approximating wavelet functions. Wavelet transforms can now be implemented given the family of wavelets described. The wavelet transforms are the wavelet series coefficients defined as $S_{j,k} = \int \Phi_{j,k}(t)f(t)dt$ and $d_{j,k} = \int \Psi_{j,k}(t)f(t)dt$, where j is the maximum integer such that 2^j is less than the number of data points. Their magnitude gives a measure of the contribution of the corresponding wavelet function to the approximation sum, and wavelet series coefficients approximately specify the location of the corresponding wavelet function. More specifically, the detail coefficients $d_{j,k}$, …..,$d_{1,k}$,which can capture the higher-frequency oscillations, represent increasingly fine scale deviations from the smooth trend. The coefficient $S_{j,k}$ represents the smooth coefficients that capture the trend. Given these coefficients, the wavelet series approximation of the original signal f(t) is given by the sum of the smooth signal $S_{j,k}$ and the detail signals $D_{j,k}$, $D_{j-1,k}$,……., $D_{1,k}$:

$$f(t) = S_{j,k} + D_{j,k} + D_{j-1,k} + \dots\dots + D_{1,k} \qquad (6)$$

Where $S_{j,k} = \sum_k S_{j,k}\Phi_{j,k}(t), D_{j,k} = \sum_k d_{j,k}\Psi_{j,k}(t), and D_{1,k} = \sum_k d_{1,k}\Psi_{1,k}(t)$. The original signal components $S_{j,k}$, $D_{j,k}$, $D_{j-1,k}$ and $D_{1,k}$ are listed in the order of increasingly fine scale components. Signal variations on high scales are acquired using wavelets with large supports. The discrete wavelet transform (DWT) calculates the coefficients of the wavelet series approximation for a discrete signal f_1, …….. fn of finite extent. The DWT maps the vector $f = (f_1, f_2, \dots\dots\dots, f_n)^{/}$ to a vector of *n*

wavelet coefficients $w = (w_1, w_2, ..., w_n)^{/}$. The vector **w** contains the coefficients $S_{j,k}$, $d_{j,k}$, ……., $d_{1,k}$, j= 1,2,….,j of the wavelet series approximation, equation (6). Our analysis adopts the maximum overlap DWT (MODWT) instead of DWT. It provides basically all functions of the DWT, such as multiresolution analysis (MRA) decomposition and analysis of variance.

4. Results and Discussion

The results are shown in tables 1-3. Both the indices are non stationary at levels and stationary at first difference confirmed by both ADF and PP results, which means the presence of unit root in original series. While estimating the OLS and confirming the unit root analysis of residual we see it is stationary at level (Table 1). Thus in accordance with the Engle Granger if the residual is stationary, the two series are co integrated. Hence we can say that both SENSEX and SHARIAH 50 are co integrated in the long run. To check the speed of adjustment for correcting the disequilibrium we used the error correction mechanism, and we see that disequilibrium is corrected promptly i.e., 93.4% disequilibrium is corrected daily (table 2).

Finally we checked the Granger Causality in original series and the decomposed series in different time scale. The data has been decomposed into 4 time scales, d1- 2 to 4 days, d2- 4 to 8 days, d3- 8 to16 days and d4- 16 to 36 days. We see that there is no causality between the indices in original, d2, d3 and d4 there is no causality between the two. But in d1 scale we see that there is bidirectional causality between the indices which means feedback relationship between the two. Both the indices are reacting to the new information in 2-4 days but, when we increase the time scale no causal relation is seen.

5. Conclusion

In this paper, we investigated the co integration and causality between the broad index of BSE SENSEX and Islamic Index SHARIAH 50. The investigation was conducted using, Engle Granger co integration, Granger Causality and Wavelet Analysis. The results suggest that both SENSEX and SHARIAH 50 are co integrated in the long run and any disequilibrium is adjusted promptly. There is feedback relation as far as Granger Causality is concerned in 2-4 days, as we go on increasing the scale we couldn't find any causality between the indices.

References

Ahlgren, N. and J. Antell (2002), "Testing for Co integration Between International Stock Prices", Applied Financial Economics, 12, 851-861.

Antoniou, A., Pescetto, G., & Violaris, A. (2003), "Modeling international price relationships and interdependencies between the stock index and stock index futures of three EU countries: a multivariate analysis", Journal of Business Finance and Accounting, 30, 645-667.

Arbelaez, H., J. Urrutia, and N. Abbas (2001), "Short-Term and Long-Term Linkages Among the Colombian Capital Market Indexes" , International Review of Financial Analysis, 10, 237-273.

Bachman, D., J.J. Choi, B.N. Jeon and K.J. Kopecky (1996), "Common Factors in International Stock Prices: Evidence From a Co integration Study" , International Review of Financial Analysis, 5, 39-53.

Banerjee,A., J. Dolado, J. Galbriath, and D. Hendry (1993), Co-Integration, Error-Correction, and the Econometric Analysis of Non-Stationary Data, Oxford University Press, Oxford.

Baur, D., & Jung, R. C. (2006), "Return and volatility linkages between the US and the German stock Market", Journal of International Money and Finance, 25, 598-613.

Caporale, G. M., Pittis, N., & Spagnolo, N. (2006), "Volatility transmission and financial crises", Journal of Economics and Finance, 30, 376-390.

Cerchi, M. and A. Havenner (1988), "Co integration and Stock Prices: The Random Walk on Wall Street Revisited", Journal of Economic Dynamics and Control, 12, 333-346.

Chan, K.C. and P. Lai (1993), "Unit Root and Co integration Tests of World Stock Prices", International Financial Market Integration, 278-287, Oxford and Cambridge Mass.: Blackwell.

Choudhry, T. (1996), "Real Stock Prices and the Long-Run Money Demand Function: Evidence from Canada and the USA", Journal of International Money and Finance, 15, 1-17.

Choudhry, T. (1997), "Stochastic Trends in Stock Prices: Evidence from Latin American Markets", Journal of Macroeconomics, 19, 285-304.

Christos Floros (2011) "Dynamic relationships between Middle East stock markets", International Journal of Islamic and Middle Eastern Finance and Management, Vol. 4 Iss: 3, pp. 227-236

Crowder, W.J. and M.E. Wohar (1998), "Co integration, Forecasting and International Stock Prices", Global Finance Journal, 9, 181-204.

Daly, K. J. (2003), "Southeast Asian stock market linkages evidence from pre- and post October 1997", Asean Economics Bulletin, 20, 73-85.

Davidson, R., W. C. Labys, and J. B. Lesourd. (1998), "Wavelet analysis of commodity price behavior", Computational Economics (11),103-28.

Dickey, D. A. and W.A. Fuller (1979), "Distribution of the Estimators for Autoregressive Time Series With a Unit Root", Journal of the American Statistical Association, 74, 427-431.

Engle, R.F. and C.W.J. Granger (1987), "Co integration and Error Correction: Representation, Estimation and Testing", Econometrica,55, 251-276.

Epps, T.W. (1979), "Co movements in Stock Prices in the Very Short Run", Journal of the American Statistical Association, 74, 291-298.

Fahmi Abdul Rahim, Noryati Ahmad, Ismail Ahmad, (2009) "Information transmission between Islamic stock indices in South East Asia", International Journal of Islamic and Middle Eastern Finance and Management, Vol. 2 Iss: 1, pp.7 - 19

Gencay, R., F. Selc ¸uk, and B. Whitcher. (2001), "Scaling properties of foreign exchange volatility", Physica 249-66.

Geweke, J., R. Meese, and D.T. Dent (1983), "Comparing Alternative Tests of Causality in Temporal Systems: Analytic Results and Empirical Evidence", Journal of Econometrics, (21), 161-194.

Granger, C.W.J. (1969), "Investigating Causal Relations By Econometric Models and Cross Spectral Methods", Econometrica, (37), 213-228.

Granger, C.W.J. (1986), "Developments in the Study of Co integrated Variables", Oxford Bulletin of Economics and Statistics, 48, 424-438.

Granger, C.W.J. (1988), "Some Recent Developments in the Concept of Causality", Journal of Econometrics, 39, 199-211.

Guilkey, D.K. and M.K. Salemi (1982), "Small Sample Properties of Three Tests for Granger Causal Ordering in A Bivariate Stochastic System" , Review of Economics and Statistics, 64, 668-680.

In F. and Kim S. (2006) "The Hedge Ratio and the Empirical Relationship between the Stock and Futures Markets: A New Approach Using Wavelet Analysis", The Journal of Business (2), 799-820.

Kasibhatla, K. M., Stewart, D., Sen, S., & Malindretos, J. (2006), "Are daily stock price indices in the major European equity markets cointegrated? Tests and evidence", American Economist, 50, 47-57.

Koutmos, G. (1996), "Modeling the dynamic interdependence of major European stock markets", Journal of Business Finance & Accounting, 23, 975-988.

Lamba, A. S., & Otchere, I. (2001), "An analysis of the dynamic relationships between the South African equity market and major world equity markets", Multinational Finance Journal, 201-224.

MacDonald, R. and C. Kearney (1987), "On the Specification of Granger Causality Tests Using Co integration Methodology", Economics Letters, (25), 149-153.

Nasseh, A. and J. Strauss (2000), "Stock Prices and Domestic and International Macroeconomic Activity: A Co integration Approach", The Quarterly Review of Economics and Finance, 40, 229-245.

Phillips, P.C.B. and P. Perron (1988), "Testing For a Unit Root in Time Series Regression" ,Biometrika, (75), 335-346.

Ramsey, J. B. (2002), "Wavelets in economics and finance: Past and future", Studies in Nonlinear Dynamics and Econometrics (6), 1-27.

Ramsey, J. B., and C. Lampart. (1998a), "Decomposition of economic relationships by time scale using wavelets", Macroeconomic Dynamics (2), 49-71.

Ramsey, J. B., and Z. Zhang. (1997), "The analysis of foreign exchange data using waveform dictionaries" , Journal of Empirical Finance (4), 341-72.

Shabri.M, Majid and Kassim (2010), "Potential Diversification benefits across Global Islamic Equity Markets", Journal of Economic Cooperation and Development, 31,4, 103-126

Shachmurove, Y. (2005), "Dynamic linkages among the emerging Middle Eastern and the United States stock markets" , International Journal of Business and Management, (10), 104-132

Soydemir, G. (2000), "International transmission mechanism of stock market movements: evidence from emerging equity markets", Journal of Forecasting, (19), 149-172.

Takala, K. And P. Pere (1991), "Testing for Co integration of House and Stock Prices in Finland", Finnish Economic Papers, (4), 33-51

Table 1: Unit Root Analysis of SENSEX, SHARIAH 50 and RESIDUAL

Index	ADF		PP	
	Level	First Difference	Level	First Difference
SENSEX	-1.233	-32.403	-1.278	-32.377
	(0.661)	(0.000)	(0.641)	(0.000)
SHARIAH 50	-0.613	-32.438	-0.676	-32.450
	(0.865)	(0.000)	(0.850)	(0.000)
Residual	-25.150	-	-32.643	-
	(0.000)		(0.000)	

Table 2: Error Correction Estimates

Speed of Adjustment (ρ)	R^2	Adjusted R^2
-0.934	0.938	0.938

Table 3: Granger Causality of Index Returns in Wavelet Domain

Causality	Original Series	d1	d2	d3	d4
SHARIAH 50 does not Granger Cause SENSEX	4.459	9.690*	2.100	0.049	1.332
	(0.011)	(0.000)	(0.122)	(0.951)	(0.264)
SENSEX does not Granger Cause SHARIAH 50	3.561	7.179*	3.013	0.446	1.828
	(0.028)	(0.000)	(0.044)	(0.640)	(0.161)

Note. — The original data have been transformed by the wavelet filter (LA (8)) up to time scale 4. The significance levels are in parentheses. The first detail (wavelet coefficient) d1 captures oscillations with a period length two to four days. The last detail d4 captures oscillations with a period length of 16-32 days.

**Significant at the 5% level*