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Sensitivity of Stock Prices to Economic Events: Econometric Evidence from Sri Lankan Stock Market and US Stock Market

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Abstract

This paper attempts to examine the sensitivity of stock prices to economic events in an emerging market and in a developed market. Historically several studies have been undertaken on the stock market sensitivity on important economic events in several markets. The sensitivity of stock prices to major economic events is measured by using the volatility test of Inclan and Tiao which objectively differentiates the volatile period from the weekly data series of both markets. The All Share Price Index (ASPI) and New York Stock Exchange (NYSE) Composite Index are used for the volatility test of Inclan and Tiao (1994). Then, the major economic events are matched with the volatility periods of the prices. It is found that the stock prices in both markets are highly sensitive to the major economic events. The findings of this study consistent with Bailey and Chung (1995) who find that important political events tend to be associated with sudden change in volatility. Thus this suggests that portfolio managers should be cautious in advising their clients in dynamic situations in the markets in this nature.

Introduction

Early, statistical literature on changes of variance started with Hsu et al., (1974) who unearth this formulation as an alternative to the Pareto distribution model stock returns. There are many works aimed at identifying the point of change in a data set of independent random variables (Hinkley 1971; Menzefricke 1981; Smith 1975). Booth and Smith (1992) used the Bayes ratio to decide whether a series presents a single change of variance at an unknown point. For example (Hsu 1979; Hsu 1982) studied the detection of the variance shift at an unknown point in a sequence of independent observations, focusing on the detection of points of change one at a time because of the computational burden involved in looking for several points change simultaneously. Worsley (1986) used maximum likelihood methods to test a change in a mean for a sequence of independent exponential family random variables, to estimate the change point and to give confidence regions. His work focused on finding one change point at a time.

For autocorrelated observations Hsu et al., (1974) studied an autoregressive model of order one, having a sudden variance change at an unknown point. Abraham and Wei (1984) used a Baufays and Rasson (1985) estimated the variances and the points of change of maximum likelihood. Tsay (1988) discussed autoregressive moving average models allowing for outliers and variance changes and proposed a scheme for finding the point of variance change of maximum likelihood. According to Dayong et al., (2005) several factors can be attributed for the volatility change of stock markets. First the prevailing regulation rules are important for the volatility change. They further conclude that tight regulation in the market leads to declining of the volatility in the market. Secondly liquidity and the economic environments are equally influence for the volatility change in the stock markets.

The link between volatility and crisis is currently growing phenomena in the area of financial economic and in the contemporary business dialogue in the world. Apparently, it seems that there is a positive relationship between volatility and world prominent crises in the world economies. Some argue that social, political and economic events cause the volatility in the stock markets. According to Aggarwal et al., (1995) the high volatility of emerging markets is marked by frequent sudden changes in variance. The periods with high volatility are found to be associated with important events in each country rather than global events. The October 1987 crisis is the only global event in the past decade that significantly increased volatility in several markets. Aggarwal's argument was re-confirmed by Bekaert and Campbell (1997) who concludes that on average the proportion of variance attributable to world factors is quite small for emerging markets. Bailey and Chung (1995) find that important political events tend to be associated with sudden change in volatility.

The link between economic events and stock market volatility in comparative form is very limited in the previous literature particularly in emerging markets. Thus, the current study attempts to link the relationship between the stock market volatility and major economic events and stock market crisis periods both in CSE and NYSE. Importantly, these two markets represent an emerging market and a developed market. This enables the specific generalization of the findings for each category of market. The period of study for the Colombo Stock Exchange (CSE) is 1999 to 2008 and for the New York Stock Exchange (NYSE) is 1985 to 2007.

The rest of the paper is organized as follows. The section 2 summarizes the main research issue. Section 3 explains the main causes of volatility of stock returns. Section 4 involves with the introduction of volatility test and its statistical properties. Section 5 discusses the ICSS and the volatility test for the CSE followed by the same test for NYSE in Section 6. The next section deals with the conclusion of the study. Section 8 lists the important references of the study.

The Research Issue

The major problem faced by the investors in the stock market is the deviation from their expected return due to the uncertainty in the market or in the economy. Stock markets as an element which operate in the whole financial system are highly sensitive to the macro economic and political environment in the country. This causes the volatility in the stock prices which results for the huge losses for the investors. Thus, this paper attempts to capture the exact point of volatility in the market return series of the two markets. The outcome of the study will be important for the investors to understand the time of the volatility of the markets.

Main Causes of Volatility of Stock Returns

It is generally believed that various economic and firm specific factors are driving forces of stock market crisis. There is also reason to believe that stock return volatility is related to the level of economic activity prevailing in the economy. For, example, if firms have large fixed costs, net profits will fall faster than revenues if demand falls. This often called operating leverage. Stock market volatility is related to the general health of the economy in any country. One interpretation of this evidence is that it is caused by financial leverage. Stock prices are a leading indicator, so stock prices fall before and during recessions. Thus, leverage increases during recessions, causing an increase in the volatility of levered stocks. Apart from these factors there can be other factors such as systematic (global oil pieces changes, inflation shocks etc.) and unsystematic (company specific and sector specific factors) factors that influence for the stock market volatility. Thus, there is a close relationship between stock market volatility and economic crisis.

Data and Volatility Identification

Inclan and Tiao (1994) introduce and refine a test for the detection of multiple changes in volatility of a time series. The test, which will be identified as ICSS because it uses Iterated Cumulative Sum of Squares method, is applied here for the CSE and NYSE return series. It is important because the changes in volatility in these series, identified using the ICSS, can be mapped onto changes from crisis periods to non-crisis periods and vise versa. The advantage of this method is that the data can be used to reveal crisis periods without human intervention, which is what makes it an objective approach. This section mainly focus on the Centered Cumulative Sum Squares Function, D_k, and outlines the how ICSS use it iteratively identify multiple volatility breaks.

Iterated Cumulative sum of squares (ICSS) Algorithm

The ICSS algorithm according to Inclan and Tiao (1994) compares well against alternative approaches available in the literature to detect changes in volatility. Inclan and Tiao (1994) make this comparison using monte carlo simulation methods which revealed that ICSS algorithm was the best for analyzing long time series with potentially multiple change points of variance in a series. Inclan and Tiao (1994) define a long time series as on with 200 or more observations. These conditions are satisfied for the weekly return processes that are studied here. In other words, they are long time series with potentially multiple volatility breaks.

Present study, for above reasons, uses the ICSS to detect structural shifts in volatility in weekly market returns series from the CSE and the NYSE. The ICSS mainly asserts that the variable D_k is more sensitive to the changes in volatility than the alternatives available. Here Dk is defined as

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \; k = 1,...,T, \quad \textbf{(1)}$$

with $D_0 = D_T = 0$ where $C_k = \sum_{t=1}^{k} R^2_{m,t}$ and $R^2_{m,t}$ is the market return series at week t. Thus the ICSS tracks the changes in D_k to detect changes in volatility. The algorithm involves several iterative steps which are followed in this paper. These steps given below closely follow the explanation by Inclan and Tiao (1994: 916). Here the notation $R[t_1 : t_2]$ represents $R_{m,t_1}, R_{m,t_1+1}, R_{m,t_1+2},..., R_{m,t_2}$, $t_1>t_2$ and notation $D_k(R[t_1 : t_2])$ represents the range over which cumulative sum of squares are sought.

Step 1. Let $t_1 = 1$,

Step 2. Calculate $D_k\left(R\left[t_1 : T\right]\right)$. Let $k^*\left(R\left[t_1 : T\right]\right)$ be the point at which $\max_k \left|D_k\left(R\left[t_1 : T\right]\right)\right|$ is obtained and let
$M(t_1 : T) = \max_{t_1 \le k \le T} \sqrt{(T - t_1 + 1/2} \left|D_k\left(R\left[t_1 : T\right]\right)\right|$
If $M\left(t_1 : T\right) > D^*$, where D* is the critical value, consider that there is a change point at $k^*\left(R\left[t_1 : T\right]\right)$ and proceed to Step 2a.

Step 2a. Let $t_2 = k^*\left(R\left[t_1 : T\right]\right)$. Evaluate $D_k\left(R\left[t_1 : t_2\right]\right)$; that is the centered cumulative sum of squares applied only to the beginning of the series up to t_2. If $M\left(t_1 : t_2\right) > D^*$, then there will be a new point of change and repeat Step 2a until $M\left(t_1 : t_2\right) > D^*$, When this occurs it can be concluded that there is no evidence of change in $t = t_1, \ldots . t_2$ and therefore the first point of change is $k_{first} = t_2$.

Step 2b. Now do a similar search starting from the first change point found in step 1 , towards the end of the series. Define a new value for t_1: let $t_1 = k^*(R[t_1 : T]) + 1$. Evaluate $D_k\left(R\left[t_1 : T\right]\right)$, and repeat Step 2b until $M\left(t_1 : T\right) > D^*$. Let $K_{last} = t_1 - 1$

Step 2c. If $K_{first} = K_{l\arg e,}$ then there is just one change point. The algorithm steps there. If $K_{first} = K_{l\arg e,}$ keep both values as possible change points and repeat steps 1 and 2 on the middle part of the series; that is $t_1 = K_{first} + 1$ and $T = K_{last.}$ Each time that steps 1 and 2 are repeated then result can be one or two more points. Call N_T the number of change points found so far.

Step 3. If there are two or more possible change points, make sure they are in increasing order. Let $\boldsymbol{p}$ be the vector of all the possible change points, found so far. Define the two extreme values $\boldsymbol{p}_0 = 0$ and $\boldsymbol{p}_{N_T+1} = T$. Check each possible change point by calculating $D_k(R[\boldsymbol{p}_{j-1} + 1 : \boldsymbol{p}_{j+1}]),\ j = 1, \ldots . N_T$. If $m(\boldsymbol{p}_{j-1} + 1 : \boldsymbol{p}_{j+1}) > D^*$ then keep the point; otherwise eliminate it. The retained points constitute the multiple volatility change points in the $R_{m,t}$ series.

The ICSS and the periods the volatility in the CSE

When the ICSS algorithm was applied to the CSE returns it revealed several structural changes in the volatility of the series. The aim of this section is to flag the importance of these breaks and how they could be used to discern information about crisis periods that the CSE would have experienced. Here an interesting attempt at linking the "objectively" identified crisis periods with historical crises occurrence in the country will be attempted. To the most part this effort resulted in plausible matches between ICSS crisis periods and country level historical crisis. Thus the main purpose of the ICSS algorithm would probably be that it allowed the determination of exact start and end weeks of a more vaguely understood crisis (volatile) periods.

Figure 1 illustrates the identified crisis periods using shaded areas. The plot of the CSE return series in Panel (a) illustrates the volatility clustering in the CSE return series. It is also clear from Panel (a) that the shaded areas roughly coincide with the more volatile periods signified by more pronounced lateral movement of the return series. This is a consolation, as it shows that the ICSS algorithm is generating accurate results that can be verified visually. However Panel (a) is also evidence that beyond the approximate/rough identification of crisis periods, the visual examination of return series is not very useful. For instance, one cannot objectively identify an exact start and end week of a given crisis periods using visual methods. This is why an algorithm such as the ICSS is indispensable to bring in objectivity into this important step of this research.

In Panel (b) a graph of approximate variances of the return series is presented. For the purpose of generating this graph the variance for any given week is calculated as the variance of the returns of the weekly returns in the preceding quarter. This is why it is described here as a moving variance. Though the calculation of such a moving variance is not required by the ICSS algorithm this moving variance is useful to illustrate the validity of the ICSS identified crisis periods. For instance in the case of the CSE weekly returns the ICSS identified crisis periods clearly coincide with the high volatility of periods in Panel (b) of Figure 1. This is corroborated by Panel (c) which graphs cumulative sum of squares of the returns which is defined as C_k in equation 1. The cumulative squared returns are also an indication of the level of volatility and Panel (c) clearly illustrates that the sharp increases in C_k coincide with the crisis periods in the CSE.

Table 1 summarizes the crisis volatility break indentified in CSE and compares their timing with the local and global economic changes. During the past periods CSE performance was badly affected by the war this resulted for the fluctuation of stock prices rapidly from time. And the political uncertainty prevailed in the country during last decades hindered the development of the market. In addition to the global stock market crises these factors can also be attributed for the high volatility in CSE during the past periods.

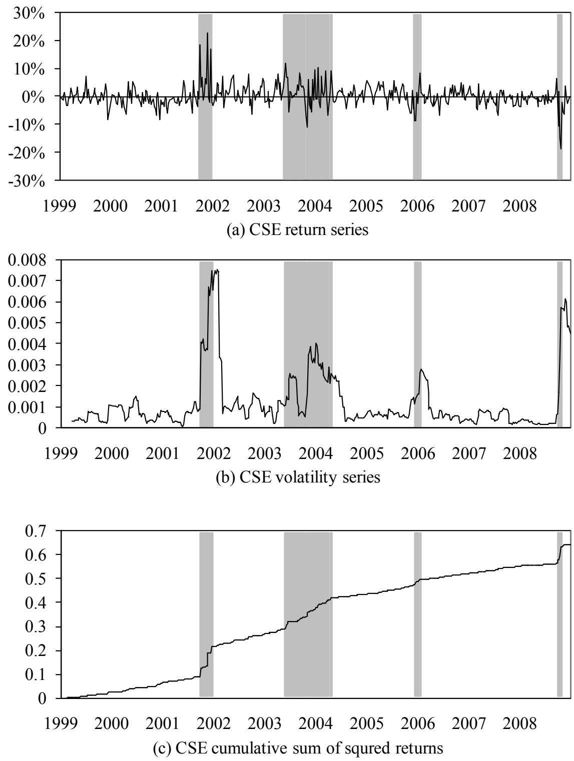


Figure 1 The application of Inclan and Tao (1994) to the CSE return series. The periods of high volatility thus identified are shaded in all three panels capturing different manifestations of the CSE return series: (a) the CSE return series, (b) the quarterly moving variance of the return series, and (c) the cumulative sum of squared return series.

Table 1 Volatility breaks and crisis periods in the CSE

Breakpoints to	**from**	**Timing**	**Local/Global events**
128	139	2001	This is the period the Sri Lankan government held General Election which led to a change of government. Impact of market crash of 2000 in the US may also have affected the local market. This impact in combination of the resumption of hostilities contributed to the negative GDP growth in 2001. It is this The Cease Fire Agreement (CFA) between the GoSL and the LTTE also came into effect during this period.
207	253	2003/2004	This is the period Tsunami hit the Sri Lankan economy and it was badly affect the Sri Lankan stock market. In addition to that impact of 2000-2003 crash in the US may also be reflected in the high volatility in the CSE.
326	331	2005/2006	The resumption of the Eelam War IV coincides with this period. This period covers the period immediately after the 2005 presidential election which heralded in much change in economic policy in the country under *Mahinda Chinthana*.
459	463	2008	This period represents the Current global market crisis. This crisis badly affected the garment industry in the country.

According to CSE and the Central Bank of Sri Lanka (CBSL) market is highly exposed to the global economy in several ways particularly in terms of foreign direct investments (FDI) and international trades. The ICSS procedure confirmed this phenomenon by identifying several breakpoints in the CSE in line with the global prominent market crises. Interestingly, in these results most of these breakpoints of the market portfolio represent economic crisis periods that experienced from time to time in the world.

The volatility periods which identified in this test satisfy the requirement of volatility series for the asset pricing test. It identified 70 observations for the assets pricing a test which is approximately 1/5 of the total series of CSE. In the return series in 1(a) after selecting the crisis periods other balance period of the series from the full sample can be identified as non-crisis (low volatile) period. In non-crisis series returns fluctuate around zero.

The performance of the market is mainly measured with the values of All Share Price Index (ASPI) which can be described as a crude measure of macroeconomic environment of the country. A plot of the ASPI during the 10 years covered in this work is given in the Figure 2. Vertical axis of the graph is measured in 100s. For example in the first week in 1999, the starting point of the figure, the ASPI was at 583. As such the graph starts at 5.83 in an axis given in 100s. It seems that the ASPI had moved approximately horizontally during the years 1999 to 2001 and had trended upward thereafter. The post 2001 movement of the ASPI, in both directions can be linked to important socio-political events in Sri Lanka. For instance the change of government in 2001, the signing of the Cease Fire Agreement in 2002, the tsunami of 2004, the election of incumbent President in 2005, resumption of Eelam War IV in 2006, are all important events. The high interest rate regime in 2008 and 2009 as well as the global financial crisis had caused the ASPI to dip in this period. Nevertheless the CSE has continued to attract much attention from the investors due to the post-war peaceful environment in the country.

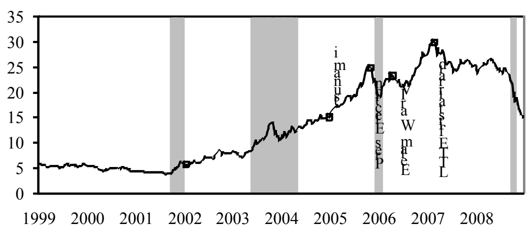


Figure 2 Volatility and Important events of CSE

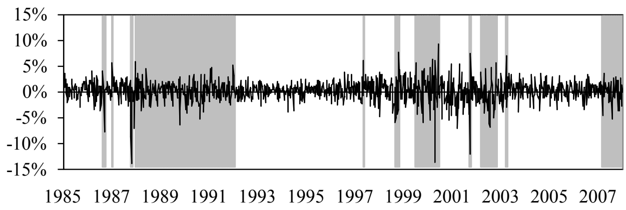
ICSS and the Volatility in the NYSE

Table 2: Volatility Breaks and Market Crashes- NYSE

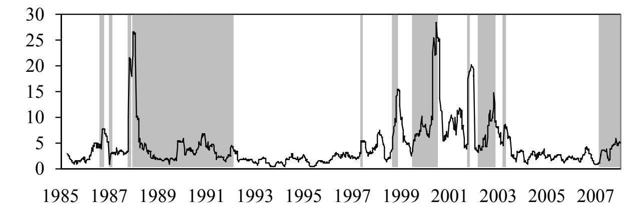
Breakpoints To	Breakpoints From	Timing	Global Crises
84 105	89 106	1987	1987- Black Monday the largest one day percentage decline in the market history
144 155 250	147 249 267	1989-1991	This period is associated with the Gulf War and United states Savings and Loan crises
367 644 720 797	643 712 756 798	1999-2000	The market crash of 2000 which was the greatest curtailment of assets values in American history
805 874	872 895	2001-2002	2001-2002 Argentine crisis during this crisis periods investors shifted funds to US market from Argentine market
914 929	916 951	2003	Nasdaq 2000-2003 crash in the US that suffered a devastating bear market
1155	1200	2007	Early periods of 2008 crisis

The NYSE return series, with 1200 weekly observations, is also subjected to the ICSS algorithm to identify the crisis periods therein. Figure 3 given below illustrates the volatility period which shaded areas highlighting the crisis periods. The 27 volatility breakpoints in the NYSE series were used to separate out the crisis periods from the non-crisis periods. The figure interestingly shows most of the volatility periods of US market and represents the world prominent crisis periods during the periods from 1985 to 2007. Table 2 shows the breakpoints derived from the volatility test of the US market with the corresponding variances for example the variance relating to 84^{th} breakpoint is 0.58 as shown in the table.

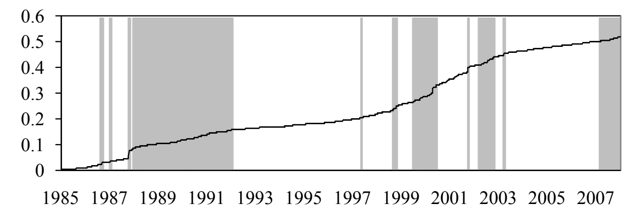
The link between economic events and the breakpoints of the NYSE series is also presented in Table 2. Interestingly the breakpoints in the NYSE are followed by major economic and political events in the US. Volatility breaks are more prominent during the economic crisis periods. The period 1987 to 2007 is considered as the periods of dynamic nature in the US economy. As similar to CSE the weekly returns of the NYSE is concentrated around zero in the NYSE in low volatile period.



(a) NYSE return series



(b) NYSE volatility series



(c) NYSE cumulative sum of squares series

Figure 3: The application of ICSS to the NYSE returns series. The periods of high volatility are shaded in the panels capturing different manifestations of the NYSE return series: (a) the NYSE return series, (b) the quarterly moving variance of the return series, and (c) the cumulative sum of squared return series.

The volatility test introduced by Inclan and Tiao (1994) effectively captures the market crises of both CSE and NYSE series. Usually the identified crisis periods could be given historical explanations in most cases for both countries. The results of ICSS suggest that stock market volatility is not an isolated event; it coincides with several structural changes in the economy.

Conclusion

The market portfolios of the two markets are highly sensitive to the major economic events historically occurred in the country. It is found that the stock markets are highly volatile when the markets are exposed to major economic events such as stock market crises. The ICSS algorithm is capable of capturing the volatility of the stock markets very prominently and objectively. It is also found that the stock market volatility is followed by world famous economic crises. This finding suggests that high volatility in the stock markets during crisis period is common phenomena in emerging stock markets and developed stock markets. The findings imply that investors should be vigilant about the socio-economic environment of the country before making investments in these stock markets.

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