# A Nonlinear New Approach to Investigating Crisis: A Case from Malaysia

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# A NONLINEAR NEW APPROACH TO INVESTIGATING CRISIS: A CASE FROM MALAYSIA

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**Abstract**

In this paper, we have investigated the effects of Asia 97 crisis on Malaysian stock exchange market by using a nonlinear approach which gives a detailed analysis with respect to linear counterparts. Specifically, we are using generalized impulse response function (GIRF) in order to see the effects of crisis on stock indices. In order to employ GIRF analysis, we need further investigation on potential nonlinearities in conditional mean and variance equation for Malaysia stock market. Specifically, we use STAR-STGARCH family models for modeling daily returns of the Investable and Non-Investable Malaysia stock indices, covering the period 1995.06.30-2003.09.05. The analysis of this paper shows that individual markets of Malaysia have strongly been affected from the Asia 97 crisis. In addition, the Asia 97 crisis has increased the variability of the Malaysia stock market and affected foreign investors more than the domestic investors.

*Keywords*: STAR-STGARCH, Generalized Impulse Response Function. 1997 Asia Crisis, stock markets

*JEL Code*: C22, G1

## 1 Introduction

In this study we have concentrated on analysing the effect of Asia 97 crises on Malaysian stock exchange market. For this purpose we have developed a new statistical concept which we have called differenced generalized impulse response function (DGIRF). Before employing GIRF analysis, we have to investigate the non-linearity of Malaysian stock exchange return data**.** Economists generally admit that many economic variables, including financial ones, follow nonlinear processes (see, for example, Granger and Teräsvirta, 1993; Campbell et al., 1997; McMillan, 2003). Nonlinearity in a variable can stem from either conditional mean or conditional variance or both. If nonlinearity of a variable originates solely from conditional variance, then such processes are more appropriately modelled by ARCH models, originally developed by Engel (1982), or their natural extensions, generalized ARCH (GARCH) models of Bollerslev (1986). The ARCH and GARCH models have widely been used for modelling financial time series. However, less attention has been paid to modelling of financial time series when there is a nonlinear behaviour in the conditional mean. The nonlinearity in conditional mean should be appropriately modelled in order to avoid misspecification of the conditional variance.

Recent developments in modelling nonlinear time series in which nonlinearity stems from conditional mean allow modelling financial time series more appropriately. A growing body of research has been devoted to examination of nonlinear behaviour of financial time series, especially in the case of developed countries. Lundbergh and Teräsvirta (1998) developed nonlinear time series models, mainly STAR-STGARCH, that allow nonlinearity in both conditional mean and conditional variance, and applied this type of models to study Swedish OMX index and the JPY-USD exchange rates. Sarantis (2001) has employed STAR models for investigating nonlinearities and cyclical behaviour in stock prices of the G-7 countries. Chan and McAleer (2002, 2003) have investigated statistical properties and empirical issues regarding estimation of STAR-STGARCH family models with application to S&P 500, Nikkei 225 and Hang Seng Indices. Busetti and Manera (2003) have used STAR-GARCH models to examine the market interactions in the Pacific Basin Region. Shively (2003) has examined nonlinear dynamics of stock prices for six developed economies using a three-regime threshold random walk model and found that stock prices are consistent with regime reverting process. McMillan (2003) has examined nonlinear predictability of UK Stock Returns. Östermark et al. (2004) have used STAR type models for modelling Finnish Banking and Finance branch index. Narayan (2005) has examined properties of the stock prices for Australia and New Zealand and found that stock prices for both countries are nonlinear processes with unit root, consistent with the efficient market hypothesis. And most recently Hasanov and Omay (2008) have examined properties of the stock prices for Turkey and Greece and found that stock prices for both countries are nonlinear processes, and found out that nonlinear out of forecasting performance is better than the linear which is inconsistent with the efficient market hypothesis. On the other hand Hagerud (1996) developed nonlinear time series models, mainly AR-STGARCH, that allow for nonlinearity in conditional variance, and applied this type of models to study four stock index series. It has been argued, however, that despite the absence of linear dependence there may be nonlinear dependence in the conditional mean Lundbergh and Teräsvirta (1998)[1].

The economic theory suggests a number of sources of nonlinearity in the financial data. One of the most frequently cited reasons of nonlinear adjustment is presence of market frictions and transaction costs. Existence of bid-ask spread, short selling and borrowing constraint and other transaction costs provide arbitrage unprofitable for small deviations from the fundamental equilibrium. Subsequent reversion to the equilibrium, therefore, takes place only when the deviations from the equilibrium price are large, and thus arbitrage activities are profitable (He and Modest, 1995). Consequently, the dynamic behaviour of returns will differ according to the size of the deviation from equilibrium, irrespective of the sign of disequilibrium, giving rise to asymmetric dynamics for returns of differing size (Dumas, 1992, 1994; Krägler and Krugler, 1993; Obstfeld and Taylor, 1997; Shleifer, 2000; Coakley and Fuertes, 2001). In addition to transaction costs and market frictions, interaction of heterogeneous agents (Hong and Stein, 1999; Shleifer, 2000), diversity in agents' belief (Brock and LeBaron, 1996; Brock and Hommes, 1998) also may lead to persistent deviations from the fundamental equilibrium. On the other hand, heterogeneity in investors' objectives arising from varying investment horizons and risk profiles (Peters, 1994), herd behaviour or momentum trading (Lux, 1995) may give rise to different dynamics according to the state of the market, i.e., whether the market is rising or falling.

Because of these arguments we have considered smooth-transition autoregressive models (originally proposed by Chan and Tong, 1987 as a generalization of the threshold autoregressive (TAR) model, and have developed further by Teräsvirta and Anderson, 1992, Granger and Teräsvirta, 1993, Teräsvirta, 1994) which are capable of capturing the nonlinear behaviour consistent with both market friction models, where market dynamics differ between large and small returns, and more general nonlinear behaviour perhaps arising from the state of the market (i.e. differing dynamics depending on whether the market is rising or falling). The smooth-transition model is selected for a number of reasons. First, it is theoretically more appealing than the simple threshold models which impose an abrupt switch on parameter values. Such instantaneous changes in regimes are possible only if all traders act simultaneously and in the same direction. For the market of many traders acting at slightly different times, however, a smooth transition model is more appropriate. Second, the STAR model allows different types of market behaviour depending on the nature of the transition function. In particular, the logistic function allows differing behaviour depending on whether returns are positive or negative, while the exponential function allows differing behaviour to arise for large and small returns regardless of sign. The former function maybe motivated by considerations of the general state of the market, while the latter function is motivated by considerations of market frictions, such as transactions costs or noise trader risk. Finally, the ability of this model to allow gradual transition between regimes of behaviour is consistent with the stylized facts of asset returns, that they exhibit momentum, or positive correlation, over a short

[1] Sarno (2000), Taylor and Sarno (2001) and Leon and Najarian (2005), among others, focused on nonlinear adjustment of exchange rates in such countries. Abutaleb and Papaioannou (2000) employed a time-varying model, which allows parameters of a conventional autoregressive model to change over time, for predicting Athens Stock Market index. Barkoulas and Travlos (1998) provide weak evidence in support of a nonlinear deterministic data generating process for the Athens stock exchange.

horizon, but reversal, or negative correlation, over a longer horizon, and hence are characterized by persistence and slow reversion (see, for example, Campbell et al., 1997).

The source of nonlinearities is explained in the above paragraphs. Therefore we have to use GIRF analysis instead of TIRF analysis. Furthermore, the generalized impulse response functions have advantages over their linear counterparts Koop *et al.* (1996). Hence, we use GIRF as an indicator tool for visualizing the effects of Asia Crisis on Malaysian stock exchange market. The traditional impulse response function TIRF has some characteristic properties in case the model is linear. First, the TIRF then is symmetric. In the sense that a shock of $-\delta$ has exactly the opposite effect as shock of size $+\delta$. Furthermore, it might be called linear, as the impulse response is proportional to the size of shock. Finally, the impulse response is history independent as it does not depend on the particular history $w_{t-1}$ van Dick (1999). These properties do not carry over to nonlinear models. In non-linear models, the impact of a shock depends on the sign and the size of the shock, as well as on the history of the process.

The difference impulse response function is obtained to analyze the effects of Asia crises. For this purpose, we have subtracted the impulse response function from each other as one of them is before crises and the other one is after crises. So this difference impulse response function is again the realization of random variables. This difference GIRF helps us to analyze the effects of Asia crises in the Malaysia stock market. From these two impulse responses we have obtained difference G.I.R.F. for investable and non-investable markets of Malaysia stock market.

The remaining of the paper is organized as follows. We define the model in section 2 and discuss its specification, estimation and evaluation again in this section. In section 3, we give explanations of STAR-GARCH and STAR-STGARCH models. In section 4, compare generalized impulse response functions of investable and non-investable stock markets of 6 Asia markets. Section 5 concludes what we will discuss in the previous sections.

## 2. A Brief Review of Asian 97 Crisis and Malaysian Economy

The Asian financial crisis resulted from the abrupt departure of large amounts of capital from Asian countries that required sufficient systems of prudential guideline, and whose foreign exchange rate proved unsuccessfully fragile. By "Asian currencies" one normally means those of Japan and of the former Asian "tiger" countries; Korea (won), China (yuan), Hong Kong (dollar), Taiwan (dollar), the Philippines (peso), Thailand (baht), Malaysia (ringgit), Singapore (dollar), and Indonesia (rupiah), all of which have been strongly forced by the profound currency and banking crisis that has effected Asia. The crisis began with the decision of an anxious Thai government to float the baht after extensive efforts to support it in the face of a severe financial overexpansion that was partially real-estate driven. At the same time Thailand had obtained a burden of foreign debt that made the country efficiently go bankrupt even before the fall down of its currency. The severely reduced import earnings that resulted from the devaluation then made a rapid or even medium-term recovery impossible without a demand for international intervention.

Asian Crisis spread from Thailand to Indonesia, the Philippines, Malaysia and Korea.

The sequences of economic impact can be summarized as: Export rates decreased, which led to the loss of investors' confidence, hence, currency devaluation due to the lack of foreign reserve and IMF emergency fund requiring contractionary budget and monetary policy, which again lead to an increase in non-performing loans and damage in domestic industries. From Thailand, the contagion quickly extended over the south closing down the Indonesian economy and severely impacting the Malaysian. Also, once the contagion turned north, Korea was severely impacted, which suffered a financial decline comparable to those of Thailand and Indonesia. In the Philippines growth dropped to almost zero in 1998. Only Singapore and Taiwan proved to be relatively protected from the shock, but both experienced serious hits in passing due to its size and geographical location between Malaysia and Indonesia. The main costs of the Asian crises have caused considerable depreciations of national currencies, sharp drop in stock indexes, and a recession in most of the formerly dynamic economies, with its corollaries of bankruptcies, rising unemployment and increase of poverty indices (Bustelo 1998)

The general cause of the Asian 97 Crises, which is due to drastic increase in international private capital inflow in the 90's, was key to understand this crisis. For example, Thailand had an economic disaster waiting to happen with an economy that was little more than a bubble increased by "hot money," that is, short-term capital inflow that is expensive and often highly conditioned. Malaysia was nearly in the same conditions, although Malaysia had better political leadership, and Indonesia, with the added complication of what has been called "crony capitalism". There are more competing explanations for the causes of Asian crises. For example, Krugman (1997) stated that the Asian crises were mainly related to a burst of a financial bubble in a context of low and declining returns to investment. An other explanation again came from Krugman (1998), in his research, he found that deficient regulation of banking activities, some lack of transparency, and various implicit governmental guarantees (which created " moral hazard"), led banks and other financial institutions in Southeast Asia to a situation of over-indebtedness and of excessively high levels of non-performing loans. The third competing explanation was (IMF, 1998a and b), fast growth in domestic credit in the East Asian developing countries created overheated economies. In turn, this resulted in asset inflations, current account deficits, and large capital inflows. The fourth competing explanation is Corsetti *et al.* (1998). They called this explanation as unsound fundamentals and international capital markets. This explanation was again very parallel to the explanations of IMF and Krugman (1997 and 1998). The fifth competing explanation is Radelet and Sachs (1998), they related the crises with self-fulfilling panics and external financial markets. The last competing explanation was Wade and Venerose (1998), they related currency crises with financial under-regulation and speculative attacks. A combined explanation can be classified as in three categories: Firstly, some analysis has maintained on a misguided macro management as the main issue: Secondly, irresponsible, and over-reactive behavior of external financial markets are blamed the causes of Asian crisis; finally, the importance of a combination of fragile domestic financial markets and large and volatile capital inflows and outflows are seen as a result.

**Table 1 Some Basic Data**

| *Years* | *93* | *94* | *95* | *96* | *97* |
|---|---|---|---|---|---|
| **Panel A** | ***Indicator of the Economic Background of Malaysia*** | | | | |
| 1. GDP growth | 8.3 | 9.2 | 9.5 | 8.6 | 7.8 |
| 2. Exports of goods and services / GDP | | | 96 | | |
| 3. Current Account Balances (as %GDP) | | | -10.0 | -4.9 | -4.8 |
| 4. Domestic Credit to the Private Sector | | 76.3 | 86.8 | 94.4 | |
| 5. Inflation Rate | | 3.7 | 3.4 | 3.5 | 2.7 |
| 6. Budget Balance (% of GDP) | | 2.5 | 3.8 | 4.2 | 1.6 |
| 7.Public Debts (% of GDP) | 59.3 | 50.1 | 42.8 | | |
| 8.Saving Rates (% of GDP) | | 35.5 | 36.4 | 38.8 | 41.2 |
| 9. Investment Rates (% of GNP) | | 42.5 | 45.4 | 45.1 | 45.6 |
| 10.Foreign Exchange Rates (in US$ billion) | | 27.2 | 25.4 | 23.7 | 27.0 |
| 11. International Reserves / M2 | 0.00478 | 0.00405 | 0.00300 | 0.00299 | |
| 12. Official foreign exchange reserves as months of imports | 6.2 | 4.5 | 3.3 | | |
| 13.Capital Inflow | | | | | |
| 13i. Portfolio Investment | | | | -0.4 (-9.3%) | |
| 13ii. Bank Loan | | | | 0.5 (11.6%) | |
| 13iii. FDI | | | | 4.2 (97.7%) | |
| Total | | | | 43 (100%) | |
| 14. Foreign Debt (as % of exports) | 48 | 43 | 40 | 42 | |
| 15. Short term debt as proportion of total foreign debt | | 61.1 | | | 59.6 |
| 16. Real effective exchange rates (1993:100) | | 98.0 | 98.7 | 103.7 | 84.8 |
| **Panel B** | ***Consequences of the Asian Crises with Malaysian Data*** | | | | |
| Years | 96 | 97 | 98 | 99 | Average |
| 17. Currency depreciation (units of domestic currency per US dollar) | | 2.5 3.3 | 4.0 3.8 | | |
| 18. Change in GDP | 8.6 | 7.8 | -5.5 | -0.5 | |
| 19. Stock Mrkt Indexes performance in percentage over June 29,1997 and June 29,1998 based on DJ Global Indexes | | -75 | | | |

Here we see some Malaysian economic and financial data before the Asian crises, we can see the general progress of the economy and the crises related variables. One of the most important variable for this study is the stock market indexes and the performance in percentage over June 29, 1997 and June 29,1998 based on DJ Global Indexes is -75 which shows a very severe decline in the general index.

## 2. Specification and Estimation of STAR-GARCH and STGARCH Models

The empirical specification procedure for STAR-GARCH and STAR-STGARCH models consist of the following steps that we have combined them from (Lundbergh and Teräsvirta (1998) and Hagerud (1996) and that we have improved by the papers of Chan and McAleer (2002) and Chan and McAleer (2003).

1. Specify an appropriate linear autoregressive model for the time series under investigation.

2. Test the null hypothesis of linearity against the alternative of STAR-type nonlinearity. If linearity is rejected, select the appropriate transition variable $s_t$ and the form of the transition function $F(s_t;\gamma,c)$.
3. Estimate the parameters in the selected STAR-GARCH model.
4. Evaluate the STAR-GARCH model using diagnostic tests. If rejected, specify a STAR-STGARCH model.
5. If linearity of GARCH is rejected, select the form of the transition function $H(u_t;\delta,\upsilon)$.
6. Estimate the parameters in the selected STAR-STGARCH model.
7. Use the model for descriptive or generalized impulse response analysis.

According to Engle (1982), parameters for the conditional mean and the conditional variance can be estimated separately, provided that the GARCH specification is symmetric. Because of block-diagonality of the information matrix, conditional mean model can be estimated first. This estimation procedure yields consistent estimates. But in this paper, all parameters are estimated simultaneously. Two-step estimation procedure has a tendency to yield over-parameterization with respect to simultaneous estimation procedure, because some effects due to the non-constant conditional variance may at first be captured by the estimated conditional mean. On the other hand Chan and McAleer (2003) try to estimate several STAR models for S&P, Hang Seng and Nikkei indexes but they could not manage to estimate proper STAR model, because estimates of the variance did not converge. The same problem occurs in this paper too. With respect to Chan and McAleer (2003) this suggests three possibilities: (i) the variance is not constant, so that STAR-GARCH should be used; (ii) the use of alternative optimization algorithms; and (iii) the use of alternative initial values can produce this problem. In our paper, we have concluded that the first reason is the main reason. We have estimated for different initial values besides, we have tried different optimization algorithm but the problem has not been solved, except the simultaneous estimation of STAR-GARCH estimation. Because of these reasons, we have changed the estimation strategy of Lundbergh and Teräsvirta (1998). On the other hand we have modified the Lundbergh and Teräsvirta (1998) by using Hagerud (1996) test procedures; hence this modification again leads to a change in estimation procedure of the said researcher.

## STAR MODELS

A STAR model for an unvaried time series $y_t$ is given by

$$y_t = \pi_{1,0} + \pi_1^{'} x_t + \left(\pi_{2,0} + \pi_2^{'} x_t\right) \cdot F(s_t;\gamma,c) + u_t \qquad (2.1)$$

where $x_t$ is a vector consisting of lagged values of the endogenous variable. The disturbance $u_t$ is white noise with zero, and is assumed to be homoskedastic over regimes with variance $\sigma^2$ and to be normally distributed. The transition function $F(s_t;\gamma,c)$ is a continuous function bounded between 1 and 0. Thus, the STAR model can be interpreted as a regime-switching model that allows two regimes, associated with the extreme values of the transition function, $F(s_t;\gamma,c)=0$ and $F(s_t;\gamma,c)=1$, whereas the transition from one regime to the other is gradual. The parameter $\gamma$

determines the smoothness of the transition, and thus, the smoothness of transition from one regime to the other. The two regimes are associated with the small and large values of the transition variable $s_t$ relative to the threshold $c$.

Two popular choices of the transition function $F(s_t;\gamma,c)$ are the logistic function

$$F(s_t;\gamma,c)=\frac{1}{1+\exp\left(-\gamma(s_t-c)/\sigma_{s_t}\right)} \tag{2.2}$$

and the exponential function

$$F(s_t;\gamma,c)=1-\exp\left(-\gamma(s_t-c)^2/\sigma_{s_t}^2\right) \tag{2.3}$$

where $\sigma_{s_t}$ is sample standard deviation of the transition variable $s_t$.

These yield, respectively, the logistic STAR (LSTAR) and exponential STAR (ESTAR) models. The logistic function is convenient for modelling differing dynamics depending on whether the returns take large or small value, i.e., the direction of disequilibrium. The LSTAR model may be consistent with the differing investor psychology between rising and falling markets, or the existence of market frictions whose impact differs between "bull" and "bear" markets. Thus, the LSTAR model can describe a situation where contractionary and expansionary periods have rather different dynamics. In contrast, the transition occurs symmetrically for $s_t$ about threshold $c$ if exponential function is used in (2.1). The ESTAR model implies that contractionary and expansionary periods have similar dynamics (see Teräsvirta and Anderson, 1992).

Since the nonlinearity tests are sensitive to autocorrelation, the lag structure of the autoregressive model should be specified so as to capture the significant autocorrelation in the linear model. The lag structure of the model can be selected by applying conventional information criteria such as Akaike Information Criterion (AIC) or Schwarz Information Criterion (SIC) as suggested by Teräsvirta (1994). The problem is that for high frequency economic time series the usual order selection criterion would typically select a model with no lags because there is normally little or no linear dependence (Lundbergh and Teräsvirta (1998)). To avoid the problem the maximum lag m>6 is used for daily observations and fixed in advance like in Lundbergh and Teräsvirta (1998)

In order to carry out the linearity test we have had to determine the maximum lag, m of the linear AR model. Once the appropriate linear model is defined we have carried out linearity tests against the alternative STAR-type nonlinearity. The linearity tests are complicated by the presence of unidentified nuisance under the null hypothesis. This can be seen by noting that the null hypothesis of linearity may be expressed in different ways. Besides equality of the parameters in the two regimes, $H_0:\pi_1=\pi_2$ the alternative null hypothesis $H_0^{'}:\gamma=0$ also gives rise to linear model. To overcome this problem, one may replace the transition function $F(s_t;\gamma,c)$ with appropriate Taylor approximation following the suggestion of Luukkonen *et al.* (1988). For example, a first order Taylor approximation results in the following auxiliary regression

$$y_t = \beta_{0,0} + \beta_0^{'} x_t + \beta_{1,0} s_t + \beta_1^{'} x_t s_t + e_t \qquad (2.4)$$

Where $\beta_{0,0}, \beta_0^{'}, \beta_1^{'}$ are functions of the parameters $\pi_1, \pi_2, \gamma$ and $c$, and $e_t$ comprises the original shocks $u_t$ as well as the error term arising from the Taylor approximation. In (2.4) it is assumed that the transition variable $s_t$ is not one of the elements in $x_t$. If this is not the case, the term $\beta_{1,0} s_t$ should be dropped from the auxiliary regression. The null hypothesis of linearity can be expressed as $H_0^{''} : \beta_1^{'} = \phi_1 = 0$, that is, the parameters associated with the auxiliary regressors are zero. This null hypothesis can be tested by a standard variable addition test in a straightforward manner. The test statistic, to be denoted as LM1, has an asymptotic $\chi^2$ distribution with degrees of freedom *p+1*, where *p* is the dimension of the vector $x_t$.

As noted by Luukkonen *et al.* (1988), the LM1 test statistic has no power in situations where only the intercept is different across regimes. Luukkonen *et al.* (1988) suggest remedying this deficiency by replacing the transition function $F(s_t; \gamma, c)$ by a third order Taylor approximation instead. This would result in the following auxiliary model

$$y_t = \beta_{0,0} + \beta_0^{'} x_t + \beta_{1,0} s_t + \beta_1^{'} x_t s_t + \beta_{2,0} s_t^2 + \beta_2^{'} x_t s_t^2 + \beta_{3,0} s_t^3 + \beta_3^{'} x_t s_t^3 + e_t \qquad (2.5)$$

The null hypothesis now corresponds to $H_0^{''} : \beta_i^{'} = 0$, $i = 1,2,3$, which again can be tested by a standard LM-type test. Under the null hypothesis of linearity the test statistic, to be denoted as LM3, has an asymptotic $\chi^2$ distribution with degrees of freedom 3(*p+1)*. Since only the parameters corresponding to $s_t^2$ and $s_t^3$ are functions of $\pi_{1,0}$ and $\pi_{2,0}$, a parsimonious or economy version of the LM3 statistic can be obtained by augmenting the auxiliary model (2.4) with regressors $s_t^2$ and $s_t^3$ , that is

$$y_t = \beta_{0,0} + \beta_0^{'} x_t + \beta_1^{'} x_t s_t + \beta_{2,0} s_t^2 + \beta_{3,0} s_t^3 + e_t \qquad (2.6)$$

The resultant statistics is the $\text{LM3}^{\text{E}}$ statistic[2].

To identify the appropriate transition variable $s_t$, the LM statistics can be computed for several candidates, and the one for which the p-value of the test statistic is smallest can be selected.

[2] This linearity test assumes constant conditional variance; and is therefore not robust against conditional heteroskedasticity. The problem arises when Ho is rejected because then we do not in principle know if that is because of nonlinearity in conditional mean or because of conditional heteroskedasticty (Lundbergh and Teräsvirta (1998)). So robust version of linearity test can be made such as the one Granger and Teräsvirta (1993,p.69). In Lundbergh and Teräsvirta (1998) research, a simulation study has been taken in consideration and the result of that simulation shows that robustification removes most of the power, so that existing nonlinearity remain undetected by a robustified linearity test. As our objective is to find and model any existing nonlinearity in the conditional mean, robustification therefore was not recommended by Lundberg and Teräsvirta (1998)

When the appropriate transition variable $s_t$ has been selected, the next step in specification of a STAR model is to choose between logistic and exponential functions. Teräsvirta (1994) suggests using a decision rule based on a sequence of tests in equation (2.5). Particularly, he proposes testing the following null hypotheses

i) $\mathrm{H}_{03} : \beta_3 = 0$
ii) $\mathrm{H}_{02} : \beta_2 = 0 | \beta_3 = 0$
iii) $\mathrm{H}_{01} : \beta_1 = 0 | \beta_3 = \beta_2 = 0$

in (2.5) by means of LM type tests. These hypotheses are tested by ordinary F tests, to be denoted as F3, F2, and F1, respectively. The decision rule is as follows: If the p-value corresponding to F2 is the smallest, then ESTAR model should be selected, while in all other cases LSTAR model should be preferred.

**STAR-GARCH and STAR-STGARCH Models**

The smooth transition generalized conditional heteroskedasticty model has a mean equation as stated in equation 2.1. We have given the features of this equation in the beginning of this section, and the generalized autoregressive conditional heteroskedasticity part is modelled as:

$$u_t = \varepsilon_t \sqrt{h_t} \tag{2.7}$$

with

$$h_t = \alpha_0 + \sum_{i=1}^{r} \alpha_{i1} u_{t-i}^2 + \sum_{j=1}^{s} \beta_i h_{t-i} \tag{2.8}$$

where $\alpha_0 > 0$, $\alpha_{i1} \geq 0$ and $\beta_i \geq 0$ (i=1,...,r) and (j=1,...,s) The main advantage of this model with respect to the ARCH specification is that the additional term $h_{t-i}$ allows us to reduce the number of parameters in the ARCH component. A STAR-GARCH model allows $u_t$ in equation (2.1) to follow a GARCH process as defined in (2.7). This extension has not been investigated thoroughly (see Chan and McAleer (2002)). Lundbergh and Teräsvirta (1998) give a comprehensive exposition of this model, but do not provide regularity conditions for stationarity of the GARCH components for the existence of its moments, or any statistical properties relating to the GARCH component, but Chan and McAleer (2002) has been analyzed these concepts in their papers, so any important points about these features can be followed by this paper. The information matrix of a STAR-GARCH model is block-diagonal if error term follows a symmetric distribution (see Lundbergh and Teräsvirta, 1998), so that a STAR-GARCH model estimated using a two stage procedure. In the first stage, the conditional mean is estimated by NLS (Nonlinear Least Squares), which is equivalent to quasi maximum likelihood based on a normal distribution. Under certain (weak) regularity conditions, which are discussed by White and Domowitz (1984) and Pötscher and Prucha (1997), among others, the NLS estimates are consistent and asymptotically normal. For obtaining initial values to facilitate the nonlinear optimization algorithm, one must conduct an extensive two-dimensional grid search over $\gamma$ and $c$, ranging $\gamma$ (after scaling) from 1 to 10000 by 1.0 increments and ranging $c$ from min{c} to max{c}by 0.01 increments[3]. Grid search can be applied to STAR models; for fixed values of the parameters in the transition function, $\gamma$ and $c$, the STAR model is linear in parameters $\pi_{1,0}, \pi_1^{'}, \pi_{2,0}$ and $\pi_2^{'}$, and therefore, can be estimated by OLS. Hence, a convenient way to obtain sensible starting values for the nonlinear optimization algorithm is to perform a two-dimensional grid search over $\gamma$ and $c$, and select those parameter estimates that minimize variance of the residual term. Chan and McAleer have also shown the efficient estimation method for STAR-GARCH models. Hence one can easily follow the asymptotic properties and efficient estimation methods of STAR-GARCH models from the papers of Chan and McAleer (2002 and 2003) respectively.

After estimation of non-linear model, we have performed misspecification tests to evaluate the estimated STAR-GARCH model. Practically we have fallowed Hagerud (1996), Eirtheim and Teräsvirta (1996), Lundbergh and Teräsvirta (1998), and Lundbergh and Teräsvirta (2002) papers. The test statistics which are obtained for conditional mean equation is performed from Eirtheim and Teräsvirta (1996) paper and some critical changes are made by van Dick (1999). For variance equation, we have used the papers that we have just mentioned above. Thus parameter constancy, autocorrelation and additive non-linearity test has been held for conditional mean equation and linearity and additive ARCH test has been held for conditional variance equation.

STAR-STGARCH models' smooth transition generalized autoregressive conditional heteroskedasticity part is modelled as for STGARCH(1,1):

$$h_t = \alpha_0 + \alpha_{11} u_{t-1}^2 + \beta_1 h_{t-1} + \left(\alpha_{01} + \alpha_{21} u_{t-1}^2\right).H(s_t, \delta, \upsilon) \tag{2.9}$$

And the transition function can be modelled as Logistic or Exponential function like the conditional mean equation. Logistic smooth transition generalized autoregressive conditional heteroskedasticity (LSTGARCH) model can be shown as:

$$H\left(u_{t-1}; \delta, \upsilon\right) = \frac{1}{1 + \exp\left(-\delta(u_{t-1} - \upsilon)/\sigma_{s_t}\right)} \tag{2.10}$$

and exponential smooth transition generalized autoregressive conditional heteroskedasticity (ESTGARCH) model can be shown as:

$$H\left(u_{t-1}; \delta, \upsilon\right) = 1 - \exp\left(-\delta(u_{t-1} - \upsilon)^2/\sigma_{s_t}^2\right) \tag{2.11}$$

Detailed information about these functions can be obtained from Lundbergh and Teräsvirta (1998) paper. We have seen that STAR-GARCH model can be estimated, by two stage estimation procedure. However, this procedure is not appropriate for STAR-LSTGARCH, for which the information matrix is not block diagonal, so the estimates have to be obtained simultaneously. In STAR-ESTGARCH case again we

[3] One can use the range for threshold value $c$ on observed range of returns by discarding the extreme values at each end.

can obtain estimates by two-stage procedure. Assuming normally distributed errors, Engle (1982) showed that the information matrix of conditional mean-ARCH model is block diagonal if some regularity conditions are hold and if the parameterization of the conditional variance is symmetric in the sense that the model responds similarly to positive and negative inputs of same size. From this discussion we can see that STAR-ESTGARCH model can fulfil these criteria. This in turn implies that if the conditional mean is estimated with a consistent estimator, the conditional variance can be estimated from the residuals of the conditional mean model without a loss of asymptotic efficiency (see Lundbergh and Teräsvirta (1998) and Hagerud (1996)). The last important point in modelling strategy of the STAR-STGARCH model is selecting the transition function of the conditional variance equation. Lundbergh and Teräsvirta (1998) did not make any specification test for determining the transition function. But in this paper, we have followed another method; we have first made specification of the transition function of the conditional variance equation then estimated the STAR-STGARCH model. This strategy is a deviation from Lundbergh and Teräsvirta (1998) strategy of modelling STAR-STGARCH. At this stage, we have followed the Hagerud (1996) test procedure, otherwise we would have to decide the type of the conditional variance and other properties of conditional variance at misspecification test phase like Lundbergh and Teräsvirta (1998). Their strategy is time consuming in a sense that you have to make misspecification test of every stage before passing to other. In our strategy, instead of making all misspecification tests after estimating STAR-STGARCH model, we have selected the proper transition function by the test that has been suggested by Hagerud (1996)[4]. While doing this test, we robustified the test by the suggestion of Lundbergh and Teräsvirta (2002), and this robustification is a deviation from the Hagerud (1996) test procedure. We have found that the robustified version of this test has produced better performance in decision stage.

## Empirical Part

In this paper we have considered daily returns for the Malaysia stock index, covering the period 1995:06:30-2003:09:05. We have computed the monthly returns as where $X_t$ is Investable and Non-investable Malaysia stock index. The linear model is initially specified with maximum lag order of 12, with intermediate lags then deleted one by one (starting with the least statistically significant according to the $t$-ratio) provided that such deletions reduce the AIC. The estimated linear models for Investable and non-investable daily returns are as follows:

[4] Lundberg and Teräsvirta (1998) have first tried LSTGARCH as a non-linear model of conditional variance. Their theoretical rationale is coming from that the conditional variance will follow the same pattern with the conditional mean. So they have justified their reasoning as follows "For the smooth transition type alternative the problem of selecting transition is not present. We only have to select the transition function of conditional variance equation. One way of doing that is to apply a decision rule similar to that suggested for the mean equation. But then one may instead simply estimate the STGARCH model in any transition function and make choice on the basis of the results, including the results of the misspecification tests." So they are proceeding from restricted models to general ones. This may be simpler than to start from the most general model and gradually reduce its size. See Hansen (1996) for a discussion of this problem. To avoid estimating unidentified models they proceed from specific to general. But in our case Hagerud (1996) avoid this problem in our identification strategy. Thus we can proceed in a more efficient way of identification, estimation and evolution phases.

$$\Delta y_t = \underset{(0.020)}{0.105}\Delta y_{t-1} + \underset{(0.021)}{0.082}\ \Delta y_{t-2} - \underset{(0.022)}{0.079}\ \Delta y_{t-4} + \underset{(0.019)}{0.069}\Delta y_{t-5} - \underset{(0.021)}{0.075}\ \Delta y_{t-6} - \underset{(0.020)}{0.032}\ \Delta y_{t-7}$$

$$\Delta y_t = \underset{(0.021)}{0.069}\ \Delta y_{t-1} + \underset{(0.019)}{0.041}\ \Delta y_{t-2} - \underset{(0.020)}{0.050}\ \Delta y_{t-4} + \underset{(0.021)}{0.028}\Delta y_{t-5} - \underset{(0.022)}{0.046}\ \Delta y_{t-6}$$

The results of the linearity tests are reported in Table 2 for investable and non-investable indexes respectively. As the table reveals, the null of linearity are rejected at conventional significance levels for a number of candidate transition variables. Thus we have selected the transition variables for all models by taking the smallest p values of every model's test statistics. The selected transition variables are highlighted by bold type characters.

**Table 2. Linearity test**

| Linearity test of Investable Indexes | | | | | |
|---|---|---|---|---|---|
| $\Delta y_{t-1}$ | $\Delta y_{t-2}$ | $\Delta y_{t-3}$ | $\Delta y_{t-4}$ | $\Delta y_{t-5}$ | $\Delta y_{t-6}$ |
| **23.693** | 16.873 | 10.391 | 13.860 | 7.029 | 4.438 |
| **(0.000)** | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| **Linearity test of Non-Investable Indexes** | | | | | |
| $\Delta y_{t-1}$ | $\Delta y_{t-2}$ | $\Delta y_{t-2}$ | $\Delta y_{t-4}$ | $\Delta y_{t-5}$ | $\Delta y_{t-10}$ |
| **9.798** | 5.211 | 2.430 | 5.756 | 2.071 | 1.444 |
| **(0.000)** | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

Having selected the most appropriate transition variable, we conducted a sequence of F tests described above to determine the form of the transition function. The F statistics and corresponding p-values are reported in Table 3 for investable and non-investable indexes. We have selected the logistic function and estimate LSTAR model for Malaysia stock market. Selection of the LSTAR model has important implications regarding dynamics of the market. The LSTAR model implies that the expansionary and contractionary periods have dissimilar dynamics, and the path of reversion to the equilibrium in both regimes is asymmetric.

**Table 3. Transition Function LSTAR against ESTAR**

| | ***Investable*** | ***Non-Investable*** |
|---|---|---|
| **F3** | 11.764 | 3.546 |
| | (0.000) | (0.003) |
| **F2** | 4.347 | 3.687 |
| | (0.000) | (0.002) |
| **F1** | 6.572 | 11.595 |
| | (0.000) | (0.000) |

* The values under the test statistics are probabilities

While estimating the model, we have used BFGS algorithm for finding maximum. The estimated LSTAR model and transition function is given in the first panel of Table 4 and estimated STGARCH model is given in the second panel of the Table 4. Here we have estimated STAR-GARCH model simultaneously as stated before. The autoregressive parameters turning out to be redundant are eliminated during joint estimation by applying the previous backward elimination algorithm. However, the two step estimation is useful for obtaining initial values for joint estimation. For obtaining initial values to facilitate the nonlinear optimization algorithm we have conducted an extensive two-dimensional grid search over $\gamma$ and $c$, ranging $c$ from min{c} to max{c} by 0.01 increments[5]. Before proceeding to estimation of the LSTAR-GARCH(1,1) model using the optimal values of the parameters $\gamma$ and $c$ obtained from the grid search, we have deleted intermediate lags one by one (starting with the least statistically significant according to the *t*-ratio), if such deletions had reduced the Akaike Information Criteria (AIC), we have conducted a new grid search. Besides these estimation procedures, we have used simplex algorithm to refine our initial values for non-linear estimation.

**Table 4. Nonlinear estimation results**

**Investable Stock Market of Malaysia** LSTAR-GARCH(1,1)

Mean Equation

$$\Delta y_t = \underset{(0.089)}{-0.142}\,\Delta y_{t-1} + \left\{ \left( \underset{(0.090)}{0.330}\ \Delta y_{t-1} \right) \frac{1}{1+\exp\left( -\underset{(619.245)}{3752.288}(\Delta y_{t-1} - \underset{(0.000)}{(-0.047)})/\sigma_{s_t} \right)} \right\}$$

Conditional Variance Equation

$$h_t = \underset{0.000001}{0.000002} + \underset{0.021}{0.887}\,u_{t-1}^2 + \underset{0.020}{0.110}\,h_{t-1}$$

**Non-Investable Stock Market of Malaysia** LSTAR-GARCH(1,1)

Mean Equation

$$\Delta y_t = \underset{(0.110)}{0.269}\,\Delta y_{t-1} + \left\{ \left( \underset{(0.106)}{-0.307}\ \Delta y_{t-1} \right) \frac{1}{1+\exp\left( -\underset{(2580.907)}{822.823}(\Delta y_{t-1} - \underset{(0.000)}{0.192})/\sigma_{s_t} \right)} \right\}$$

Conditional Variance Equation

$$h_t = \underset{0.0001}{0.0003} + \underset{0.103}{0.387}\,u_{t-1}^2 + \underset{0.267}{0.458}\,h_{t-1}$$

*The values below the parameter estimates are heteroskedasticity consistent standard errors.

The values below are the parameter estimates referring to heteroskedasticity consistent standard errors. The estimated value range of the slope coefficient $\gamma$ is different form Investable and Non-Investable stock markets. The estimated value slope coefficient of Malaysia investable market speed of transition between regimes is high but still slower than Markov regime switching and TAR models. Estimated conditional variance parameters satisfy the restriction conditions. For the Non-investable markets we observed similar dynamics with respect to slope (gamma) and other parameter estimates.

**Misspecification Tests**: **An Evaluation of STAR-GARCH model**

We have estimated the STAR-GARCH model, now it is necessary to check whether the models are suitable for inference and other descriptive statistics. After estimation of non-linear model, we perform diagnostic tests to evaluate the estimated STAR-GARCH model. For this purpose, we have to test the assumption for the residual of the estimates whether they are normally distributed. Second important phenomenon is the two-stage estimation. If the information matrix is block-diagonal the test statistic can be computed by simply by two artificial regressions (see

[5] We have based our range for threshold value *c* on observed range of returns by discarding the extreme values at each end.

Lundbergh and Teräsvirta (2002)). For STAR-GARCH specification the condition is satisfied, so we can compute the test statistics by two artificial regressions, one for conditional mean and one for conditional variance equation. As we mentioned before, practically we have fallowed Hagerud (1996), Eirtheim and Teräsvirta (1996), Lundbergh and Teräsvirta (1998), and Lundbergh and Teräsvirta (2002) studies. The test statistics which are obtained for conditional mean equation is performed from Eirtheim and Teräsvirta (1996) paper and some critical changes are made by van Dick (1999). For variance equation, we have used the papers of Hagerud (1996), Lundbergh and Teräsvirta (1998, 2002) papers. Thus parameter constancy, autocorrelation and remaining non-linearity test is held for conditional mean equation and linearity (remaining non-linearity) and additive ARCH test is done for conditional variance equation. The test statistics are given in the below tables:

**Table 5 . Diagnastic Check For Investable Markets Mean and GARCH Equation**

***Mean Equation***

| | **Remaining Autocorrelation** | | | | | **Parameter Constancy** | **Remaining Nonlinearity** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\ell = 1$ | $\ell = 2$ | $\ell = 3$ | $\ell = 4$ | $\ell = 5$ | | $d = 1$ | $d = 2$ | $d = 3$ | $d = 4$ | $d = 5$ |
| **Inv Mrk.** | 1.313 | 1.215 | 0.787 | 1.928 | 2.378 | 14.488 | 11.493 | 14.312 | 12.733 | 10.461 | 7.959 |
| | 0.251 | 0.270 | 0.374 | 0.164 | 0.123 | 0.105 | 0.243 | 0.111 | 0.175 | 0.314 | 0.538 |
| **N-I Mrk.** | 0.225 | 1.870 | 0.004 | 2.600 | 0.750 | 10.941 | 11.573 | 11.727 | 9.971 | 12.073 | 7.707 |
| | 0.634 | 0.171 | 0.947 | 0.106 | 0.386 | 0.279 | 0.238 | 0.229 | 0.352 | 0.209 | 0.563 |

***GARCH Equation***

| | **Remaining ARCH** | **GARCH versus STGARCH (Remaining Nonlinearity** |
|---|---|---|
| **Inv Mrk.** | 0.112 | 0.044 |
| | 0.736 | 0.832 |
| **N-I Mrk.** | 0.002 | 0.895 |
| | 0.958 | 0.343 |

* The values under the test statistics are probabilities

**After estimation of non-linear model, we perform misspecification tests to evaluate the estimated STAR-GARCH model for Investable markets. Practically we have fallowed Hagerud (1996) panel (5), Eirtheim and Teräsvirta (1996), Lundbergh and Teräsvirta (1998), and Lundbergh and Teräsvirta (2002) papers. The test statistics which are obtained for conditional mean equation is performed from Eirtheim and Teräsvirta (1996) paper (panel 1) and some critical changes are made by van Dick (1999) (panel 2,3). The test statistics which are obtained for conditional variance equation is performed from Hagerud (1996) panel (5), Lundbergh and Teräsvirta (1998), and Lundbergh and Teräsvirta (2002) papers panel(4,5) . Thus parameter constancy, autocorrelation and additive non-linearity test is held for conditional mean equation and linearity and additive ARCH test held for conditional variance equation.

From the first part of the Table 5, we can evaluate the remaining autocorrelation of conditional mean equations of investable and non-investable stock markets of Malaysia stock market. This test statistics is obtained from Eitrheim and Teräsvirta (1996), and robustified by using the test procedure Wooldridge (1991, procedure 4.1). The result of the misspecification test of remaining autocorrelation for investable and non-investable market of Malaysia shows that there is no remaining autocorrelation.

From the second part of the Table 5, we can evaluate parameter constancy of conditional mean equations of investable and non-investable stock markets of Malaysia stock market. This test statistics is obtained from van Dijk (1999), and robustified by using the test procedure Wooldridge (1991, procedure 4.1). According to van Dijk (1999) this test statistics has better power properties than the diagnostic test of Eitrheim and Teräsvirta (1996). He has investigated this by means of simulation experiments in his study (see van Dijk (1999) for details). The result of the misspecification test of parameter constancy for investable and non-investable market of Malaysia stock market shows that all parameters are constant.

From the third part of the Table 5, we can evaluate the remaining additional nonlinearity of conditional mean equations of investable and non-investable stock markets of Malaysia stock markets. This test statistics is obtained from van Dijk (1999), and robustified by using the test procedure Wooldridge (1991, procedure 4.1). According to van Dijk (1999) this test statistics has better power properties than the diagnostic test of Eitrheim and Teräsvirta (1996). The result of the misspecification test of remaining additional nonlinearity of conditional mean equations for investable and non-investable market of Malaysia stock markets shows that there is no evidence of remaining additional nonlinearity either.

From the fourth part of the Table 5, we can evaluate the remaining ARCH structure of conditional variance equations of investable and non-investable stock markets of Malaysia stock markets. This test statistics is obtained from Lundbergh and Teräsvirta (2002), and robustified by using the test procedure Wooldridge (1991, procedure 4.1). In Lundbergh and Teräsvirta (2002), they advise that the robust version of their test statistics must be used. They have concluded this result from a Monte Carlo experiment; at the sample size 1000, used in their simulation study and rather typical for GARCH applications, the efficiency loss compared to nonrobust tests appears to be minimal when the errors are normal. The result of the misspecification test of ARCH structure of conditional variance equations for investable and non-investable markets of Malaysia stock market shows that there is no evidence of remaining ARCH structure either.

From the fifth part of the Table 5, we can evaluate the remaining additional nonlinearity of conditional variance equations of investable and non-investable stock markets of Malaysia stock market. This test statistics is obtained from Hagerud (1996) and Lundbergh and Teräsvirta (2002), and robustified by using the test procedure Wooldridge (1991, procedure 4.1). Hagerud (1996) is a special case of Lundbergh and Teräsvirta (2002). The result of the misspecification test of remaining additional nonlinearity of conditional variance equations for investable and non-investable market of Malaysia stock market shows that there is no evidence of remaining nonlinearity.

For the last stage of misspecification test, we have organized a test for selecting the transition function of the smooth transition conditional variance equation. For this purpose we have used Hagerud (1996) test procedure for GARCH type. This test is a kind of deviation from the estimation strategy of Lundbergh and Teräsvirta (2002). In our strategy, instead of making all misspecification tests after estimating STAR-STGARCH model, we have selected the proper transition function by the test that suggested by Hagerud (1996). While doing this test, we robustified the test by the suggestion of Lundbergh and Teräsvirta (2002), and this robustification is a deviation from the Hagerud (1996) test procedure. We have found that the robustified version of this test has better performance in decision stage.

## 3. Interpretation of STAR-GARCH and STAR-STGARCH Models

For the STAR-GARCH conditional mean of the models are asymmetric and their conditional variance models are symmetric. On the other hand, our backward elimination strategy had caused very significant parameter estimates of both for conditional mean and variance. However, estimated value slope coefficient of Malaysia investable market speed of transition between regimes is high but still slower than Markov regime switching and TAR models. For the Non-investable market of the Malaysia stock market have similar dynamics with respect to slope (gamma) and other parameter estimates. As we have discussed above, there is no asymmetry to be modelled in the conditional variance. Hence, positive and negative shocks of the same size have the same impact on the conditional variance.

## 4. Generalized impulse response analyzes of 1997 Asia Crisis on Malaysia Stock Markets

In this section, we have organized a generalized impulse response analysis in order to detect the effects of the 1997 Asia crisis on the stock market of Investable and Non-investable Malaysia stock indexes. Generalized impulse response functions have advantages to their linear counterparts Koop *et al.* (1996). Hence we have used GIRF as an indicator tool for visualizing the effects of Asia Crisis on these markets.

In order to evaluate the properties of estimated regime-switching model (STAR-GARCH and STAR-STGARCH), we have examined the effects of the shocks $\varepsilon_t$ on the evaluation of the time series $\Delta y_t$. Impulse response functions are a convenient tool for carrying out such an analysis. Traditional impulse response function (TRIF) is given by

$$TIRF_y(h,\delta,w_{t-1}) = E[y_{t+h} \;|\varepsilon_t = \delta, \varepsilon_{t+1} = \ldots = \varepsilon_{t+h} = 0, w_{t-1}] - E[y_{t+h} \;|\varepsilon_t = 0, \varepsilon_{t+1} = \ldots = \varepsilon_{t+h} = 0, w_{t-1}] \tag{4.1}$$

for $h = 0,1,2,\ldots$ . The second conditional expectation usually is called the benchmark profile. The TIRF as defined above has some characteristic properties in case the model is linear. First, the TIRF is symmetric. In the sense that a shock of $-\delta$ has exactly the opposite effect as shock of size $+\delta$ . Furthermore, it might be called linear, as the impulse response is proportional to the size of shock. Finally, the impulse response is history independent as it does not depend on the particular history $w_{t-1}$ van Dick (1999). These properties do not transmit over to nonlinear models. In non-linear models, the impact of a shock depends on the sign and the size of the shock, as well as on the history of the process.

The Generalized Impulse Response Function (GRIF), introduced by Koop *et al.* (1996) provides a natural solution to the problems involved in defining impulse responses in non-linear models. The GIRF for an arbitrary shock $\varepsilon_t = \delta$ and history $w_{t-1}$ is defined as

$$GIRF_y(h,\delta,w_{t-1}) = E[y_{t+h} \;|\varepsilon_t = \delta, w_{t-1}] - E[y_{t+h} \;|w_{t-1}] \tag{4.2}$$

for $h = 0,1,2,...$ . In GIRF, the expectations of $y_{t+h}$ are conditioned only on the history and/or on the shock. To put it differently, the problem of dealing with shocks occurring in intermediate time periods is dealt with by averaging them out. Given this choice, the natural benchmark profile for the impulse response is the expectation of $y_{t+h}$ conditional only on the history of the process $w_{t-1}$. Thus, in the benchmark profile the current shock is averaged out as well.

$$\begin{aligned} GIRF_y(h,\delta,w_{t-1}) = E[y_{t+h} \;|\varepsilon_t = \delta, \varepsilon_{t+1},...,\varepsilon_{t+h}, w_{t-1}] - \\ E[y_{t+h} \;|\varepsilon_t = 0, \varepsilon_{t+1},...,\varepsilon_{t+h}, w_{t-1}] \end{aligned} \tag{4.3}$$

The GIRF is a function of $\delta$ and $w_{t-1}$, which are realizations of the random variables $\varepsilon_t$ and $\Omega_{t-1}$, and stressed by Koop *et al.* (1996), hence the GIRF as defined in (4.2) itself is a realization of a random variable. Using this interpretation of the GIRF as a random variable, various conditional versions can be defined which are of potential interest. In our case we consider only particular histories like we have mentioned before Asia Crisis 1997 and after Asia Crisis 1997 and we treat the GIRF as a random variable in terms of $\varepsilon_t$. For analysing the Asia crises we give shock to estimated model before the 15 days of Asia crises and after 15 days Asia crises.

The difference impulse response function is obtained for analyzing the effects of Asia crises. For this purpose we have subtracted the impulse response function from each other as one of them before crises and the other one is after crises. So this difference impulse response function is again the realization of random variables. The difference generalized impulse response function can be stated as:

$$\begin{aligned} &DGIRF_y(h,\delta,w_{t-1}) = \\ &(E[y_{t+h} \;|\varepsilon_t = \delta, \varepsilon_{t+1},...,\varepsilon_{t+h}, w_{t-1}^A] - E[y_{t+h} \;|\varepsilon_t = 0, \varepsilon_{t+1},...,\varepsilon_{t+h}, w_{t-1}^A]) - \\ &(E[y_{t+h} \;|\varepsilon_t = \delta, \varepsilon_{t+1},...,\varepsilon_{t+h}, w_{t-1}^B] - E[y_{t+h} \;|\varepsilon_t = 0, \varepsilon_{t+1},...,\varepsilon_{t+h}, w_{t-1}^B]) \end{aligned} \tag{4.4}$$

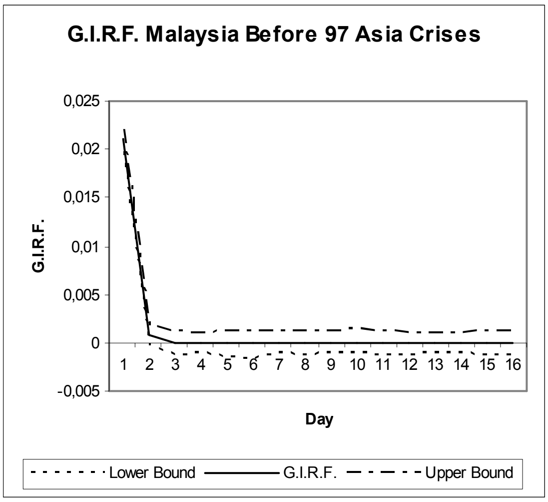
or a more compact way,

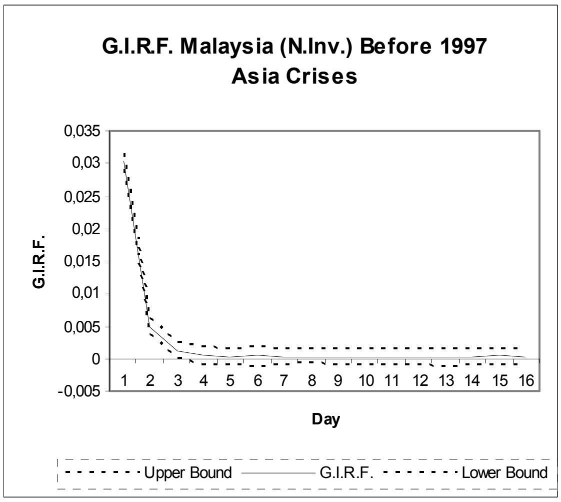
$$DGIRF_y(h,\delta,w_{t-1}) = GIRF_{yA}(h,\delta,w_{t-1}^A) - GIRF_{yB}(h,\delta,w_{t-1}^B) \tag{4.5}$$

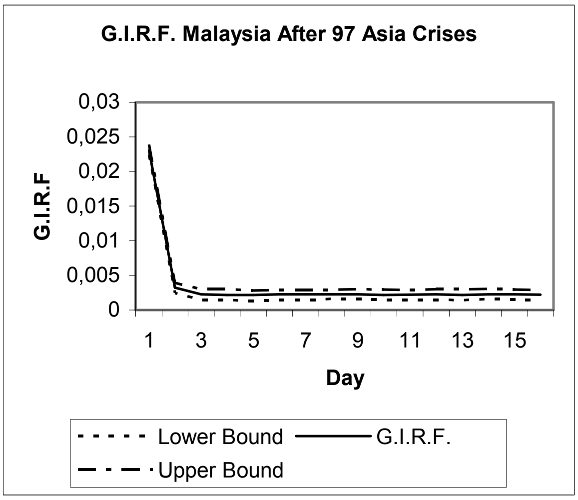
This difference GIRF helps us to analyze the effects of Asia crises in the Malaysia stock market.

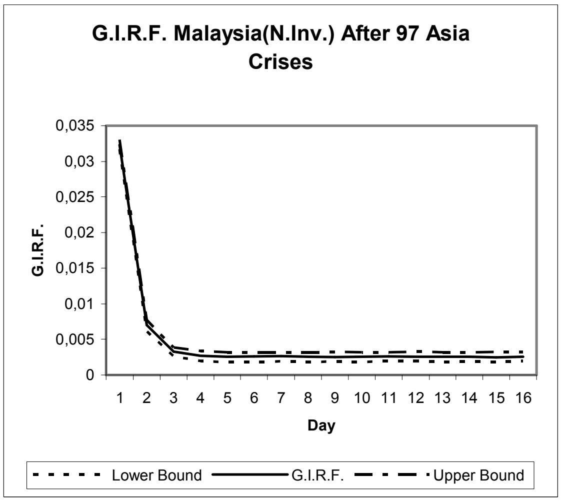
**Figure 1. GIRF and DGIRF of Malaysian stock individual markets**

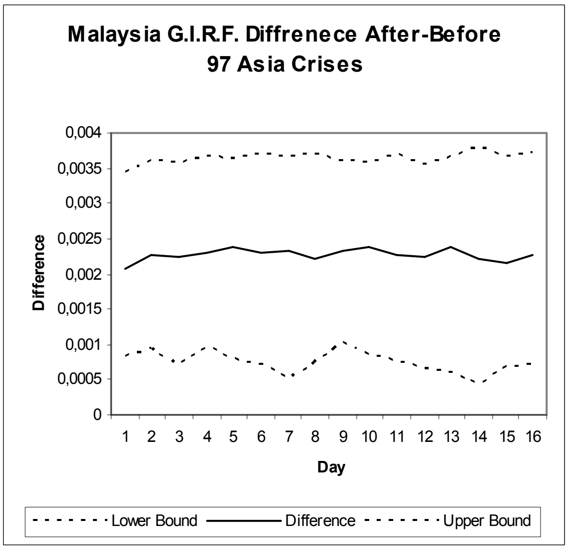
| Malaysia Investable Market | Malaysia Non-Investable Market |
|---|---|

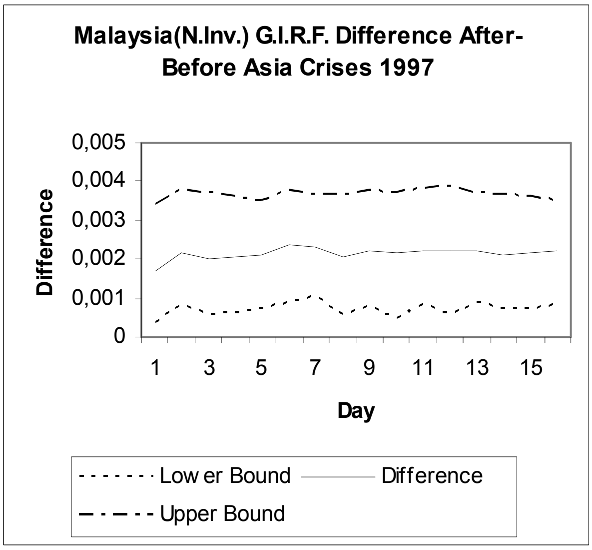


G.I.R. Functions are obtained from the mean equations of estimated STAR-GARCH models. While computing the G.I.R.F, we have taken the GARCH effects in to consideration by bootstrapping the shocks from the estimated GARCH models. In order to analyze the effects of Asia 1997 crises we have given one standard positive shock to equations and obtained the G.I.R.F. for before and after 1997 Asia crises. From these two impulse responses we have obtained difference G.I.R.F. for investable and non-investable markets of Malaysia stock market.

| $DGIRF_y(h,\delta,w_{t-1}) = GIRF_{yA}(h,\delta,w_{t-1}^A) - GIRF_{yB}(h,\delta,w_{t-1}^B)$ /N | | | |
|---|---|---|---|
| **Countries** | **Average Difference of Investable Market** | **Average Difference of Investable Non-Investable Market** | **Result** |
| Malaysia | 0,002423 | 0,002291 | I>NI |

From the above table it can be noticed that the investable market of Malaysia have bigger average difference than the non-investable markets. From these analyses we can conclude that the individual markets (investable and non-investable) of Malaysia affected from the Asia crises. From these results, we can suggest two main results; Asia crises have increased the variability of the Malaysian individual stock markets and foreign investors are given more reaction than the domestic investors to this crises.

## Conclusion

In this paper, we have investigated the effects of Asia 97 crisis on Malaysian stock exchange market by using a nonlinear approach which gives a detailed analysis with respect to linear counterparts. Specifically, we are using generalized impulse response function (GIRF) in order to see the effects of crisis on stock indices. On the other hand, we have found out that the most suitable model for modeling daily returns of the Investable and Non-Investable Malaysia stock indices is LSTAR-GARCH model. The analysis of this paper shows that individual markets of Malaysia have strongly been affected from the Asia 97 crisis. The positive difference obtained from DGRIF is around 0,002 shows a significant decline in the returns of the Malaysian stock markets after Asian crises. Moreover, the results of estimation and DGIRF shows that the Asia 97 crisis has increased the variability of the Malaysia stock market and affected foreign investors more than the domestic investors.

## Appendix for GIRF

Generalized Impulse Response Functions have been obtained by making bootstrapping. Hence, we have had to construct their confidence band again by designing a bootstrapping instead of Monte-Carlo design. For GIRF, we have handled 2 hundred of impulse response in order to get one specific histories' impulse response. We have obtained this 2 hundred impulse response in order to average the effect of intermediate shocks. For their confidence band again we have designed a bootstrap and handle the confidence band from this computation. For this purpose we have run 1000 impulse response which are the averaged from 200 impulse response and create %10 confidence band for every histories impulse response.

For the difference series, we have the same process that we have mentioned above. But this time, we have two impulses one for after and one for before Asia crisis and we have differenced these two impulse responses for 1000 times and we get the differenced series and confidence band at the same time.

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