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# Index futures trading, spot volatility and market efficiency

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*Abstract: This paper examines the impacts of the listing of index futures trading on spot market volatility, market efficiency and volatility asymmetric responses. To study the effects of the introduction of index futures contracts, a modified GJR-GARCH model has been applied to examine the structural change of conditional variances before and after the introductions of index futures trading in S&P 500, Nikkei 225, ASX all Ordinaries, and an equally weighted international portfolio. Additionally, the coefficient dynamic tests have been adopted to examine whether the identified impacts of index futures are consistent over time in both the individual indices and international portfolio. This paper finds the increases of conditional volatility and market efficiency in both Nikkei 225 and the equally weighted international portfolio in a post-futures period. In U.S. and Australia, however, no significant structural change on conditional variance has been found in a post futures period. The identified increases of volatility and market efficiency in the international portfolio are consistent over time.*

*Keywords:* trading, Spot volatility, GARCH, international portfolio and stock market

# 1 Introduction

A stock index futures contract can be defined as a futures contract with the underlying asset is a stock index. In finance, a futures contract is a standardized contract between the two parties to buy or sell a specified asset of standardized quantity and quality for a price agreed today with a delivery and payment occurring at a specified future date[1]. Since 24 February 1982, Kansas City Board of Trade has introduced the world's first stock index futures contract-Value Line futures. The index futures contracts have grown to become one of the main instruments of on portfolio diversification, price discovery, and risk hedging. From the statistic of futures industry association, the total volume of traded equity index futures and option were 8.46 billion[2] in 2011, an 14.1%

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[1]The definition of future contract sourced from Federal Reserve Bank of Chicago. http://chicagofed.org/webpages/publications/understanding_derivatives/index.cfm

[2]Sourced from 2011 annual volume survey report published by Future industry association. The measured volume by the number of contracts traded.

increase compared to 2010.

To discuss the effects of index futures trading on the spot market volatility, we need to identify the clear definition of volatility. In literatures, there are two distinct meanings of volatility. The first one means the variability of bond prices as interest rates alter[3], and the second one defines the volatility as a measure of variability over some period of time. The second concept is typically describesed as the standard deviation of return[4]. Our discussion of volatility is based on the second concept.

Index futures trading allows the investors either to hedge some pre-existing risks in the spot markets by taking an opposite position in the futures markets, or to take the advantage of leverage to profit more from the anticipated price movements. Because of the lower transaction cost and higher degrees of leverage, the futures market is a natural entry point for the new information (Miller, 1991).However, some criticize[5] that an introduction of futures market tends to make the spot market more volatile by encouraging speculation from uninformed traders and there is a social cost associated with the "excess" volatility .This belief seems to be more prevail during the stock market crisis such as those of 1987,1989 and 2007.

On the other hand, researchers[6] argue that futures market brings more traders into the spot market and, therefore, increases the liquidity in the spot market, and then the spot volatility may actually be reduced. In addition, Friedman(1953) suggests that the uninformed traders cannot survive in the market in the long run since informed traders can take advantage of their information and arbitrage uninformed traders away.

To solve above debate, a lot of empirical researches have been undertaken. However, there are several problems associated with previous empirical studies. Firstly, many previous works just focus on the stabilization-destabilization effects and failed to recognize the link between information and volatility, leading to inappropriate policy implements since there may be a trade-off between the market efficiency improvement and volatility reduction[7]. Secondly, most previous empirical studies concentrate only on the impacts of certain single index and the results are mixed even for the same underlying index. Thirdly, major previous works ignore the asymmetric response to information, leading to an inappropriate model specification. Fourthly, most previous works simply compare spot volatility of pre-futures period to the spot volatility of one post-futures period; This ignorance of the development of futures may lead to an improper conclusion.

Different from previous studies, this paper identifies the impacts of the list-

[3] Macaulay (1938)

[4] (Taylor, 2011), Asset price Dynamics, Volatility, and Prediction. Princeton University Press .Chapter 8.Page 189.

[5] As Cox (1979), Figlewski(1981)

[6] Danthine(1978)Powers(1970)Schwartz and Laatsch(1991)

[7] Ross(1989),evidences a perfectly positive correlation between the volatility of price and information flow under an arbitrage-free assumption, which can be expressed as equation $\sigma_p = \sigma_s$. According to this relationship, any regulation can reduce the volatility may reduce the market informativeness simultaneously.

ings of index futures trading on spot market volatility, market efficiency and volatility asymmetric response. Furthermore, we expand the scope from the single index to international portfolio, thereby helping us understand more about the general impacts of an introduction of index futures trading. Besides, by lagging the post sample period, we study whether the identified impacts of the listing of index futures trading on spot volatility and information flow vary over time.

The rest of the paper proceeds as follows. In Section 2, we briefly review the previous theoretical and empirical studies about the impacts of index futures trading on spot volatility. Besides, we have a comparison of three main methods used to study the impacts of index futures trading on spot volatility in previous studies. In Section 3, we describe our methodology and provide the results of several preliminary statistic tests. In Section 4, we provide the results of our empirical research. Section 5 concludes the paper and has several extensions for further study.

# 2 Literature Review

## 2.1 Theoretical Discussion

In the previous literature, Cox (1976) demonstrates that if futures prices can quickly adjust to the arrival of innovation (new information) and if this process could be transferred to the spot market through arbitrage mechanisms, spot market volatility and market efficiency would increase simultaneously. On the other hand,Weller and Yano(1987) conduct a general equilibrium analysis and find that the listing of futures market may reduce cash market volatility and how large does this volatility reduction impact may depend on people's risk preference to income.Pericli and Koutmos (1997), suggest that it is possible that derivatives increase market liquidity by bringing more investors to the cash market and thus resulting in a less volatile spot market.

## 2.2 Empirical studies in US

Many empirical studies are conducted to compare the level of stock market volatility before and after the introduction of stock index futures, in U.S. equity market.Santoni (1987) finds no statistically significant change in both daily and weekly return volatility in the S&P 500 index following the introduction of index futures. However, Edwards(1988b)(1988a) studies the daily price volatility of S&P 500 from 1972 to 1987 and finds the volatility of S&P 500 decreased significantly(excluding 1979-1982) after an introduction of index futures trading. By using a cross-sectional analysis of covariance regression model to estimate the volatility difference between the S&P500 stocks and a comparable set of non-S&P 500 stocks,(Harris, 1989),however, discovers a significant increase of volatility after an introduction of index future and suggests that trade in index futures market increases cash market volatility. Being different from the normal volatility studies[8], Becketti and Roberts (1986) analyse the frequency of jumps in daily stock returns and conclude that stock market volatility is not related to either the existence of, or the level of activity in the stock index futures market. Brorsen (1991)finds that S&P 500 stock index futures lead to a reduction of autocorrelations and an increase in volatility in daily spot price. In addition,Darrat and Rahman (1995) present a Granger-causality test to study the relationship between index futures and spot market jump volatility. They suggest that the index futures trading is not a force behind the increase of jump volatility. Excluding the 1987 stock crash,Pericli and Koutmos (1997) employ an E-GRACH model to study the effect of index futures on the volatility of S&P 500 in the period between 1953 and 1994. They conclude that the introduction of index futures produced no further structural changes on either the conditional or unconditional variance. Similarly,Rahman(2000) examines structural change of conditional variance of the component stocks in the Dow Jones Industrial Average after the introduction of index futures. He suggests that the conditional volatility of component stocks has not changed with the introduction of derivatives.

## 2.3 Empirical studies in Japan and Australia

Hodgson and Nicholls (1991), by using a test of equity of variances, find that the introduction of neither the index futures nor option trading has had any effect on the long term volatility of the All Ordinary Index, either on a daily or weekly basis.

Similarly,Lee and Ohk (1992) reveal that the spot volatility does not change in All Ordinary index but increases significantly in Nikkei 225 index after a listing of index futures trading. However, different result about Nikkei 225 has been given by Antoniou, Holmes, and Priestly (1998). By applying a GJR-GARCH model, they find indifference on spot volatility after the introduction of index futures trading. In order to control the broad economic factors,Chang, Cheng, and Pinegard (1999) form a new group of volatility tests by decomposing PVOL ( spot portfolio volatility) into the CSD (cross-sectional dispersion) and the AVOL (average volatility). Their study suggests that the listing of futures trading on the Osaka Securities Exchange (OSX) increase the spot volatility of Nikkei stocks. Through employing the same GRJ-GARCH model as AHP Antoniou et al.(1998) , Gulen and Mayhew(2000) find an inconsistent result with AHP that there is a significant increase of spot volatility in Nikkei 225 but a significant decrease in All Ordinary after the introduction of index futures trading . On the other hand, Yu (2001) employs a symmetric GARCH model rather than asymmetric GARCH model(GJR-GARCH, EGARCH) to test the spot volatilities in both Nikkei 225 and All Ordinary. His result shows that the

[8]Stock market volatility can be divided into two types, normal volatility and jump volatility. Normal volatility represents to the ordinary ups and downs in stock prices while jump volatility refers to the sudden extreme price movement(Becketti & Sellon, 1989)

spot volatilities in both indices increase significantly after the listing of index futures trading.

Overall, in the existing literature, the results of the impacts of the index futures trading on spot volatility are mixed. The mixed results may be caused by three reasons. First, they study different indices with different microeconomic structures or macroeconomic fundamentals. Second, the empirical results may be sensitive to the frequency and interval of time series data which has been used. Third, different model in each case was applied to examine the volatility change.

## 2.4 Methodology comparison

In the previous studies, three main methods have been applied to examine the impacts of index futures trading on spot market volatility. In order to choose a proper method for our study, we make a comparison of these three methods here.

### 2.4.1 Cross-sectional analysis

The cross-sectional comparison of covariance regression model, which initially applied by Harris (1989), can be used to identify volatility difference between underlying assets and control group assets. This approach is reliable only when determinants of volatility are properly modelled by cross-sectional regression. Harris (1989) estimates the mean difference in return standard deviation for S&P 500 stocks and a comparable set of non-S&P 500 stocks as following equation.

$$STD_i = \beta_0 + \beta_1 lnS\&P_1 + \beta_2(AbsBeta_i * MkSTD) + \beta_3 InvPrice_i + \\ \beta_4 LogMkVal_i + \beta_5 NoTradeFreq_i + \epsilon_i$$

where $STD_i$ is the log return standard deviation of stock i,$lnS\&P_i$ is a dummy variable which takes the value of one if the stock is on the S&P 500 list and zero otherwise. Other four independent variables are used to control the cross-sectional differences in beta, price level, market value, and trade frequency in each stock. The parameter estimates reported in harris's paper as the main interest of study. The result suggests that the listing of index futures trading increase, decrease or un affect spot volatilities if $\beta_1$ are significant positive, significant negative or statistically insignificant to zero respectively at post-futures trading period.

However, there are several drawbacks to conduct a cross-sectional research

1) In order to control the cross-sectional differences ,the cross sectional study requires a bundle of firm-specific data such as equity beta, price level, market value, and trade frequency for each individual stocks which may not be available in some indices

2) Regardless of well control for cross-sectional differences, cross-sectional analysis is likely to underestimate the volatility increase if index futures trade

does increases volatility. This is because that well diversified portfolios can be very good substitutes for each other and, therefore, a spill-over effect of volatilities between the underlying index and control group index is resulted from stock-to- stock arbitrage and pricing off indices, making the difference of post-futures volatilities decrease in the cross-sectional comparison.

3) The cross-sectional analysis cannot be used to identify the relationship between the volatility and information flow and, therefore, it says nothing about the relationship between the volatility and information flow therefore the relationship between the futures trading and market efficiency.

### 2.4.2 Decomposition method

The Decomposition method has been employed by Chang et al. (1999) in their research about the impacts of futures trading on spot volatilities of Nikkei stocks. In their tests, they decompose spot portfolio volatility(PVOL) into the cross-sectional dispersion E(CSD) and the average volatility of returns on the portfolio's constituent securities (AVOL).Basing from the relationship between these three variables, they develop regressions from the common volatility test which could be expressed as following single factor regression:

$$PVOL_t = \alpha 1 + \alpha_{post} D_{post,t} + \epsilon_t$$

Where, $PVOL_t$ is the measure of spot portfolio volatility at the time t ,$\alpha 1$ is the intercept of regression, $\epsilon_t$ is the residual at the time t,$D_{post,t}$ is a dummy variable that equals 1(0) after(before) the listing of futures trading on the exchange. The impacts of futures trading on spot market volatility can be captured by the coefficient $\alpha_{post}$.If $\alpha_{post}$ is significantly positive (negative) , the listing of futures trading increase(decrease) the volatility of spot portfolio and has no effect otherwise. Since this method is lack of control for board economic factors, the change in volatility may be attributed to the change of board economic factors rather than the listing of futures trading.

To filter out the effects of broad economic factors, they develop the above test to four new tests and since we are just be interested in how the future trading affects the spot market volatility. Only expression of test first is provided here as below[9]

$$PVOL_t = \gamma_0 + \gamma_1 AVOL_t + \gamma_{OCT} D_{OCT} + \gamma_{OSAKA} D_{OSAKA} + \epsilon_t$$

$$\begin{aligned} PVOL_{non,t} = \gamma_{non,0} + \gamma_{non,1} AVOL_{non,t} + \gamma_{non,OCT} D_{non,OCT} \\ + \gamma_{non,OSAKA} D_{non,OSAKA} + \epsilon_{non,t} \end{aligned}$$

Where $AVOL_t$ is the average volatility of individual security and could be used to capture the subtle, persistent, effects of broad economic disturbances. $D_{OCT}$ is the dummy variable equal 1 in the 1987 October Crash period and 0 otherwise to control the big crash effect. D_(post,t) and D_OSAKA are the

[9]Other three tests and relevant proofs can be found in Chang et al.(1999)'s paper.

dummy variables that equals 1 for the whole post-future period and OSAKA post-future period[10], respectively, and Zero otherwise. The non-subscription in the equation (2) is for the non-Nikkei 225 securities traded on the same exchange which could be used as control group. If there is a change of volatility only caused by the introduction of index future trading, the coefficients of $c_{post}$ and $c_{OSAKA}$ should be significant while the coefficients of $c_{(non,post)}$ and $c_{(non,OSAKA)}$ should be insignificant[11].

However, there are several issues for the decomposition method:

1) Chang et al.(1999) assume the return $R_i$ can be explained by a single factor model which is an oversimplification of real-world uncertainty and misses some important sources of dependence In stock returns such as industrial factor[12]

2) Similar to the cross-sectional analysis, the decomposition method can test the effects of futures trading on volatility but is silent to the relationship between the futures trading, spot volatility and market efficiency.

### 2.4.3 Conditional variance analysis

The conditional variance analysis is to use bundle of ARCH family models to model the conditional variances of stock returns to see whether there is a structural change in the conditional variance after an introduction of index futures trading. The first ARCH model was derived by Engle (1982) in his study of UK inflation rate. Since that time, researchers have developed numerous extensions to the basic linear ARCH model. For example, Bollerslev (1986)develops a generalized form of ARCH model (GARCH), and Nelson(1991) provides an exponential GARCH model(EGARCH) that captures the volatility asymmetry that bad news have a greater impact on volatility than good news. Glosten, Jagannathan, and Rundle(1993) suggest another asymmetric GARCH model (GJR-GARCH) to deal with the volatility asymmetry of stock return.

In the current literature, there are two potential explanations of the volatility asymmetry: leverage effects and volatility feedback. The former was introduced by F.Black (1976). who suggests that volatilities seems to go down when the stock prices go up (positive shocks) and volatilities seems to go up when the

[10]OSAKA post-future period indicates the time period from 3 September to 30 December and whole post-future period starts from 3 September 1986 to 30 December. The reason for this specification is that the first future contract for Nikkei 225 had been introduced by SIMEX(Singapore International Money Exchange) at 3 September 1986 and second Nikkei 225 future contract had launch by OSE(OSAKA Stock Exchange) at 3 September 1988 and may both have effect on spot market volatility of Nikkei 225 since their large trading volume and closely time zone.

[11]The change of spot volatility may still only caused by the futures trading even the coefficients of $C_{non,post}$ and $C_{non,Osaka}$ are significant if there is a spill-over effect between Nikkei 225 and non-Nikkei 225 stocks.However the insignificant values of $C_{non,post}$ and $C_{non,Osaka}$ reported in their paper had excluded the spill-over effect hypothesis.

[12]The industrial factor is the factor may affect many firms within an industry without substantially affecting the broad macro-economy.

stock prices go down (negative shocks). He explains that as the negative return drops more value in firm's equity than its debt and then it increases the financial leverage ratio of firm which implies stock of firm should be more risky and volatile. However,Christie (1982) and Schwert (1990) find that volatility asymmetry cannot be fully accounted by the leverage effects hypothesis. Therefore, some scholars[13] suggest a feedback story to explain the different impacts of positive and negative shocks on volatility. They claim that a higher risk premium required by investors when there is an anticipated increase in volatility, leading to an immediate stock price decline (negative shock). Alternatively, the feedback story claims that the negative shocks are caused by the increase of volatility level, whereas the leverage effects theory contends that negative shocks actually lead to a volatility increase. It is still an open question that which story can explain the volatility asymmetry better.

Since there are plenty of ARCH family models, it is worth to know which ARCH model will perform best in modelling the stock volatility. Engle and Ng(1993) apply three diagnostic[14] tests to several ARCH family models. They find that GJR-GARCH(1,1) is the best model to fit the daily stock return data and model the asymmetric volatility, while EGARCH(1,1) works poorly for modelling the asymmetric volatility when there are extreme shocks in the market.Gulen and Mayhew(2000) test both symmetric GARCH model (basic GARCH) and three alternative asymmetric GARCH models (GJR-GARCH, the nonlinear GARCH model (NGARCH), EGARCH) in their study about the effect of futures trading on spot volatility in international equity markets and find asymmetric GARCH models fit the data better than the symmetric GARCH model, with GJR-GARCH performing marginally better than the other two asymmetric models.

Therefore, motivated by the above arguments, we apply a modified GJR-GARCH model to model the conditional volatility of daily stock return in this paper.

# 3 Methodology and Data

## 3.1 Model

### 3.1.1 The ARMA model

In order to model the conditional variances of return, an ARMA (p, q) model is applied to remove the serially autocorrelation of return data. The ARMA (p, q) model can be defined as follows:

$$R_t = \omega_0 + \epsilon_t + \sum_{i=1}^{p} \omega_i R_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j,\epsilon t} \sim iid(0, \sigma_t) \tag{1}$$

[13]French and Stambaugh(1987) Campbell and Hentschel (1992).
[14]The Sign Bias Test, the Negative Size Bias Test and the Positive Size Bias Test.

Where $\omega_0$ is a constant, Where are $\omega_i$ and $\theta_j$ are the parameters, $R_t$ is the natural log return at time t and $\epsilon_t$ is the error terms at time t. P and q are the orders of AR and MA processes respectively . In order to fit ARMA (p, q) model, firstly, we need to set the values of p and q .Since the ACF (autocorrelation function) and PACF (partial autocorrelation function) are the powerful instruments to identify the appropriate orders for ARMA (p, q) process. We choose (p, q) for each index based on the ACF and PACF graphs (Appendix) .Besides, the results of Ljung-box (1976) tests will be provided to justify our choices.

### 3.1.2 The ARCH model

The ARCH stands for autoregressive conditional heteroskedasticity. It was initially introduced by Engle (1982) to model the inflation in UK and is commonly employed in modelling financial time series that exhibit time-varying volatility clustering and leptokurtosis. An original ARCH (q) process can be defined as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + ... + \alpha_q\epsilon_{t-q}^2 \tag{2}$$

With $\alpha_0 > 0$ and $\alpha_q \geq 0$, q > 0, Where q is the length of ARCH lags. $\alpha_0$ is the constant and $\alpha_q$ are the parameters .$\epsilon_t$ is the error term at time t (which is the residual of equation 1).$\sigma_t$ is the conditional variance at time t . Since the value of $\sigma_t$ (conditional variance of $\epsilon_t$) depends on the values of past error terms , larger past shocks($\epsilon_{t-1}$, $\epsilon_{(t-q)}$) indicate larger conditional variance of recent shock ($\epsilon_t$).Alternatively it indicates the large past shocks tend to induce large recent shock. This character makes ARCH(q) powerful to model the volatility clustering which had been well documented in financial time series studies.

### 3.1.3 The GARCH model

Although ARCH(q) model can be used to model the time-varying volatility. It requires many parameters and a high order q to get the effective results from the data. Bollerslev (1986) solved this problem by introducing a GARCH (generalized autoregressive conditional heteroskedasticity) model. The general GARCH(q, p) can be defined as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\alpha_i\epsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 \tag{3}$$

Similarly, p and q are the orders of the ARCH terms and the GARCH terms respectively, $\alpha_0$ is the constant term in the equation, $\alpha_i$ and $\beta j$ are the parameters, $\epsilon_{t-i}^2$ and $\sigma_t^2$ are the previous squared shocks and previous conditional variances respectively. Usually, a GARCH(1,1) model is good enough to capture the ARCH effect of financial time series .Therefore, compared to the ARCH(q) model , GARCH model requires less lags to have a good model fit ,which makes GARCH model more efficient and flexible. Even it performs quite well in explaining the time-varying volatility, the symmetry GARCH model fail to model the volatility asymmetry of financial time series data since it assumes that the magnitude of positive and negative past shocks have same effects on conditional variance. This could be clearly observed in the equation (3). The value of conditional variance $\sigma_t^2$ just depends on the value of past shock $\epsilon_{t-1}$ rather than their signs. Therefore, the positive and negative shocks have the same impact on conditional variance $\sigma_t^2$.

### 3.1.4 GJR-GARCH model

Since the asymmetric effect cannot be modelled by the symmetric GARCH models, several asymmetric GARCH models has been introduced. One famous example of them is the GJR-GARCH model which was introduced by Glosten, Jagannathan and Runkle in 1993. The standard model can be defined as:

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + \gamma_1 D_1^-)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

Where dummy variable

$$D_1^- = \begin{cases} 1, & \text{if } \epsilon_{t-1}<0 \\ 0, & \text{if } \epsilon_{t-1}>0 \end{cases}$$

Where p and q are the orders of ARCH and GARCH terms, $\alpha_0$ is the constant term. $\alpha_1$,$\gamma_1$ and $\beta_1$ are the parameters. Different from the symmetric GARCH model, the GJR-GARCH model includes a dummy variable $D_1^-$ which takes on a value of 1 if the past shock is negative and 0 otherwise. The coefficient of dummy variable $\gamma_1$ describes the difference of impact on volatility between the positive and negative shocks. A significant positive (negative) value of $\gamma_1$ means that the bad news has a larger (smaller) impact on the conditional variance than the good news does.

### 3.1.5 The modified model

To test the relationship between the spot volatility, index futures trading and market efficiency, we take an ARMA (p, q) process to remove the serial autocorrelation of daily stock return data and then model conditional variance by applying a modified GJR-GARCH (1, 1) model[15] .Our model can be defined as:

The ARMA (p, q) process:

$$R_t = \omega_0 + \epsilon_t + \sum_{i=1}^{p} \omega_i R_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}, \epsilon_t|\Omega_{t-1} \sim N(0, \sigma_t)$$

The GRJ-Garch(1,1)Process:

$$\sigma_t^2 = \alpha_0 + \mu_0 D_t + (\alpha_1 + \gamma_1 D_1^-)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{5}$$

[15] A lot of empirical studies had showed that the GARCH (1, 1) model is sufficient to capture the ARCH effect of daily stock return.Besides, our residuals have not been found any ARCH effect after a GJR-GARCH (1, 1) fitting.

or,

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + \gamma_1 D_1^- + \delta_1 D_t)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{6}$$

or,

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + \gamma_1 D_1^- + \gamma_2 Dp^-)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{7}$$

$$Where, D_1^- = \begin{cases} 1, & \text{if } \epsilon_{t-i} < 0 \\ 0, & \text{if } \epsilon_{t-i} \geq 0 \end{cases}$$

$$D_t^- = \begin{cases} 0, & \text{if } 1 \leq t \leq \text{t* -1} \\ 1, & \text{if } t* \leq t \leq T \end{cases}$$

$$D_p^- = \begin{cases} 1, & \text{if } \epsilon_{t-1} < 0 \text{ and } t* \leq t \leq \text{T}, \\ 0, & \text{Otherwise} \end{cases}$$

In the above model, the dependant variable, $R_t$, denotes the rate of return at time t; $R_t = ln(\frac{p_t}{p_(t-1)})$, where $p_t$ is the stock index value at time t.The shock $\epsilon_t$ is assumed to follow a conditional normal distribution. The set of all relevant and available information at time t-1 is denoted by $\Omega_{(t-1)}$. t* is the event date(the listing date of stock index futures) and T is the last sample day. $D_t$ is the dummy variable which takes value of 0 in the pre-futures trading days and 1 in the post-futures trading days. Equation 5 is used to test whether there is a change in the overall level of conditional variance. Equation (6) and equation (7) can be used for the information flow test and asymmetric effect test respectively. If there is not structural change on the conditional volatility after the start of trade in stock index futures, the coefficients $\mu_0$,$\sigma_1$ and $\gamma_2$ would not be significantly different from zero. Similarly, the significant positive (negative) value of $\mu_0$,$\sigma_1$ and $\gamma_2$ indicates an increase(decrease) in the overall level of conditional variance, information flow and asymmetric effect.

## 3.2 Volatility and Information Flow Test

Since the main interest of this paper is to test the general effects of futures trading on spot market rather than a simple multi-countries volatilities comparison, we conduct both individual market volatility and international portfolio volatility tests. Following the literatures which have controlled for the factor of 1987 crash, we report both the original (including 1987 crash) and adjusted (excluding 1987 crash) results in both individual market volatility and international portfolio volatility tests[16]

[16]For the individual market test, only results of Nikkei 225 have been report both including 1987 crash and excluding 1987 crash because only sample period of Japan had experienced 1987 crash.

### 3.2.1 Individual market volatility

In our individual market volatility study, the daily spot price data of S&P 500, ASX All Ordinaries and Nikkei 225 have been collected from Data Stream, CRSP and Yahoo Finance. The selection of sample based on the following five criterias.

1) To avoid the downside bias, the underlying indices needed to be the first or nearly first introduced the equity futures contract to the country.

2)The selected spot indices should be one of the most representative equity indices and its futures contract had been well developed after the listing.

3)Since we do not sure that whether the difference of calculation methods applied by the futures index has impacts on our volatility study and arithmetic average indices dominate the world equity index futures market[17]. In order to simplify our study, only the sample spot index data which are underlying by arithmetic average index futures contracts had been collected.[18]

4)the selected data are the highest frequent index data available.

5)The selected market indices required to have long enough data[19] to fit the GARCH model.

In order for robust inferences to be made, 16 February 1982(S&P500), 16 February 1983(ALL Ordinary) and 3 September 1986(Nikkei 225 (SIMAX)) are the threshold points to separate pre-and post-stock index futures periods. The total sample size for each country is 1000 trading days and covering period is from the $500^th$ trading days before the listing of the index futures trading to the $500^th$ trading days after the listing in each three stock markets.

Since then non-stationary price series is non-sense to model the conditional volatility, we transform daily prices data to daily natural logarithm returns data by using the following equation.

$$R_{t+1} = logP_{t+1} - logP_t \tag{8}$$

Where $R_t$ is the log return of underlying index at time t and $P_t$ is the price level of underlying index at time t.After modelling conditional variance of $R_t$ by our modified GJR-GARCH(1,1), the Coefficients $\mu_0$ and $\sigma_1$ could tell us that whether any spot volatility and information flow change occur after the listing of index futures trading in each market.

[17]ValueLine index futures was the only geometric average futures index and had employed arithmetic average method from March, 1988.

[18]Even Value Line index contract is the world first index future contract and had been introduced at 24 February 1982 by Kansas City Board of Trade, we exclude Value Line in our research because it was a geometric average contract.

[19]Since we need to study the structural change of volatility between pre-future period and post-future period, at least 500 observations in each period need to be guaranteed.

### 3.2.2 International portfolio volatility

Some studies[20] suggest both macroeconomic factors and market micro-structures have substantial effects on stock return volatility, and since, macroeconomic conditions, trading mechanisms, settlement days, forms of taxation and regulation differs from country to country, our individual market study may not be able to identify the general relationship between the futures trading listing, the change of volatility and the change of market efficiency. Therefore, in order to control the impact of other determinants on volatility, we apply Lee and Ohk(1992) method to conduct international portfolio volatility study. According to their study, there are two ways to build up the international portfolio. The first one is an equally weighted international portfolio which gives equal weight to each component index in the portfolio. The second one is a value weighted international portfolio which is constructed by using the ratios of total market capitalization. Since the results from both methods are similar and we do not have the data of market capitalization, we only apply equal weighted method to build up our international portfolio in this research. Beside, to control for extraneous influences better and make our results more robust , we remove our first criteria to allow more stock indices(show in table 1) to be included into our international portfolio[21]

Table 1: The Composition of International Portfolio

| Country | Underlying index | launch date |
|---|---|---|
| Australia | All Ordinaries | 16 February 1983 |
| Belgium | BEL 20 | 29 October 1993 |
| EuropeanUnion | Euro Stoxx 50 | 22 June 1998[22] |
| Japan(SIMEX) | Nikkei 225 | 3 September 1986 |
| (Osaka) | Nikkei 225 | 3 September 1988 |
| United States | S&P 500 | 21 April 1982 |
| | NASDAQ-100 | 4 October 1996 |
| | DJIA | 6 October 1997 |

Sources :Gulen and Mayhew (2000)

After the release of this constraint, our international portfolios are constructed by eight stock indices (Table1), centred on the futures trading listing date of each market. That is, a compilation is made of returns of a portfolio made up by investors who buy a stock index in each stock market on the $500^th$ trading day before the stock index futures listing and subsequently sell the stock index 1000 trading days later. Then, similar to our individual market volatility study, we regress the daily return data of international portfolio by our modified GRJ-GARCH model and the coefficients $\mu_0$ and $\sigma_1$ tell us whether any

[20] Anihund, Mendelson and Murgia (1990) find the volatilities of same stocks differ significantly over different market structures in the Italian stock market.

[21] Downside bias does not affect our conclusion since our result of international portfolio is statistically significant.

volatility and information flow change associated with a list of index futures trading. Besides, we use equation (7) to test whether the volatility asymmetry changes after the listing of index futures. If the coefficients $\gamma_2$ are significantly positive (negative), it means that there is an increase (decrease) in the volatility asymmetric response.

### 3.2.3 Coefficients dynamic test

The existing literatures just focuses on one period change of spot volatility and information flow, which ignores the fact that the effects of index futures may vary with the development of index futures market. Besides, without the confidence on control for extraneous influences, one period regression may not give us a reliable result. Then, it is necessary to have multiple period regressions for conditional variance and see whether our coefficients $\mu_0$,$\sigma_1$ and $\gamma_2$(for individual index market we use $\mu_0$ and $\sigma_1$ are consistent over time. In order to have multiple period regressions, we lag our listing date for 20 business days[23] each time. Therefore we have a new post-futures period data (500 trading days) each time. After taking the above manipulation for 25 times, we have 25 groups of new post-futures period data .And then we apply the same modified GJR-GRACH model to get 25 groups of new coefficients of $\mu_0$,$\sigma_1$ and $\gamma_2$ [24] (both for our individual index and international portfolio.

## 3.3 The Descriptive Statistics of Data and the results of preliminary statistic tests

The descriptive statistics of logarithmic first-difference of the daily spot prices in all indices have been reported. The basic statistical properties such as standard deviation, excess skewness and kurtosis have been provided. The Jarque-Bera test for departure from normality has been conducted in logarithmic first difference of spot prices. Besides, for testing the stationarity of data, we use two groups of Augmented Dickey Fuller tests (1981)in both the logarithmic and the logarithmic first-difference in the daily index price data. The Ljung-Box test has been applied here to test the independence of residual and squared residual data. The ARCH-LM test has been applied here to test the heteroskedasticity of logarithmic first-difference in the daily index price data. The P-value has been reported to indicate the significance level of confidence to reject the relevant null-hypotheses.

In a statistician's Utopia one can simultaneously minimize both types of errors. However, as type 1 error is decreased (the significance level moved from 10% to5%, or 5% to 1%) type 2 error is increased. Most introductory statistics

[23]Since 20 trading days are almost a calendar month, we can study the coefficient dynamic month by month.
[24]Coefficient $\gamma_2$ is not for individual index study

textbooks suggest that the exact relationship between two types of errors depends on the underlying probability distributions for the test statistic and on the hypothesis and alternative hypothesis. Mandersheid (1965)suggests that people must consider following three points to choose a best significance level.1)the costs associated with each type of error,2)the prior probabilities of the hypothesis and the alternative, and 3)the size of the type 2 error associated with each significance level. However, since we have no idea about the costs associated with each type of error to choose the best significance level, we provide both 1%,5% and 10% statistic significance levels in this study.

In table 2, which is divided into nine panels and each panel, indicates one group of sample. Two main characteristics are worth to be mentioned here. First, none of our samples follows the normal distribution since they all get very large value in the J-B test and strongly reject the normality hypothesis at 1% significant level .Second, although null hypothesis of non-stationary in the first group of ADF tests fail to be rejected by prices data in all our samples. The logarithmic first difference of prices data strongly rejects the non-stationary hypothesis in the second group of ADF tests. It means that the first order difference is powerful enough to transfer the index prices data from non-stationary to stationary.

Table 3 provides the results of Ljung-Box tests for both residual and squared residual series. Except for Nasdaq100, all sample residual series reject the Null-hypothesis of Ljung-Box test in 1% significance level ,which indicates that they are all serial-correlative before an autoregressive process adjustment. Besides, all samples reject the Null-hypothesis of Ljung-Box in squared residual level , which indicates all the samples are heteroskedastic[25] . The results above show us that an adjustment of ARMA (p,q) process may be necessary for our data and the GARCH (p, q) may be a good fit model.

After taking an ARMA (1,0)[26] and GARCH (1,1) process, we report another group of results for both Ljung-Box and ARCH-LM tests[27] in table 4. Different from table 3, all sample fail to reject the null-hypothesis of Ljung-Box test in residuals, which indicates autoregressive models capture the serial-correlation in the residual series, suggesting that the ARMA procedure removes the predictable part of the return series. Besides, the results of squared residuals and ARCH-LM test both suggest that there is no ARCH effect left after the adjustment .Therefore GARCH(1,1) model is good enough to remove the heteroskedasticity from our time series data.

[25]Since the null hypothesis of Ljung-Box test is that the data are independent, a rejection of null hypothesis in squared residual level means the squared residual series is no independent. Therefore, the variance of residual at time t [the quadratic form of residual] is dependent on the past residuals.

[26]For BEL 20 and All Ordinaries, ARMA (2,0) and ARMA(1,2) have been taken respectively.

[27]ARCH-LM test also be named as Lagrange multiplier test.

Table 2: The statistic properties of Logarithmic First difference of Spot prices of individual index

| SD | Skew | Kurt | J-B | ADF# | ADF |
|---|---|---|---|---|---|
| Panel A: S&P500 Spot prices for whole period, sample period(25 April 1980- 3 April 1986 ) | | | | | |
| 0.00881 | 0.257521 | 4.390492 | 137.4210*** | 0.717501 | -35.22813*** |
| Panel B: All Ordinaries Spot prices for whole period, sample period(17 March 1981-16 December 1986) | | | | | |
| 0.008395 | -0.084408 | 4.156983 | 85.44436*** | 2.236463 | -29.54422*** |
| Panel C: Nikkei225(SIMAX)Spot prices for whole period, Sample period(10 August 1984-20 September 1990) | | | | | |
| 0.011564 | -1.765317 | 36.86213 | 72444.33*** | -1.527233 | -38.47873*** |
| Panel D: DJIA spot prices for whole period, sample period(30 October 1995-22 august 2001) | | | | | |
| 0.011111 | -0.426822 | 6.727504 | 913.9373*** | -1.829558 | -38.38933*** |
| Panel E: Nikkei225(OSX) spot prices for whole period, sample period(21 August 1986-24 September 1992) | | | | | |
| 0.015083 | -0.335229 | 17.99828 | 14087.37*** | -1.087294 | -29.99859*** |
| Panel F:Bel 20 spot prices for whole period, Sample period(23 August 1991-8 September 1997) | | | | | |
| 0.006873 | -0.041408 | 5.601278 | 423.3440*** | 1.562853 | -33.97163*** |
| Panel G:NASDAQ 100 spot prices for whole period, sample period(12 October 1994-20 September 2000) | | | | | |
| 0.020008 | -0.257654 | 5.319718 | 352.9147*** | 0.244533 | -41.20254*** |
| Panel H:Euro Stoxx50 spot prices for whole period, sample period(10 July 1996-23 May 2002) | | | | | |
| 0.014183 | -0.230365 | 4.894327 | 237.5467*** | -1.755967 | -37.31116*** |
| Panel J: Equal weighted international portfolio spot prices for whole period | | | | | |
| 0.004559 | -0.334415 | 4.732206 | 215.4919*** | -0.668736 | -37.98901*** |

All series are measured in logarithmic first difference of index level (except#, which is measured in logarithmic index level).SD, Skew and Kurt are the estimated centralized second, third and fourth moments of the data. J-B is the Jarque-Bera(1980) test for normality.ADF is the Augmented Dickey Fuller (1981). The null hypothesis for Jarque-Bera test is that the data follow normal distribution. The null hypothesis for ADF test is that the data is non-stationary.

*** indicates statistic significance at the 1% level.

**indicates statistic significance at the 5% level.

*indicates statistic significance at the 10% level.

Table 3: Ljung-Box Statistics for Residuals without Autoregressive Process

| Sample | Q(1) | Q(12) | $Q^2(1)$ | $Q^2(12)$ |
|---|---|---|---|---|
| S&P500 | 8.8792*** | 18.739* | 1.2156 | 88.590*** |
| All Ordinaries | 79.327*** | 102.27*** | 27.974*** | 74.370*** |
| Nikkei225(SIMAX) | 5.4232*** | 20.910** | 161.73*** | 185.84*** |
| DJIA | 5.1852*** | 14.392 | 51.139*** | 156.30*** |
| BEL 20 | 14.808*** | 25.270*** | 2.024 | 12.084*** |
| NASDAQ 100 | 0.3455 | 12.302 | 68.248*** | 141.08*** |
| Euro Stoxx50 | 5.8626*** | 34.409*** | 31.521*** | 344.77*** |
| Nikkei225(OSX) | 0.0866*** | 33.563*** | 158.53*** | 196.36*** |
| International portfolio | 2.5687*** | 7.7833 | 24.769*** | 50.101*** |

Q(L) and $Q^2(L)$ are the Ljung-Box (1978) Q statistics on the first L lags of the sample autocorrelation function of the residual series and squared residual series without any autoregressive process. These tests are distributed as $\chi^2(L)$. The null hypothesis for Q(L) is that the residual series is independent. The null hypothesis for $Q^2(L)$ is that the square residual series is independent.
*** indicates statistic significance at the 1% level.
**indicates statistic significance at the 5% level.
*indicates statistic significance at the 10% level.

Table 4: Ljung-Box and ARCH Statistics for Residuals with Autoregressive Process

| Sample | Q(1) | Q(12) | $Q^2(1)$ | $Q^2(12)$ | L ARCH-LM |
|---|---|---|---|---|---|
| S&P500 | 0.0342 | 7.6321 | 2.0586 | 11.345 | -0.152 |
| All Ordinaries | 0.1395 | 9.2316 | 0.0911 | 6.998 | -0.7632 |
| Nikkei225(SIMAX) | 0.0863 | 12.142 | 0.1295 | 5.6085 | -0.7194 |
| DJIA | 0.0482 | 8.4496 | 0.3637 | 9.2272 | -0.5477 |
| BEL 20 | 0.0387 | 4.7589 | 1.519 | 7.5715 | -0.2186 |
| NASDAQ 100 | 1.0684 | 8.6529 | 0.0657 | 11.449 | -0.798 |
| Euro Stoxx50 | 0.0722 | 10.022 | 0.5824 | 16.861 | -0.4464 |
| Nikkei225(OSX) | 0.1396 | 13.771 | 1.9741 | 5.9844 | -0.1608 |
| International portfolio | 0.0797 | 5.2385 | 0.9696 | 15.614 | -0.3256 |

Q(L) and $Q^2(L)$ are the Ljung-Box (1978) Q statistics on the first L lags of the sample autocorrelation function of the residual series and squared residual series from several Autoregressive processes. ARCH is the ARCH-LM test for heteroskedasticity and only probability value had reported. All these tests are distributed as $\chi^2(L)$.The null hypothesis for Q(L) is that the residual series is independent. The null hypothesis for $Q^2(L)$ is that the square residual series is independent. The null hypothesis for ARCH-LM test is that the series is not heteroskedastic.
*** indicates statistic significance at the 1% level.
**indicates statistic significance at the 5% level.
*indicates statistic significance at the 10% level.

# 4 Empirical results

## 4.1 The empirical results for individual market volatility tests

$$R_t = \omega_0 + \epsilon_t + \sum_{i=1}^{p} \omega_i R_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}$$

$$\epsilon_t|\Omega_{t-1} \sim N(0, \sigma_t)$$

$$\sigma_t^2 = \alpha_0 + \mu_0 D_t + (\alpha_1 + \gamma_1 D_1^-)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, or,$$

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + \gamma_1 D_1^- \sigma_t + D_t)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

Table 5 provides the results of one period modified model. The coefficients $\omega_1$,$\theta_1$ and $\theta_2$ are all in the 1% significance level, which shows us that our ARMA processes are good to fit our data. The negative values of $\mu_0$ for S&P 500 and All Ordinaries indicate a decrease of volatility in these two indices in the post-futures period. However, these decreases are not reliable since the coefficients $\mu_0$ are statistically insignificant. In contrast, both the original and adjusted(excluding the 1987 crash data) samples of Nikkei 225 indicate a significant increase of volatility and information flow in the spot level after the introduction of index futures trading. No surprisingly, the original sample shows a greater increase in volatility and information flow since extreme volatile data have been included. For the asymmetric volatility, the coefficient $\gamma_1$ is positively significant for Japan but insignificant for other two countries, which indicates only Japan has the volatility asymmetry.

Comparing our results to the previous studies, we find that our identified findings in Nikkei 225 and All Ordinary are consistent to the results of Hodgson and Nicholls(1991),(Lee & Ohk, 1992),Chang et al.(1999), (Gulen & Mayhew, 2000)[28], while our findings are inconsistent to Antonious, Holems and Priestley(1998). By using the same asymmetric conditional variance model (GJR-GARCH) as AHP, We believe that the inconsistency should not result from the model selection but the listing date selection since they use 5 September 1988(OSAKA) as the listing date in Nikkei 225.

[28]Our Australian result is not fully consistent with Gulen and Mayhew since they find a significant decrease in spot volatility in All Ordinaries after the listing of index futures trading, while we find an insignificant decrease in spot volatility. We believe this difference may contribute to the control of macro-economic factors because they had used a world index to control the macro-economic factors in the individual index study.

Table 5: index futures listing and structural change in conditional variance for individual index

| | Individual market index | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | S&P500 | | All Ordinaries | | Nikkei225 | | $Nikkei225^C$ | |
| Parameter | | | | | | | | |
| $\omega\_o$ | 0.00021 | 0.00019 | 0.000132 | 0.000112 | 0.000736*** | 0.000831*** | 0.000976*** | 0.001014*** |
| | -0.4964 | -0.5359 | -0.7532 | -0.794 | -0.0152 | -0.0083 | -0.0005 | -0.0003 |
| $\omega\_1$ | 0.09649*** | 0.098219*** | 0.889309*** | 0.888656*** | 0.124504*** | 0.139960*** | 0.107400*** | 0.109334*** |
| | -0.0048 | -0.0041 | 0 | 0 | -0.0038 | -0.0016 | -0.004 | -0.0024 |
| $\omega\_2$ | | | | | | | | |
| $\theta\_1$ | | | -0.56433*** | -0.56726*** | | | | |
| | | | 0 | 0 | | | | |
| $\theta\_2$ | | | -0.25074*** | -0.24840*** | | | | |
| | | | 0 | 0 | | | | |
| $\alpha\_0$ | 3.27E-06*** | 3.41E-06*** | 6.48E-06*** | 4.81E-06*** | 1.90E-05*** | 2.05E-05*** | 6.93E-06*** | 5.10E-06*** |
| | -0.0012 | -0.0013 | -0.0058 | -0.0077 | 0 | 0 | 0 | 0 |
| $\alpha\_1$ | 0.043127*** | 0.035266** | 0.105636*** | 0.111015*** | 0.060672* | 0.032995 | 0.054702*** | 0.042501*** |
| | -0.0016 | -0.0235 | 0 | -0.0005 | -0.052 | -0.2106 | -0.005 | -0.0055 |
| $\gamma\_1$ | 0.008735 | 0.017001 | -0.003497 | -0.00087 | 0.760519*** | 0.568885*** | 0.210339*** | 0.142235*** |
| | -0.6812 | -0.4494 | -0.9021 | -0.9761 | 0 | 0 | 0 | 0 |
| $\beta\_1$ | 0.918986*** | 0.915130*** | 0.817190*** | 0.83118*** | 0.349338*** | 0.423940*** | 0.721141*** | 0.798671*** |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $\mu\_0$ | -4.08E-07 | | -1.60E-06 | | 1.99E-05*** | | 6.47E-06*** | |
| | -0.4469 | | -0.1434 | | 0 | | -0.0002 | |
| $\sigma\_1$ | | 0.007264 | | -0.017087 | | 0.215402*** | | 0.052511*** |
| | | -0.3565 | | -0.3248 | | -0.0002 | | -0.0058 |
| Log Likelihood | 3267.294 | 3267.393 | 3387.132 | 3386.415 | 3346.522 | 3335.999 | 3381.938 | 3379.331 |

Note:$R_t$ is the log first difference of daily spot price in each index at the time $t$; $D_i^-$ =1 if $_t < 0$ and zero otherwise, $D_t$=1 if the t is at the post-futures period and zero otherwise; the coefficients $\mu_0$ and $\sigma_1$ are the interest of our study which indicate the change of average conditional volatility and information flow respectively. Figure in the brackets (.) indicates p-value. $Nikkei225^c$ is the data excluding the 1987 October stock market crash. Log Likelihood is the value of the maximized likelihood function.
*** indicates statistic significance at the 1% level.
**indicates statistic significance at the 5% level.
*indicates statistic significance at the 10% level

## 4.2 The empirical results for international portfolio tests

$$R_t = \omega_0 + \epsilon_t + \sum_{i=1}^{p} \omega_i R_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}$$

$$\epsilon_t | \Omega_{t-1} \sim N(0, \sigma_t)$$

$$\sigma_t^2 = \alpha_0 + \mu_0 D_t + (\alpha_1 + \gamma_1 D_1^-)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, or,$$

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + \gamma_1 D_1^- \sigma_t + D_t)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

Table 6: Structural change in conditional variance for international portfolio

International portfolio

| | Original sample | | | Adjusted sample | | |
|---|---|---|---|---|---|---|
| Parameter | | | | | | |
| ω_o | 0.000634*** | 0.000661*** | 0.000659*** | 0.000699*** | 0.000698*** | 0.000697*** |
| | 0 | 0 | 0 | 0 | 0 | 0 |
| ω_1 | 0.121387*** | 0.113630*** | 0.111395*** | 0.108044*** | 0.112139*** | 0.113174*** |
| | -0.0003 | -0.0004 | -0.0005 | -0.0011 | -0.0007 | -0.0006 |
| ω_2 | | | | | | |
| θ_1 | | | | | | |
| θ_2 | | | | | | |
| α_0 | 5.44E-06*** | 2.19E-06*** | 2.13E-06*** | 1.44E-06*** | 1.30E-06*** | 1.26E-06*** |
| | -0.0018 | -0.0027 | -0.0027 | -0.0058 | -0.0023 | -0.0014 |
| α_1 | 0.034855 | -0.000759 | 0.012187 | 0.012292 | 0.000273 | 0.009126 |
| | -0.3648 | -0.9727 | -0.5669 | -0.5383 | -0.987 | -0.55853 |
| γ_1 | 0.198520*** | 0.11029*** | 0.087664*** | 0.049054* | 0.041784* | 0.019088 |
| | -0.0017 | -0.0026 | -0.01 | -0.0982 | -0.0723 | -0.5168 |
| β_1 | 0.460748*** | 0.792972*** | 0.797711*** | 0.845406* | 0.875735*** | 0.880822*** |
| | -0.0024 | 0 | 0 | 0 | 0 | 0 |
| μ_0 | 2.21E-06** | | | 5.30E-07* | | |
| | -0.0153 | | | -0.0821 | | |
| σ_1 | | 0.029189 | | | 0.023736* | |
| | | -0.1798 | | | -0.1 | |
| γ_2 | | | 0.049286 | | | 0.047233* |
| | | | -0.235 | | | -0.0854 |
| Log Likelihood | 4122.054 | 4118.996 | 4118.694 | 4166.061 | 4164.903 | 4165.202 |

Note: $R_t$ is the log first difference of daily spot price in each international portfolio at the time t;$D_i^- = 1$ if $t < 0$ and zero otherwise, $D_t = 1$ if the t is at the post-futures period and zero otherwise; The coefficients $\mu_0$ ,$\sigma_1$ and $\gamma_2$ are the interest of our study which indicates the change of average conditional volatility, information flow and asymmetric volatility respectively. Figure in the brackets (.) indicates p-value. Adjusted sample is the data excluding the 1987 October stock market crash in an equally weighted international portfolio. Log Likelihood is the value of the maximised likelihood function. *** indicates statistic significance at the 1% level **indicates statistic significance at the 5% level *indicates statistic significance at the 10% level

For the results of international portfolio, the significantly positive coefficient $\mu_0$ in both samples indicate that an increased volatility is accosiated with the listing of index futures trading and this volatility increase is not correlated with the 1987 stock crash itself(our adjusted sample come up with similar resultas original sample and just be less statsitically significant). Actually , figure. 1 and 2, Shows that it is clear that the conditional volatility jump to a higher level after the listing of index futures trading.

Besides,the positive $\sigma_1$ is observed in both samples that indicate an increase of information flow in the post-futures period.However, we are not too confident in the information flow increase since the significance level of coefficient $\sigma_1$ are weak.Come to the asymmetric volatility, the coefficient $\gamma_1$ are positively significant in both original and adjusted samples , which indicates the existence of volatility asymmetry in both samples.Therefore asymmetric conditional variance model should be preferred to the symmetric conditional variance model for the international portfolio.

Figure. 1 : The conditional standard deviation of international portfolio(excluding 19 crash)

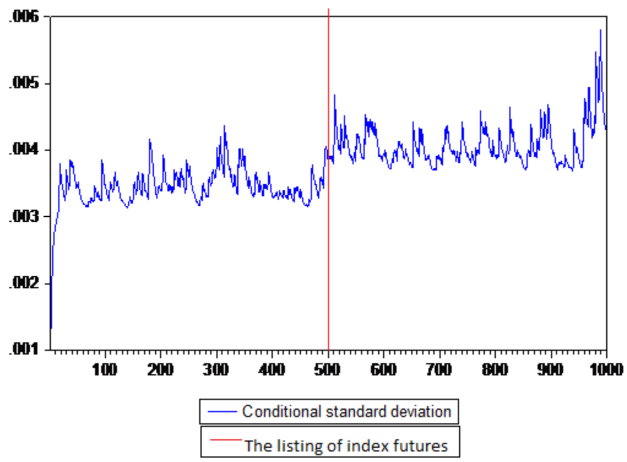
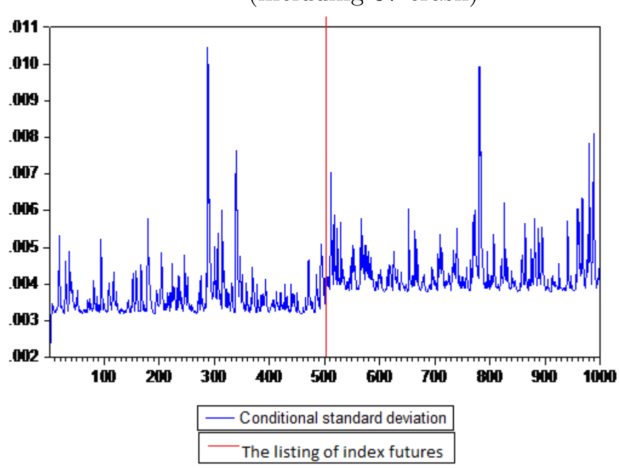



Figure. 2 : The conditional standard deviation of international portfolio (including 87 crash)



### 4.3 The empirical results for coefficients dynamic tests

Table 7 shows us how the coefficients $\mu_0$ and $\sigma_1$ vary over time for each individual market index. For the S&P 500 and All Ordinaries, the coefficients $\mu_0$ are changing from insignificantly negative to significantly negative, which indicates the volatilities in these two indices decrease after an introduction of index futures trading .These decreases in volatilities are getting bigger over time. Similarly, in S&P 500 and All Ordinaries, the coefficients of information flow $\sigma_1$ are changing from significantly negative to insignificantly negative over the lagged periods, which is the same pattern of change as is identified with volatility. It indicates that the market efficiencies in these two markets are decreasing over the time.

However, the conditional variances of Nikkei 225 experience a different pattern of change to previous two indices. The coefficients $\mu_0$ and $\sigma_1$ are significantly positive in the first several lagged periods and then become insignificantly positive and then finally change to negative. It indicates that both the spot volatilities and market efficiencies in Japan decrease over time[29] . The results of the $Nikkei225^c$ are quite similar to the results of unadjusted Nikkei 225 samples (including 1987 Crash) and the only difference is the change of $\mu_0$ and $\sigma 1$ are smaller resulting from the exclusion of extreme shocks(we plot the time-varying coefficients $\mu_0$ and $\sigma 1$ in Appendix).

In the individual market time-varying study, nevertheless, we do not find the clear pattern for either the coefficients or the change of coefficients in all indices. Since we have not control for the macro-economic factors in each individual index, hence these results may be influenced by the difference of macro-economic conditions in different indices over different sample periods.

Since the results of individual index cannot tell us too much about the general effects of index futures trading on volatility, we need to move on to the results of international portfolio in Table 8. In Table 8, it is clear that coefficients $\mu_0$ for both original and adjusted samples are positively significant over all lag periods.

[29]The identified decrease in volatility in the Nikkei 225 is consistent with the change in spot prices of the Nikkei 225. The Nikkei 225 experienced a booming market in the sample periods. As we discussed before, the positive returns (positive shocks) tend to be related to the decrease in volatility.

Table 7: The coefficients $\mu_0$ and $\sigma_1$ for each lag period in each individual index

| | Individual market index | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | S&P500 | | AllOrdinary | | Nikkei225 | | $Nikkei225^C$ | |
| Parameter | $\mu_0$ | $\sigma_1$ | $\mu_0$ | $\sigma_1$ | $\mu_0$ | $\sigma_1$ | $\mu_0$ | $\sigma_1$ |
| Lag(0) | -4.08E-07 | 0.007264 | -1.60E-06 | -0.017087 | 1.99E-05*** | 0.215456*** | 6.47E-06*** | 0.052511*** |
| | -0.4469 | -0.3565 | -0.1427 | -0.3248 | 0 | -0.0002 | -0.0002 | -0.0058 |
| Lag(1) | -3.66E-07 | 0.008089 | -2.24E-06 | -0.021905 | 1.88E-05*** | 0.156701*** | 4.29E-06*** | 0.031751* |
| | -0.5008 | -0.314 | -0.1144 | -0.3174 | 0.0000 | -0.0048 | -0.0014 | -0.0554 |
| Lag(2) | -4.50E-07 | 0.007758 | -1.39E-06 | -0.017498 | 1.59E-05*** | 0.112815** | 2.85E-06*** | 0.026987* |
| | -0.4119 | -0.3376 | -0.1101 | -0.1954 | 0.0000 | -0.0379 | -0.0078 | -0.0736 |
| Lag(3) | -5.46E-07 | 0.007402 | -1.71E-06* | -0.021871 | 1.48E-05*** | 0.11338** | 3.04E-06*** | 0.033418** |
| | -0.3223 | -0.3681 | -0.0861 | -0.1525 | 0.0000 | -0.0362 | -0.0041 | -0.035 |
| Lag(4) | -1.03E-06** | -0.002704 | -2.17E-06* | -0.027268 | 1.41E-05*** | 0.123387** | 2.75E-06*** | 0.033925** |
| | -0.0256 | -0.7183 | -0.0867 | -0.1533 | 0.0000 | -0.024 | -0.0055 | -0.0312 |
| Lag(5) | -7.47E-07 | 0.003535 | -1.78E-06* | -0.021654 | 1.31E-05*** | 0.121786** | 1.51E-06** | 0.026483* |
| | -0.2304 | -0.7008 | -0.0872 | -0.1481 | 0.0000 | -0.0258 | -0.0402 | -0.0562 |
| Lag(6) | -1.10E-06* | -0.00119 | -2.02E-06* | -0.027081* | 1.10E-05*** | 0.103692* | 9.46E-07 | 0.026568* |
| | -0.0704 | -0.8919 | -0.0535 | -0.0758 | 0.0000 | -0.0535 | -0.1305 | -0.0575 |
| Lag(7) | -9.76E-07 | -0.003374 | -2.93E-06* | -0.036041* | 1.12E-05*** | 0.014667 | 5.91E-07 | 0.011101 |
| | -0.1408 | -0.6952 | -0.0563 | -0.093 | 0.0000 | -0.7497 | -0.268 | -0.3519 |
| Lag(8) | -1.08E-06 | -0.007377 | -2.68E-06** | -0.035617* | 6.83E-06*** | 0.024801 | 3.86E-07 | -0.00348 |
| | -0.1368 | -0.4219 | -0.0399 | -0.0649 | -0.0006 | -0.5926 | -0.5423 | -0.8251 |
| Lag(9) | -1.34E-06* | -0.012929 | -3.40E-06** | -0.040931* | 5.40E-06*** | -0.005051 | 1.55E-07 | -0.00664 |
| | -0.0987 | -0.1942 | -0.0435 | -0.0853 | -0.0032 | -0.9061 | -0.7863 | -0.655 |
| Lag(10) | -1.47E-06 | -0.017635 | -3.21E-06** | -0.041306* | 4.72E-06*** | 0.000427 | -4.42E-09 | -0.01127 |
| | -0.1051 | -0.1204 | -0.0437 | -0.0753 | -0.0078 | -0.9926 | -0.9933 | -0.4201 |
| Lag(11) | -1.58E-06* | -0.019667* | -3.25E-06* | -3.73E-02 | 2.81E-06 | 0.013413 | -4.72E-08 | -0.00597 |
| | -0.0912 | -0.0855 | -0.0623 | -0.1229 | -0.1009 | -0.7906 | -0.9295 | -0.6869 |
| Lag(12) | -1.50E-06* | -0.01879* | -3.29E-06** | -0.0385* | 1.96E-06 | 0.019797 | -4.10E-07 | -0.01027 |
| | -0.0767 | -0.0844 | -0.0446 | -0.0915 | -0.2334 | -0.7013 | -0.2761 | -0.3558 |
| Lag(13) | -1.66E-06* | -0.019401* | -2.79E-06** | -0.032517* | 1.33E-06 | 0.010383 | -5.23E-07 | -0.01366 |
| | -0.059 | -0.0724 | -0.0274 | -0.0866 | -0.4123 | -0.8352 | -0.1815 | -0.2524 |

Note: Lag(x) means x lag had been took for the post-futures period . The coefficients $\mu_0$ and $\sigma_1$ are the interest of our study which indicate the change of average conditional volatility and information flow respectively. Figure in the brackets (.) indicates p-value. $Nikkei225^c$ is the data excluding the 1987 October stock market crash.
*** indicates statistic significance at the 1% level.
**indicates statistic significance at the 5% level.
*indicates statistic significance at the 10% level.

Table 7: The coefficients $\mu_0$ and $\sigma_1$ for each lag period in each individual index

| | Individual market index | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | S&P500 | | AllOrdinary | | Nikkei225 | | $Nikkei225^C$ | |
| Parameter | $\mu_0$ | $\sigma_1$ | $\mu_0$ | $\sigma_1$ | $\mu_0$ | $\sigma_1$ | $\mu_0$ | $\sigma_1$ |
| Lag(14) | -1.60E-06** | -0.018481* | -3.07E-06** | -0.03622* | -1.00E-06** | -0.07070*** | -6.75E-07 | -0.01962 |
| | -0.0421 | -0.0701 | -0.0358 | -0.0992 | -0.0194 | 0 | -0.1538 | -0.1729 |
| Lag(15) | -1.69E-06** | -0.018587* | -3.33E-06** | -0.037106 | -8.08E-07 | -0.032841** | -8.08E-07 | -0.03284** |
| | -0.0265 | -0.052 | -0.0403 | -0.1115 | -0.1014 | -0.0289 | -0.1014 | -0.0289 |
| Lag(16) | -1.97E-06** | -0.02259** | -1.87E-06* | -0.02254 | -1.36E-06** | -0.05467*** | -1.36E-06** | -0.05467*** |
| | -0.0302 | -0.0387 | -0.0739 | -0.1304 | -0.0185 | -0.0025 | -0.0185 | -0.0025 |
| Lag(17) | -1.91E-06** | -0.02343** | -1.81E-06** | -0.02549** | -1.90E-06** | -0.07102*** | -1.90E-06** | -0.07102*** |
| | -0.0324 | -0.0428 | -0.0185 | -0.0278 | -0.0228 | -0.0078 | -0.0228 | -0.0078 |
| Lag(18) | -2.01E-06** | -0.02418** | -1.67E-06** | -0.019783* | -1.79E-06* | -0.061872** | -1.79E-06* | -0.06187** |
| | -0.0291 | -0.0388 | -0.0325 | -0.0833 | -0.0695 | -0.0439 | -0.0695 | -0.0439 |
| Lag(19) | -1.92E-06** | -0.021865* | -2.15E-06** | -0.031474** | -1.06E-06* | -0.024608 | -1.06E-06* | -0.0246 |
| | -0.0354 | -0.0544 | -0.0119 | -0.016 | -0.074 | -0.2171 | -0.074 | -0.2171 |
| Lag(20) | -1.92E-06** | -0.021446* | -2.08E-06** | -0.026504** | -1.32E-06* | -0.033347 | -1.32E-06* | -0.03334 |
| | -0.0321 | -0.0559 | -0.0191 | -0.0467 | -0.0516 | -0.1254 | -0.0516 | -0.1254 |
| Lag(21) | -1.88E-06** | -0.021688* | -2.50E-06** | -0.031013** | -8.63E-07* | -0.009436 | -8.63E-07* | -0.00943 |
| | -0.0343 | -0.0533 | -0.0116 | -0.0375 | -0.0993 | -0.5689 | -0.0993 | -0.5689 |
| Lag(22) | -1.81E-06** | -0.02193** | -2.31E-06** | -0.028837* | -7.92E-07 | -0.008033 | -7.92E-07 | -0.00803 |
| | -0.0261 | -0.0468 | -0.0187 | -0.0536 | -0.1348 | -0.6355 | -0.1348 | -0.6355 |
| Lag(23) | -2.23E-06** | -0.03123** | -2.02E-06** | -0.025881* | -6.71E-07 | -0.012631 | -6.71E-07 | -0.01263 |
| | -0.0345 | -0.0333 | -0.0275 | -0.0618 | -0.1473 | -0.3856 | -0.1473 | -0.3855 |
| Lag(24) | -2.49E-06** | -0.03497** | -2.08E-06** | -0.023351 | -8.28E-07 | -0.002429 | -8.28E-07 | -0.00242 |
| | -0.0482 | -0.0331 | -0.0429 | -0.1444 | -0.1181 | -0.8946 | -0.1181 | -0.8946 |
| Lag(25) | -2.47E-06* | -0.03311** | -2.03E-06** | -0.022981 | -8.75E-07 | -0.003921 | -8.75E-07 | -0.00392 |
| | -0.0602 | -0.0429 | -0.0465 | -0.146 | -0.1034 | -0.8286 | -0.1034 | -0.8286 |

Note: Lag(x) means x lag had been took for the post-futures period .The coefficients $\mu_0$ and $\sigma_1$ are the interest of our study which indicate the change of average conditional volatility and information flow respectively. Figure in the brackets (.) indicates p-value. $Nikkei225^c$ is the data excluding the 1987 October stock market crash.
*** indicates statistic significance at the 1% level.
**indicates statistic significance at the 5% level.
*indicates statistic significance at the 10% level.

The finding indicates that there is volatility increases associated to the listing of index futures trading, and the identified volatility increases are consistent over time.For the change of information flow, both samples evidence an improvement of information flow over time. Even though some values of coefficients $\sigma_1$ are not significant at 10% confidence level in original and adjusted samples, most of $p$ values are close to 10%. Besides, there is a clear trend that both the significance level and value of coefficients $\sigma_1$ are increasing over the lagged sample periods, which implies that the impact of index futures trading on market efficiency is increasing over time. This evidence is consistent with the fact that the index futures trading have been developed quickly after their listings. Regarding the change in volatility asymmetric effects, most coefficients $\gamma_2$ in original samples are significant positive (at either 5% or 10% significance level), while most coefficients $\gamma_2$ in adjusted samples are insignificantly positive.

This suggests that there is an increase in volatility asymmetric effect in original sample but no difference in adjusted sample (the increase in volatility asymmetric effect means that the post-futures negative shocks have more impacts on volatility than pre-futures negative shocks). In addition, the value of coefficients $\gamma_2$ in Original sample are far bigger than those in adjusted sample(167%-2126%).The above difference of change of volatility asymmetric effect in two samples may be caused by the exclusion of 1987 crash data (we plot the time-varying coefficients $\mu_0$ and $\sigma_1$ in Appendix).

## 5 Conclusion

This paper examines the impact of index futures trading on spot market in three individual indices and an equally weighted international portfolio. We apply a modified GJR-GARCH model to test the relationship between the listing of index futures trading, spot market volatility and market efficiency. In order to test whether the identified impacts are consistent over time, we lag the post-futures data to allow multiple period regressions to be included, therefore the coefficient dynamics can be studied.

There are several striking findings from our study. First, without any control for macro-economic factors, the impacts of individual index futures trading on spot volatility and information flow vary over the indices and time. Second, after using an equally weighted international portfolio to control the macro-economic conditions and market micro structures, we find that there is a general increase in both spot volatility and information flow in both original and adjusted samples.

Table 8: The coefficients$\mu_0$ and$\sigma_1$ for each lag period in each international portfolio

| | International portfolio | | | | | |
|---|---|---|---|---|---|---|
| | Original sample | | Adjusted sample | | Original sample | Adjusted sample |
| parameter | $\mu\_0$ | $\sigma\_1$ | $\mu\_0$ | $\sigma\_1$ | $\gamma\_1$ | $\gamma\_2$ |
| Lag(0) | 2.21E-06** | 0.02919 | 5.30E-07* | 0.023736* | 0.049286 | 0.047233* |
| | -0.0153 | -0.1798 | -0.0821 | -0.1 | -0.2352 | -0.0854 |
| Lag(1) | 2.20E-06** | 0.028363 | 4.60E-07* | 0.023606* | 0.054741 | 0.024976 |
| | -0.0186 | -0.1265 | -0.0672 | -0.0701 | -0.1502 | -0.2074 |
| Lag(2) | 2.00E-06** | 0.031471 | 4.76E-07* | 0.024959* | 0.067634 | 0.025669 |
| | -0.0189 | -0.1249 | -0.0703 | -0.0786 | -0.1281 | -0.2443 |
| Lag(3) | 2.12E-06** | 0.032881 | 5.00E-07* | 0.026055* | 0.074523* | 0.020169 |
| | -0.0186 | -0.1119 | -0.0656 | -0.0819 | -0.0921 | -0.3164 |
| Lag(4) | 2.15E-06** | 0.030288 | 4.51E-07* | 0.023113 | 0.072962 | 0.023147 |
| | -0.0128 | -0.1625 | -0.0864 | -0.1354 | -0.1372 | -0.3049 |
| Lag(5) | 1.84E-06** | 0.040916* | 6.29E-07** | 0.033273** | 0.096472* | 0.029928 |
| | -0.0201 | -0.0869 | -0.0484 | -0.0475 | -0.0824 | -0.1894 |
| Lag(6) | 1.91E-06** | 0.036962 | 6.14E-07* | 0.029957* | 0.085172* | 0.022428 |
| | -0.0215 | -0.1033 | -0.0537 | -0.0652 | -0.1 | -0.2811 |
| Lag(7) | 1.99E-06** | 0.038081 | 6.56E-07* | 0.031847* | 0.092317* | 0.005107** |
| | -0.0204 | -0.114 | -0.0526 | -0.0647 | -0.0873 | -0.0389 |
| Lag(8) | 1.94E-06** | 0.037657 | 6.64E-07* | 0.031682* | 0.100594* | 0.0292 |
| | -0.0222 | -0.1337 | -0.0564 | -0.0759 | -0.0852 | -0.2398 |
| Lag(9) | 2.23E-06** | 0.042168 | 8.06E-07** | 0.03385* | 0.111139* | 0.006642*** |
| | -0.0165 | -0.1078 | -0.0481 | -0.0518 | -0.0702 | -0.0059 |
| Lag(10) | 2.51E-06** | 0.040646 | 8.70E-07** | 0.031984* | 0.103668* | 0.004874* |
| | -0.0149 | -0.1123 | -0.0496 | -0.0619 | -0.0786 | -0.062 |

Note: Lag(x) means x lag had been took for the post-futures period .The coefficients $\mu_0$ ,$\sigma_1$ and $\gamma_2$ are the interest of our study which indicates the change of average conditional volatility, information flow and asymmetric volatility respectively. Figure in the brackets (.) indicates p-value. Equally $weighted^c$ is the data excluding the 1987 October stock market crash in equally weighted international portfolio.
*** indicates statistic significance at the 1% level.
**indicates statistic significance at the 5% level.
*indicates statistical significance at the 10% level.

Table 8: The coefficients$\mu_0$ and$\sigma_1$ for each lag period in each international portfolio

| International portfolio | | | | | | |
|---|---|---|---|---|---|---|
| | Original sample | | Adjusted sample | | Original sample | Adjusted sample |
| parameter | $\mu\_0$ | $\sigma\_1$ | $\mu\_0$ | $\sigma\_1$ | $\gamma\_1$ | $\gamma\_2$ |
| Lag(11) | 2.72E-06** | 0.037378 | 8.59E-07** | 0.030353* | 0.09882* | 0.006631** |
| | -0.0128 | -0.1203 | -0.0496 | -0.0536 | -0.0849 | -0.0133 |
| Lag(12) | 2.47E-06** | 0.035599 | 8.31E-07** | 0.031017* | 0.090561* | 0.007346*** |
| | -0.0157 | -0.121 | -0.0476 | -0.0537 | -0.0896 | -0.0074 |
| Lag(13) | 2.44E-06** | 0.028762 | 6.86E-07* | 0.025721* | 0.078351* | 0.016159 |
| | -0.017 | -0.1671 | -0.0724 | -0.0955 | -0.0985 | -0.4351 |
| Lag(14) | 9.57E-07* | 0.025694 | 6.42E-07* | 0.030586* | 0.054677 | 0.024182 |
| | -0.0967 | -0.2335 | -0.0772 | -0.0837 | 0.2152 | -0.3214 |
| Lag(15) | 1.12E-06* | 0.028727 | 6.81E-07* | 0.031875* | 0.06645 | 0.027486 |
| | -0.0795 | -0.1881 | -0.0715 | -0.0759 | -0.1586 | -0.2838 |
| Lag(16) | 1.70E-06** | 0.031687 | 8.40E-07* | 0.034969* | 0.08805* | 0.042816 |
| | -0.0444 | -0.1544 | -0.0542 | -0.0566 | -0.0863 | -0.1889 |
| Lag(17) | 1.19E-06** | 0.045073* | 9.26E-07** | 0.04849** | 0.122094** | 0.057453 |
| | -0.0373 | -0.0551 | -0.0373 | -0.0186 | -0.0264 | -0.1273 |
| Lag(18) | 1.11E-06** | 0.043681** | 8.38E-07** | 0.045169** | 0.100354** | 0.040716 |
| | -0.0414 | -0.0452 | -0.0388 | -0.019 | -0.0238 | -0.2183 |
| Lag(19) | 1.29E-06** | 0.048049** | 8.39E-07** | 0.047683** | 0.12416** | 0.037398 |
| | -0.0322 | -0.0373 | -0.0405 | -0.0179 | -0.014 | -0.2508 |
| Lag(20) | 1.19E-06** | 0.049626** | 8.56E-07** | 0.049542** | 0.121296** | 0.046304 |
| | -0.0306 | -0.0284 | -0.0316 | -0.0103 | -0.0117 | -0.1532 |

Note: Lag(x) means x lag had been took for the post-futures period .The coefficients $\mu_0$ ,$\sigma_1$ and $\gamma_2$ are the interest of our study which indicates the change of average conditional volatility, information flow and asymmetric volatility respectively. Figure in the brackets (.) indicates p-value. Equally $weighted^c$ is the data excluding the 1987 October stock market crash in equally weighted international portfolio.
*** indicates statistic significance at the 1% level.
**indicates statistic significance at the 5% level.
*indicates statistical significance at the 10% level.

Table 8: The coefficients$\mu_0$ and$\sigma_1$ for each lag period in each international portfolio

International portfolio

| | Original sample | | Adjusted sample | | Original sample | Adjusted sample |
|---|---|---|---|---|---|---|
| parameter | $\mu\_0$ | $\sigma\_1$ | $\mu\_0$ | $\sigma\_1$ | $\gamma\_1$ | $\gamma\_2$ |
| Lag(21) | 1.07E-06** | 0.046729** | 8.19E-07** | 0.047777*** | 0.10309*** | 0.036595 |
| | -0.0253 | -0.0151 | -0.0219 | -0.0061 | -0.005 | -0.2028 |
| Lag(22) | 1.23E-06** | 0.047451** | 9.18E-07** | 0.048318*** | 0.108868*** | 0.032513 |
| | -0.0233 | -0.0166 | -0.0215 | -0.0076 | -0.0044 | -0.2566 |
| Lag(23) | 1.41E-06** | 0.048294** | 1.00E-06** | 0.048895*** | 0.108656*** | 0.030676 |
| | -0.0194 | -0.017 | -0.0206 | -0.0093 | -0.0047 | -0.2914 |
| Lag(24) | 1.53E-06** | 0.054392** | 1.02E-06** | 0.052073** | 0.117724*** | 0.02104 |
| | -0.0188 | -0.0165 | -0.0244 | -0.0113 | -0.0049 | -0.4493 |
| Lag(25) | 1.40E-06** | 0.052706** | 1.01E-06** | 0.052427** | 0.117468*** | 0.01824 |
| | -0.0226 | -0.0196 | -0.0251 | -0.0114 | -0.0055 | -0.5199 |

Note: Lag(x) means x lag had been took for the post-futures period .The coefficients $\mu_0$ ,$\sigma_1$ and $\gamma_2$ are the interest of our study which indicates the change of average conditional volatility, information flow and asymmetric volatility respectively. Figure in the brackets (.) indicates p-value. Equally $weighted^c$ is the data excluding the 1987 October stock market crash in equally weighted international portfolio.
*** indicates statistic significance at the 1% level.
**indicates statistic significance at the 5% level.
*indicates statistical significance at the 10% level.

When we go further and apply a coefficient dynamic test to our international portfolio, different from the results of individual index, the identified increases in spot volatility and information flow are consistent over time in both original and adjusted samples. Third, the amount of increase in spot volatility and information flow increase over time in the adjusted sample, which is consistent to the fact that the index futures trading have been developed quickly after their listings. Finally, we find that there are increases in asymmetric volatility in the international portfolio (original sample) in the post-futures periods. Nevertheless, the increases of asymmetric volatility response in the international portfolio may be partially contributed by the October 1987 crash since that the increases of asymmetric volatility response become less statistically significant in the adjusted sample (in Table 8, less values of coefficient $\gamma_2$ are statistically significant at each given significance level).

In the comparison with previous literatures, our identified volatility increase is consistent with those results from the cross-sectional and decomposition methods. Besides, our results are consistent with Lee and Ohk(1992) symmetric GARCH international portfolio study. However, by using an asymmetric model, we find a significant volatility asymmetric feature in the international portfolio, which has been ignored by Lee and Ohk(1992). Different from all prior literature, we introduce a coefficient dynamic test to examine whether the identified structural changes of conditional variance is consistent over time. Our results for individual index in the coefficients dynamic test may partially explain two inconsistencies in the previous studies. The first, without controlling for macroeconomic factors control, studies in different indices may come up to the mixed results for the impacts of index futures on spot volatility. Second, some similar studies utilize an analogous sample model however through the use of different data period in the same index a mixture of results have been observed. Our results for the international portfolio tend to be stable through time. Alternatively, they should be more reliable than most of the previous studies since we exclude the possibility that our identified increases in spot volatility are influenced by the data periods we used.

## Areas for Future Research

However, there are still some problems we need to solve to make our results more robust. First, we do not find a method to estimate that how good is our international portfolio in controlling the extraneous influences (especially macro-economic factors). So, we cannot confidently reject the hypothesis that our identified increase of spot volatility does not result or partially result from the change of macro-economic conditions. We believe, our results of international portfolio can be more robust if more indices data is incorporated (a more diversified international portfolio). Or if we have the data of a comparable world equity index to remove the macro-economic factors. Besides, similar to the previous empirical studies, what we only identify is the correlation rather than the causation between the index futures trading, spot volatility and information flow. Third, we find no concrete reason to explain why the original data have higher increase in spot volatility but less significant increase in information flow. Fourth, without availability of the data on open interest, futures trading volume and futures price, there are two things we cannot do *i.e.*

1) we cannot study the direct link between the spot market and futures market, which may help us understand whether the introduction of a volatile futures market leads to the increase in volatility in spot market.

2) we are not able to relate the identified increase in increase of spot volatility to the development of futures market. Fifth, since our increased volatility results come from the study of an international portfolio which is less volatile than the individual stock indices, the identified volatility increase may be underestimated when we apply it to estimate the general effect of index futures trading on spot volatility for individual country. The above empirical issues remain to be examined in the future study.

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# Appendix

Figure 1: The movement of coefficients $\mu_0$ and $\sigma$_1 in the international portfolio (excluding 1987 crash)

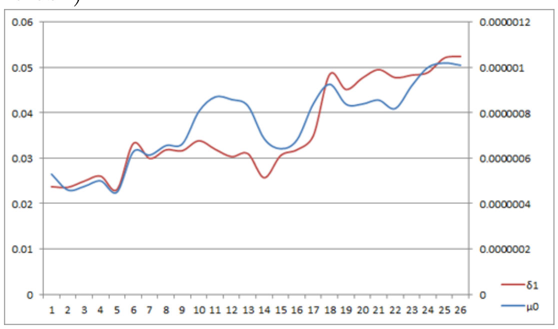



Figure 2: The movement of coefficients $\mu_0$ and $\sigma$_1 in the international portfolio (including 1987 crash)

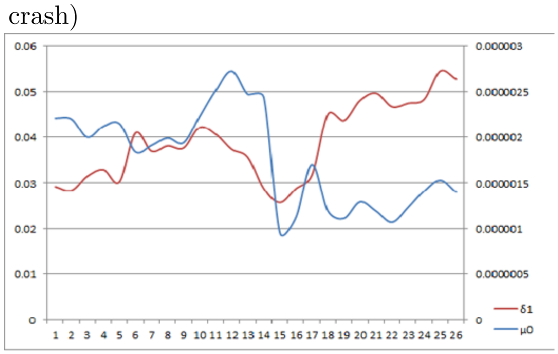



Figure 3: The movement of coefficients $\mu_0$ and $\sigma$_1 in S&P 500

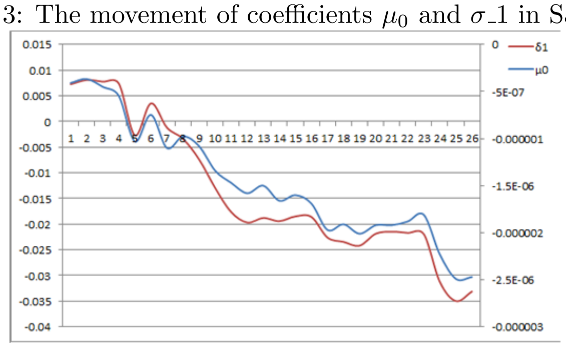


Figure 4: The movement of coefficients $\mu_0$ and $\sigma\_1$ in the all ordinary

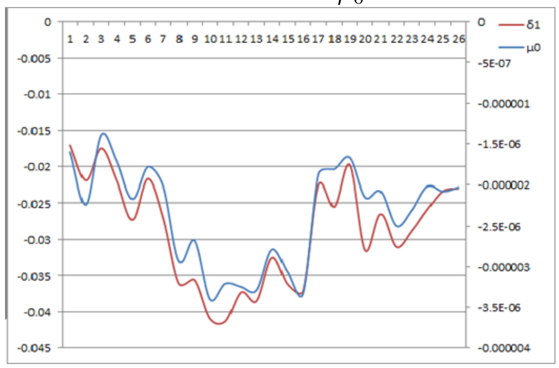


Figure 5: The movement of coefficients $\mu_0$ and $\sigma\_1$ in the Nikkie 225 (including 1987 crash)

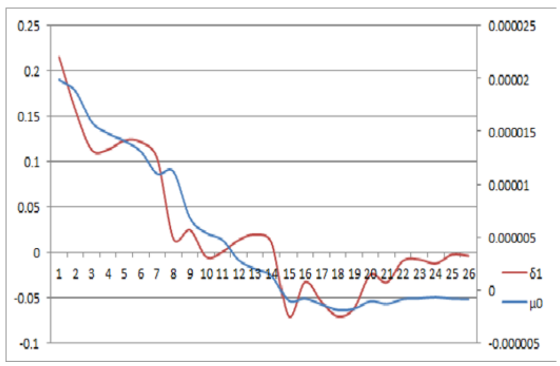
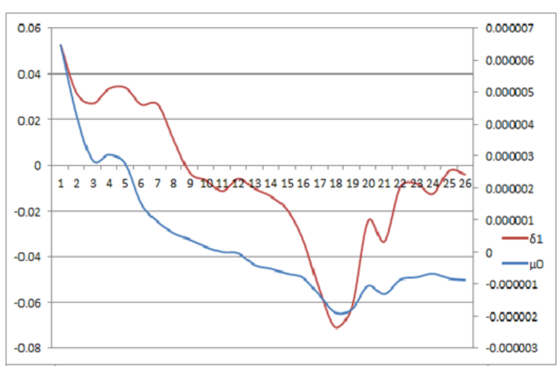


Figure 6: The movement of coefficients $\mu_0$ and $\sigma\_1$ in the Nikkie 225 (excluding 1987 crash)



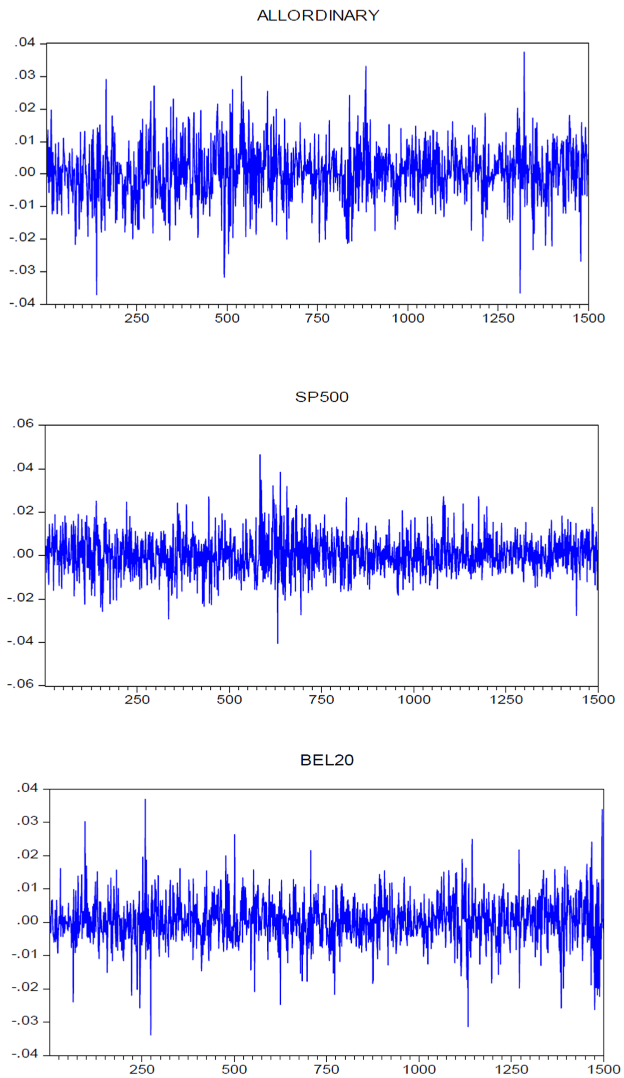

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Figure 7: 9

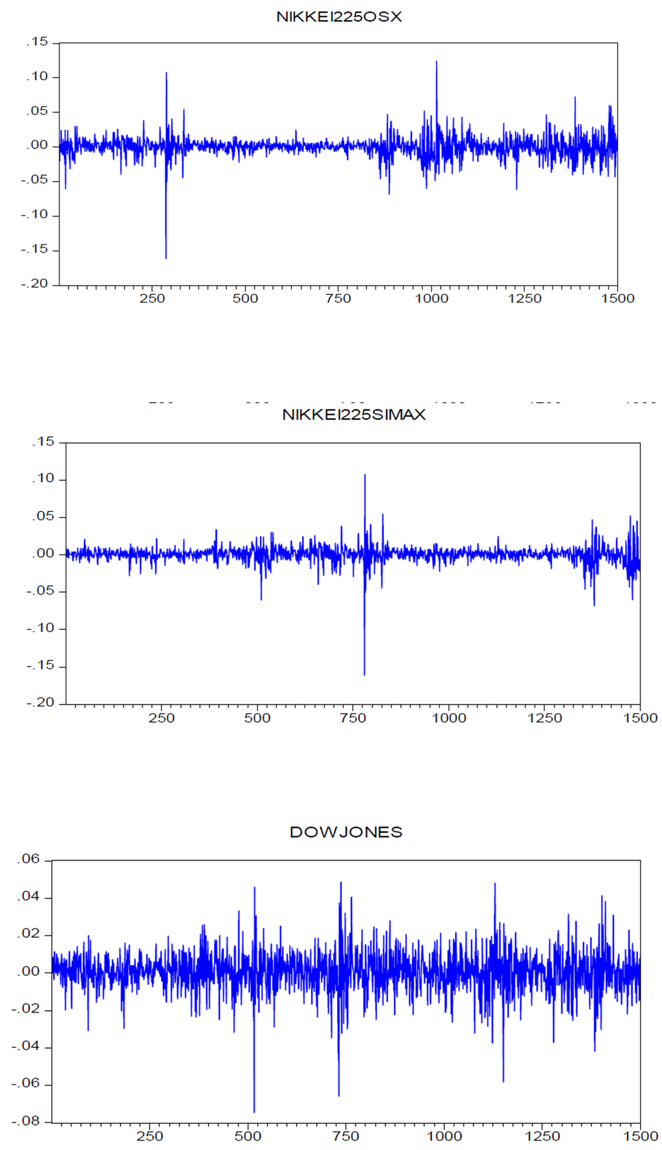
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Figure 8: 6

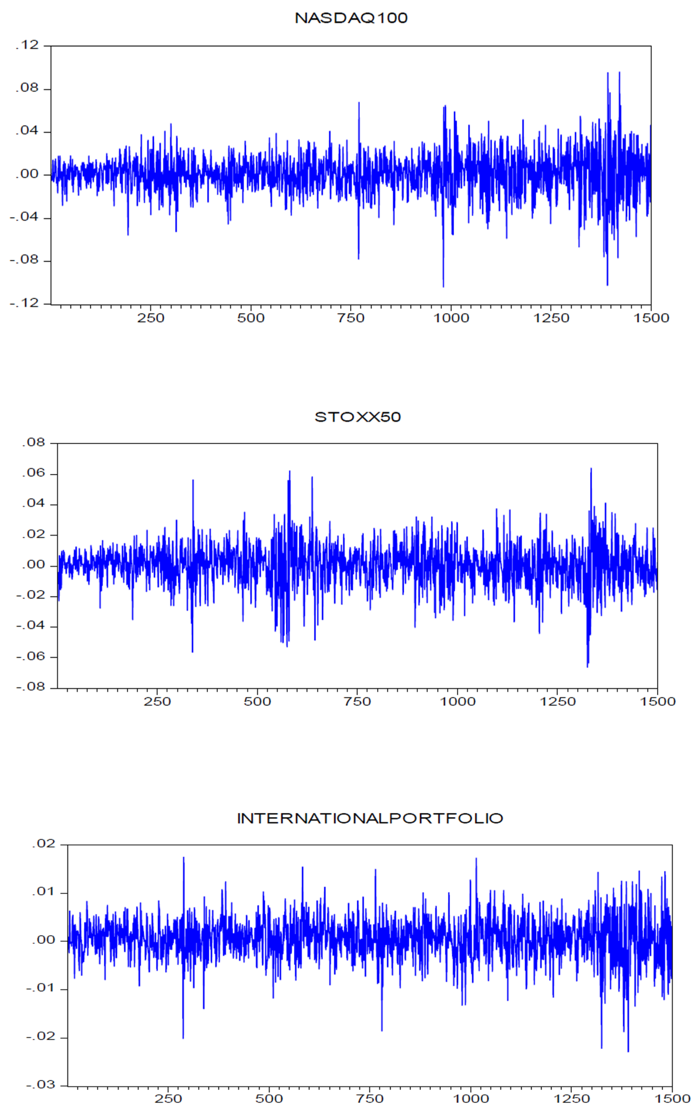
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Figure 9: 3

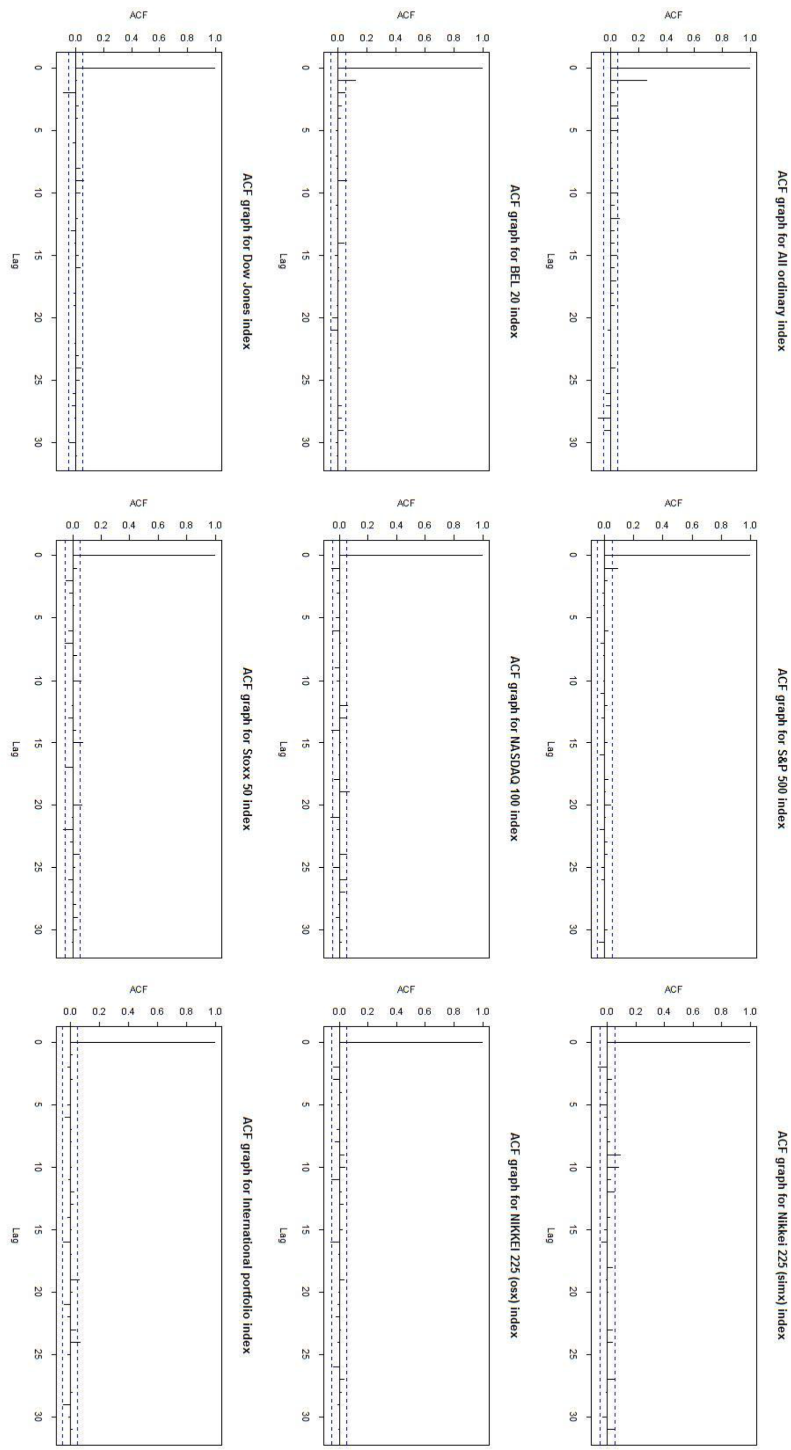


Figure 10: The caption goes here

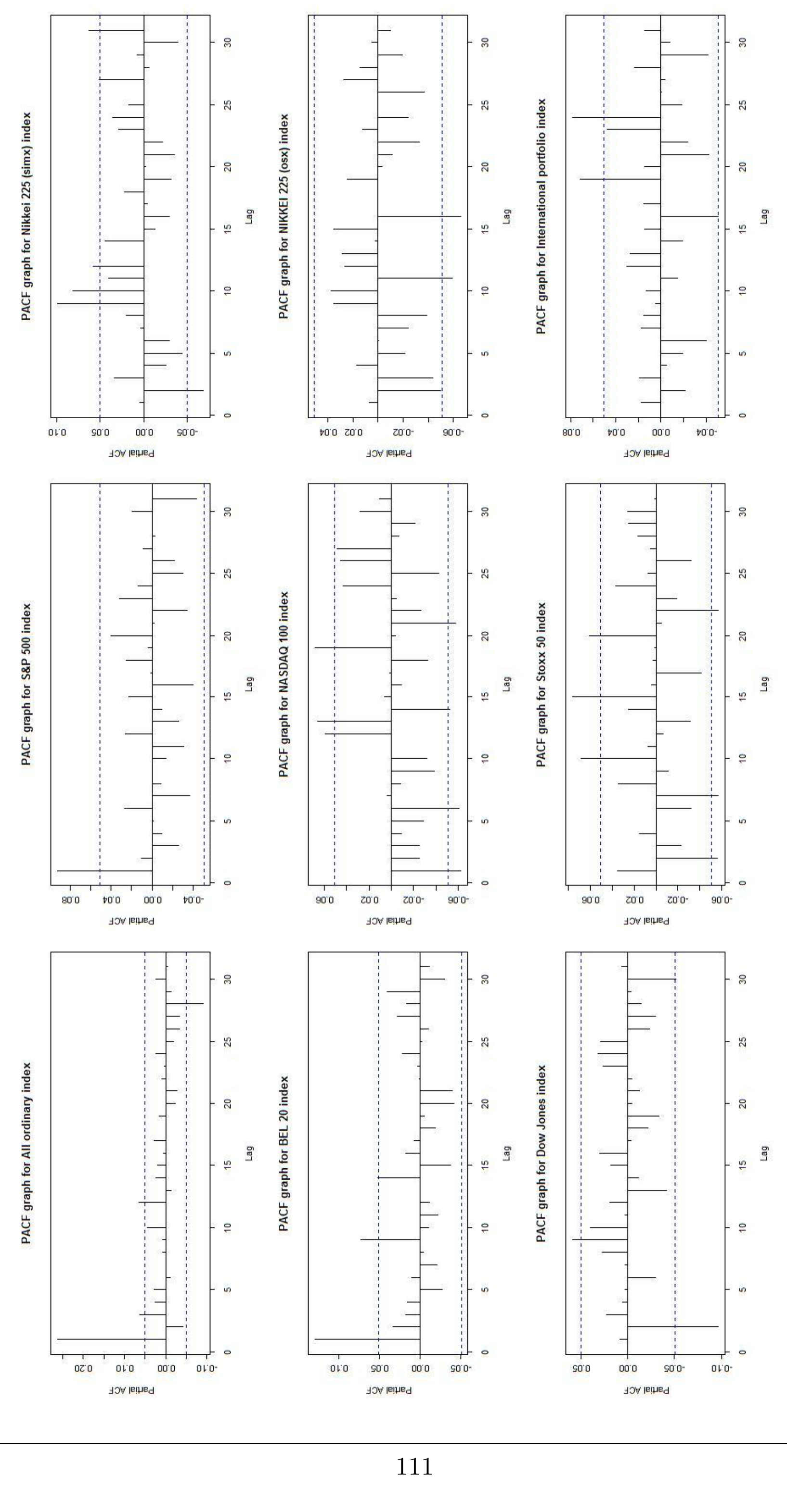


Figure 11: The caption goes here