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Examining the Impact of Index Futures on Information Efficiency of Stock Market: Evidence from US, Japan, HongKong and India

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Abstract

While much research has been done on the impact of futures trading on the volatility of the stock market, little is interested in the relationship between information flows and volatility on the introduction of futures trading. Futures trading can increase the channels through which information is transmitted into prices of the underlying market. Examining the impact of futures trading on information efficiency of stock market depends on the link between information and volatility. The objective of this study is to consider the impact of futures trading on information efficiency of stock market. Several cases of stock indices, such as S&P 500, Nikkei225, HSI and BSE Sensex were empirically examined. The application of GJR model in Econometrics and Approximate Entropy (ApEn) approach in time series analysis would help to find a comprehensive solution of the objective in this study. By using Wald tests to compare the structural changes of volatility in pre-futures and post-futures, our results suggest that the introduction of futures has improved information efficiency flowing to the spot market.

Keywords: stock index futures, information efficiency, stock market, volatility, time series

1. Introduction

The issue of the impact of futures trading on stock market volatility has received considerable attention, particularly after the financial crash in 2008. In fact, stock index futures has developed in mature markets for a long history and also introduced in emerging markets several years before, such as S&P 500 index futures, Nikkei 225 index futures, Hang Seng Index futures, and so on. Futures are used for hedging risk but at the same time this may cause changes in market efficiency as well as increase or decrease in the volatility. Futures trading is still viewed with suspicion by policymakers and investors. The problem what policymakers worried about is whether futures trading may impact positively or negatively on the underlying spot market. Therefore, it is necessary to analyze the effect of stock index futures on spot market volatility in detail. Theoretically, as an important financial innovation, stock index futures play a vital role in the development of stock market. It can be used to hedge the risk in a well-diversified portfolio of stocks. Furthermore, the introduction of index futures would not have a large impact on the longer-term trend of the stock market, but serving as a risk-hedging tool, may help stabilize the stock market. Nevertheless, it is argued that derivatives encourage speculation, which takes the form of higher spot market volatility. Almost since stock index futures began in 1982, discussions on this topic are being continued. On one hand, some commentators argue that increased volatility, following the onset of futures trading, has been viewed as a consequence of destabilizing forces. This view gained impetus following the stock market crash. On the other hand, some researchers suggest that futures trading should not be blamed for causing jump volatility of stock prices, however, futures markets provide a means by which the mechanism for the transmission of news is improved. The purpose of this article is to examine the impact of futures trading on information efficiency of stock market.

Researchers began to do much empirical analysis on this argument since the 1987 crash. By comparing the market volatility of S&P 500 in pre- futures and post-futures period, Edwards (1988) shows that futures induced short-run volatility, but this volatility does not appear to carry over to longer periods of time. Brown-Hruska and Kuserk (1995) indicate that a higher expected level of futures trading relative to cash market trading is associated with lower cash price volatility. Mckenzie, Brailsford and Faff (2001) model the mean return for individual share futures with TARCH method and draw that futures trading contributes to a general reduction in systematic risk and so on. Mazouz and Bowe (2006) investigate volatility effect of SSF's contract on London's stock exchange.

There was the reduction in unconditional volatility and systematic risk. Due to futures trading, the current news is incorporated in prices more rapidly, shorter impact of old news and lower shocks effect. Beer (2009) investigates single stock futures effect on South African stock market and finds a reduction in the level and changes in the structure of spot market volatility post single stock futures. There is faster incorporation of new news, shorter impact of old news and lower shocks effect. Das and Mishra (2011) employ GARCH model to examine the impact of index futures trading on the volatility of the index. There is evidence that the volatility has decreased significantly after the introduction of the index futures.

However, there exist several opposing views that stock index futures might increase the volatility of markets. By employing GARCH to examine the impact of trading in the FTSE 100 stock index futures on the volatility of spot market, Antoniou and Holmes (1995) suggest that futures trading has led to increased volatility, but improved the speed and quality of information flowing to the spot market. Chang, Cheng and Pinegar (1999) examine whether stock index futures affect stock market volatility and concludes that futures trading increases spot portfolio volatility. Bae, Kwon and Park (2004) measure the impacts of futures on spot market volatility and trading efficiency, and find that the introduction of KOSPI 200 index futures trading is associated with greater market efficiency with greater volatility in the underlying stock market. Shastri, Thirumalai and Zutter (2008) analyze on single-stock futures and find that the quality of the stock market improves substantially after the introduction of futures. Gahlot and Datta (2011) use EGARCH model to capture the asymmetric nature of the volatility and find that bad news has greater impact on the volatility as compared to good news and there is high persistence of volatility in the stock market.

Besides, some researchers turn to demonstrate the effect of futures trading on stock markets efficiency. Emphasizing the important effect of asymmetric information, GJR model is employed by Antoniou, Holmes and Priestley (1998) to find that there has been transference of asymmetries from the spot market to futures market. Ang and Cheng (2005) test market efficiency by applying a "specific announcement of news". Their results support that market become efficient after SSF trading. They attribute market efficiency to increase trading in futures market, high leverage and low transaction cost, which benefited arbitrageurs rather than speculators. Floros and Vougas (2008) discuss the relationship between Greek spot and futures markets and conclude that futures prices contain useful information about spot prices and futures markets are more efficient than stock markets in Greece. Debasish (2009) utilizes GARCH models to investigate volatility in NSE Nifty prices before and after the onset of futures trading. The results imply that futures improve pricing efficiency and the quality of information flowing to spot markets. Yang, Yang and Zhou (2012) investigate intraday price discovery and volatility transmission between Chinese stock index and the newly established stock index futures markets in China, and find that the cash market plays a more dominant role in the price discovery process. Lee, Stevenson and Lee (2014) reveal that futures trading has improved the speed and qualify of information flowing to the spot market.

Whether the introduction of futures can impact on volatility of the underlying market deserves discussion. To answer this question, we should make clear the effect mechanism of futures. Futures trading can increase the channels through which information is transmitted into prices of the underlying market. Examining the impact of futures trading on information efficiency of stock market depends on the link between information and volatility. The question of whether futures could impact on stock market lies in the nature of changes in volatility via information transmission before and after futures trading. Therefore, to fully understand the impact of futures trading on stock market volatility and whether any such impact is considerable, it is necessary to understand and take account of the causes of volatility.

The objective of this study is to consider the impact of futures trading on information efficiency of stock market. We empirically examine several global representative stock indices, such as S&P 500, Nikkei 225, HSI and BSE Sensex. Firstly, we model these time series data with advanced GJR-GARCH approach and decompose the volatility factors into four terms, including original systematic uncertainties, impact of recent market-specific news, impact of old news relating to days prior to the previous day, and asymmetric response. By using Wald tests to compare the structural changes of volatility in pre-futures and post-futures, an important connection is set up that any change in the recent and old information flow will change the volatility of the underlying spot market. Then, the Approximate Entropy (ApEn) method is applied to calculate the time series system complexity. By comparing the ApEn values pre-futures and post-futures, we draw the conclusion that greater impact of recent news and less persistent of old information improve the efficiency of the spot markets after the advent of futures trading.

2. Method

2.1 GJR-GARCH Model

An appropriate way to capture the time varying nature of volatility is to model the conditional variance as a GARCH process. Firstly introduced by Engle (1982), Autoregressive Conditional Hetero- skedasticity (ARCH) model is used to measure and forecast volatility of financial markets. However, in an ARCH (p) model, old news which arrived at the market more than p periods ago has no effect at all on current volatility. Furthermore, in many empirical applications with the linear ARCH (p) model a relatively long lag length in the conditional variance equation is often called for. In this light, the Generalized ARCH, or GARCH (p, q) model allowing for both a longer memory and more flexible lag structure is advanced by Bollerslev (1986). The GARCH (p, q) process is then given by:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{2}$$

Where ε_t denotes a real-valued discrete-time stochastic process, Ψ_t is the information set of all information through time t, ht is known as the conditional variance since it is a multi-period ahead estimate for the variance calculated based on any past relevant information. Using the GARCH model, it is possible to interpret the current fitted variance h_t. Following the idea of Bollerslev, Engle and Jeffrey (1988), p=q=1 is found to suffice in most applications. Then, GARCH (1, 1) formula is:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \theta_1 h_{t-1} \tag{3}$$

It is widely applied to empirical studies as it can capture important characteristics of the high frequency time series data, as described by Cont and Fonseca (2001, 2002). The most interesting feature not addressed by this model is asymmetric effect confirmed by French Schwert and Stambaugh (1987), Nelson(1991). This effect occurs when a negative shock (bad news) to financial time series is likely to cause volatility to rise by more than a positive shock (good news) of the same magnitude. One popular asymmetric formulation is explained below: the GJR model, named after the authors Glosten, Jagannathan and Runkle (1993). By modelling daily Japanese stock returns with many approaches, Engle and Ng (1993) indicate that GJR model is the best one in capturing the correct impact of news on volatility, especially is adequate to test the asymmetric effect. Abhyanka, Copeland and Wong (1997) use BDS test to indicate persistent nonlinear structure in the time series of stock market. The GJR model is a simple extension of GARCH with an additional term added to account for possible asymmetries. The conditional variance is expressed in this form:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma I_{t-1} \varepsilon_{t-1}^2 \tag{4}$$

Where $I_{t-1}=1$ if $\varepsilon_t<0$, $I_{t-1}=0$ otherwise. For a leverage effect, we would see $\gamma>0$. Notice now that the condition for non-negativity will be $\omega>=0$, $\alpha>=0$, $\beta>=0$, and $\alpha+\gamma>=0$. The detailed explanations are as follows.

h_t is decomposed into four terms: first, ω is the long-term average value, indicating original systematic uncertainties. Second, $\alpha\varepsilon_{t-1}^2$ is the lagged error term relating to the impact of recent market-specific news, i.e. information about volatility during the recent period. Hence, α can be viewed as a "news" coefficient, with a higher value implying that recent news has a greater impact on price changes. The increase in α post-futures suggests that information is being impounded in prices more quickly due to the introduction of futures trading. Third, βh_{t-1} is the fitted and lagged variance term which reflects the impact of old news relating to days prior to the previous day. β is the coefficient on the lagged variance term and thus to news which arrived before yesterday. The increase in the rate of information flows to be anticipated from the onset of futures trading is expected to lead to a reduction in uncertainty regarding previous news. This in turn will lead to a fall in the persistence of information. In other words, "old news" will have less impact on today's price changes. At last, $\gamma I_{t-1}\varepsilon_{t-1}^2$ is the asymmetric response, i.e. the leverage effects exist while the negative return shocks cause higher volatility than positive return shocks and it implies how volatility rised more after a large negative shock than a large positive one.

Examining the impact of futures trading on information efficiency of stock market depends on the link between information and volatility. Futures trading can increase the channels through which information is transmitted into prices of the underlying market. The question of whether futures trading could impact on stock market lies in the nature of changes in volatility via information transmission before and after futures trading. Therefore, to fully understand the impact of futures trading on stock market volatility and whether any such impact is considerable, it is necessary to understand and take account of the causes of volatility.

As mentioned above, volatility measured by conditional variance is decomposed into four terms (original systematic uncertainties, impact of recent market news, impact of old news, and asymmetric response). The market dynamics is related to both the transmission of news and the asymmetric response of volatility to news. For example, if market dynamics are a cause of asymmetries, then innovations, such as the introduction of futures, may be expected to impact not only on the level of volatility in the underlying market, but also on the structure and characteristics of that volatility.

By using Wald tests to examine whether differences between coefficients in the two sub-periods is significant, a structural change is suggested and we can say that there is indeed a difference emerging due to futures trading. This paper seeks to address the issue of the impact that the onset of futures trading has on stock market volatility.

2.2 Approximate Entropy (ApEn)

Approximate entropy (ApEn), is a recently developed statistic quantification measure of regularity or complexity in time series data. In the stochastic setting, analytic techniques to calculate ApEn(m, r), estimate ApEn(m, r, N), and give rates of convergence of the statistic to the formula all are reasonable problems for which a machinery can be developed along established probabilistic lines. The purpose applying the method in this paper is to give a mathematical formulas and statistics to quantify the concept of changing complexity of financial time series data. For many stochastic processes, we can analytically evaluate ApEn. Then the ApEn formula is indicated as follows.

Given a time series data, u(l), u(2), …, u(N), from measurements equally spaced in time, fix m (positive integer) and r (positive real), and form a sequence of vectors {x(i)} in R^m, defined by x(i) = [u(i), u(i+l), ..., u(i+m-l)]. For each i, 1≤ i ≤N-m+1, we define d[x(i),x(j)], the distance between vectors x(i) and x(j) as

$$d[x(i),x(j)] = \max_{k=1,2,...,m} |u(i+k-1) - u(j+k-1)| \quad (5)$$

Next define $C_i^m(r)$=(number of j such that d[x(i),x(j)]≤r)/(N-m+l)

Define

$$\Phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \log C_i^m(r) \quad (6)$$

Fix m and r, define

$$ApEn(m,r) = \lim_{N\to\infty} [\Phi^m(r) - \Phi^{m+1}(r)] \quad (7)$$

Given N data points, we implement this formula by defining the statistic

$$ApEn(m,r,N) = \Phi^m(r) - \Phi^{m+1}(r) \quad (8)$$

The value of m represents the window length of compared runs of data, and r specifies a real filtering level: superposition of noise of magnitude much smaller than r minimally affects the ApEn calculation. The probabilistic form of ApEn insures robustness to outliers. We interpret ApEn as a parameter that measures correlation, persistence, or regularity: smaller ApEn values mean more persistence and correlation, and larger ApEn values mean more independence.

ApEn measure the likelihood that runs of patterns that are close remain close on next incremental comparisons. ApEn can be computed for any time series, chaotic or otherwise. The intuition motivating ApEn is that if joint probability measures that describe each of two systems are different, then their marginal distributions on a fixed partition are likely different. Based on more complex time series data, ApEn value is larger, which indicates that the probability of similar pattern caused by old news and historical changes is lower, however, the new pattern probability is larger. In other words, old news have less impact on today's price changes, but recent news has greater impact on price changes as that the efficiency of the markets is improved and information flows more quickly.

To answer question of whether futures trading could impact on information efficiency of stock market, we propose the family of system parameters ApEn(m, r), and related statistics ApEn(m, r, N). By comparing the ApEn statistics of index between pre-futures and post-futures, we have effectively discriminated the pattern changes of time series before and after the introduction of futures. The capability to discern changing complexity from a relatively small amount of data holds promise for applications of ApEn in this problem.

3. Results

3.1 Data Description

The data include daily figures for the price and return series of four stock indices, such as S&P 500, Nikkei 225, HSI and BSE Sensex. All data are obtained from Yahoo finance (http://finance.yahoo.com/). By modeling the return series with GJR (1, 1) approach on each stock index, volatilities between pre-futures period and post-futures period would be calculated and compared later. Then, detailed analysis on the results appeared to demonstrate the effects of futures trading on the underlying spot market, especially on the process of information transmission. The return of stock index was calculated as:

$$R_t = \ln(p_t / p_{t-1}) = \ln(p_t) - \ln(p_{t-1}) \quad (9)$$

Where R_t denotes the natural logarithm return of the closing price, and p_t is the closing price of stock index at t day.

Figure 1 illustrates the volatility features of S&P 500 index and its return series before and after the introduction of futures trading. The S&P 500 index futures trading was introduced in Chicago Board of Trade on Apr. 21st, 1982. This index represents the bulk of the value in the US equity market. The data of this index at daily levels are examined from Jan. 3rd, 1977 through the end of December 1987. It is easy to see the great growth of index over the period and the largest one-day percentage decline on Oct. 19th, 1987. On the “Black Monday”, stock volatility jumped dramatically. In addition, there are two other important features can be seen. For one thing, the tendency for volatility appears in bunches. In other words, large returns are expected to follow large returns, and small returns to follow small, due to clustering of information arrivals. This is the effect named volatility clustering that GARCH is designed to measure. For another, it is apparent that volatility is higher when prices are falling than growing. This is the asymmetric response or leverage effect mentioned above in section 2.

Figure 2 illustrates the volatility features of Nikkei index and its return series pre-futures and post-futures.The Nikkei 225 index futures trading was first introduced at Singapore Exchange (SGX) in Sept. 3rd, 1986. The data of this index at daily levels are examined from Jan. 4th, 1984 through the end of December 1989.

Figure 3 depicts the volatility features of HSI and its return series in two sub-periods. The HSI futures trading was introduced in Hong Kong Futures Exchange on May 6th, 1986. The daily data of this index are examined from Jan. 4th, 1982 through the end of December 1990. It is noted that on Oct. 19th, 1987, Hang Seng Index (HSI) slumped 420 points in one day which represented a significant margin. Facing the crisis, the government closed the stock exchange for four days and dropped a further 1211 points after the four-day suspension of trading. The crash then spreads west through international time zones to Europe, hitting the United States. Finally, it takes several years to recover.

Figure 4 illustrates the volatility features of Sensex index and its return series in two periods. As the futures trading launched in emerging markets, Sensex index futures began on June 9th, 2000 in Bombay Stock Exchange (BSE) of India. The data of this index at daily levels are examined from July 1st, 1997 through the end of December 2003. Sensex is the benchmark index for the Indian stock market and it is the most frequently used indictor while reporting on the state of the market.

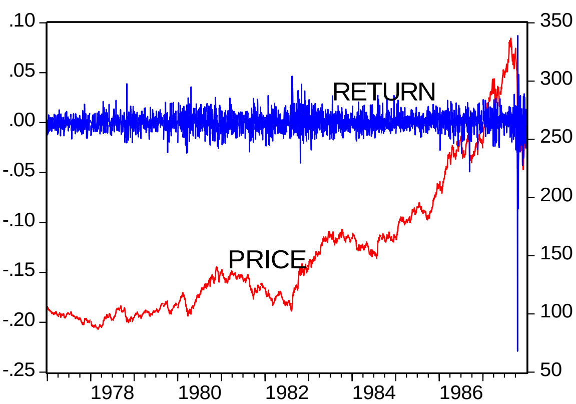

Figure 1. Series of S&P 500

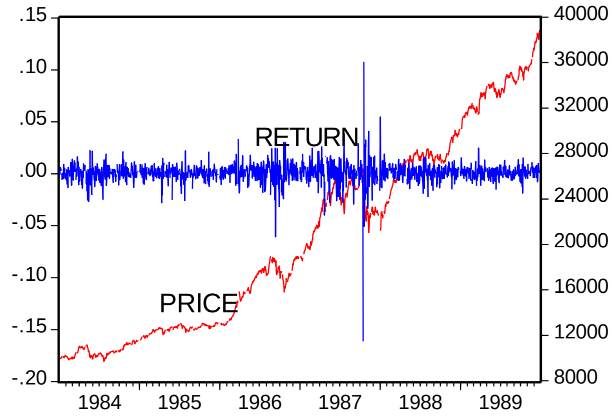

Figure 2. Series of Nikkei 225

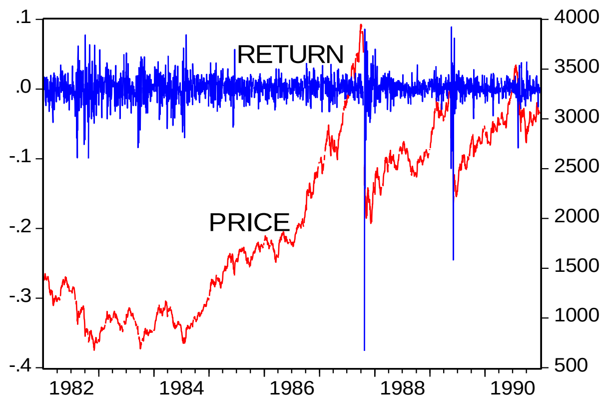

Figure 3. Series of HSI

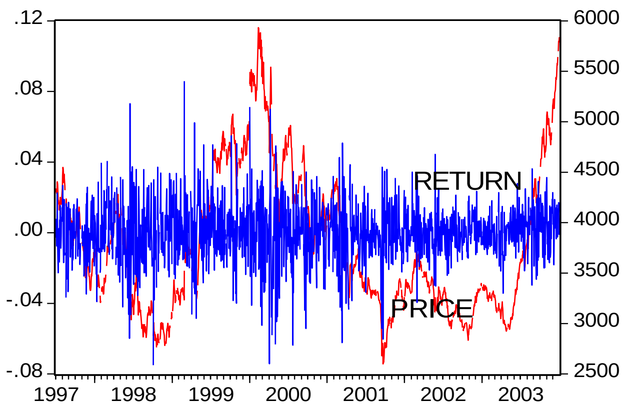

Figure 4. Series of Sensex

3.2 Empirical Results

To fully understand the impact of futures trading on the volatility of the stock market, it is necessary to model volatility pre and post futures by using a technique that takes account of possible asymmetric responses to news. To determine whether the existence of futures has led to changes in the asymmetric response of volatility, the data set is partitioned into two subperiods (pre- and postfutures). By establishing GJR (1, 1) model on return series of all four stock indices, eq. (4) is estimated for both subperiods , and comparisons of the estimates are made. The empirical results were collected in Table 1.

Table 1. Coefficient estimate results on return series of S&P 500, Nikkei 225, HSI and BSE Sensex

Index	periods	Coefficient	Estimation	StdError	z-Statistic	Prob.
S&P 500	Pre-futures 1/03/1977 —4/21/1982	ω_{pre}	8.75E-07	3.29E-07	2.658499	0.0078
		α_{pre}	0.021769	0.010939	1.990005	0.0466
		β_{pre}	0.948563	0.010704	88.61548	0.0000
		γ_{pre}	0.033322	0.012314	2.705926	0.0068
	Post-futures 4/22/1982 —12/31/1987	ω_{post}	5.25E-06	1.04E-06	5.047270	0.0000
		α_{post}	0.057295	0.01334	4.295059	0.0000
		β_{post}	0.829663	0.01534	54.08518	0.0000
		γ_{post}	0.144065	0.014515	9.925451	0.0000
Nikkei 225	Pre-futures 1/04/1984 —9/03/1986	ω_{pre}	6.99E-06	1.76E-06	3.974837	0.0001
		α_{pre}	0.095781	0.03148	3.042575	0.0023
		β_{pre}	0.726403	0.053246	13.64243	0.0000
		γ_{pre}	0.096535	0.043213	2.233931	0.0255
	Post-futures 9/04/1986 —12/29/1989	ω_{post}	1.32E-05	1.65E-06	8.018934	0.0000
		α_{post}	0.014713	0.025466	0.577774	0.5634
		β_{post}	0.579622	0.026841	21.59503	0.0000
		γ_{post}	0.698528	0.041379	16.88103	0.0000
HSI	Pre-futures 1/04/1982 —5/06/1986	ω_{pre}	1.27E-05	2.55E-06	4.980356	0.0000
		α_{pre}	0.040494	0.014908	2.716275	0.0066
		β_{pre}	0.869464	0.015707	55.35507	0.0000
		γ_{pre}	0.100754	0.019796	5.089711	0.0000
	Post-futures 5/07/1986 —12/31/1990	ω_{post}	1.82E-05	2.39E-06	7.629219	0.0000
		α_{post}	0.127244	0.032429	3.923725	0.0001
		β_{post}	0.610948	0.006911	88.39594	0.0000
		γ_{post}	0.787551	0.040412	19.48822	0.0000
BSE Sensex	Pre-futures 7/01/1997 —6/09/2000	ω_{pre}	3.56E-05	9.81E-06	3.628477	0.0003
		α_{pre}	0.002338	0.016699	0.140024	0.8886
		β_{pre}	0.837672	0.038727	21.63023	0.0000
		γ_{pre}	0.126867	0.038903	3.261081	0.0011
	Post-futures 6/10/2000 —5/13/2003	ω_{post}	1.88E-05	4.26E-06	4.411568	0.0000
		α_{post}	0.059156	0.029597	1.998745	0.0456
		β_{post}	0.742666	0.042971	17.28311	0.0000
		γ_{post}	0.200369	0.045926	4.362860	0.0000

Table 1 indicates the weights which are estimated during pre-futures period and during post-futures period respectively. These coefficients are statistical significant and are satisfied with the constraint conditions of the GJR model. In the GJR model the asymmetric response of conditional volatility to information is captured. As shown in Table 1, all the countries' stock indexes, exhibit statistically significant asymmetric effects, and all the coefficients were different from the ones pre-futures. The implications of the results are as follows.

As already explained in section 2, volatility factors were decomposed into four terms whose weights are now calculated on the long run average, the impact of recent market-specific news (the symmetric news), the impact of old news (the previous forecast), and asymmetric response (the negative news). First of all, all the weights of the four combinations post-futures are quite different from the ones pre-futures. It implies that there exist effects of futures on the volatility of spot market. Secondly, the increase of α in post-futures period indicates that recent news which are attributable to market-specific factors has a greater impact on the spot market following the onset of futures. Thus, information is being transmitted in prices more quickly since the onset of futures trading. Thirdly, the fall in value of β post-futures implies a reduction in uncertainty regarding pervious news and less persistent of information owing to the introduction of futures trading. Fourthly, the asymmetry term, γ, has the positive sign and significant. The increase of γ post-futures suggests that there exists an leverage effect and the effect of the same magnitude on volatility rises more due to bad news than good. Accordingly, it is quite obvious that the impact of information (recent and old news) on volatility is much greater and less persistent post-futures. Even though the coefficients are different between the two sub-periods, there needs to be a test which suggests that there has been a structural change in the two sub-periods. A Wald test could be used to test that.

The Wald test is a way of testing the significance of particular explanatory variables in a statistical model. If a structural break is suggested it will consolidate the results and we can say that there is indeed a difference emerging due to futures trading. However if the test suggests that the difference between the two is not significant then it might not suggest that futures has indeed have an effect on the spot. So this test is important to be performed to authenticate the validity of the objective in this paper. In principle, it is possible to proceed by specifying the restrictions α_{post}-α_{pre}=0, β_{post}-β_{pre}=0, γ_{post}-γ_{pre}=0 in the Wald test option.

Table 2. Wald tests on coefficients in two sub-periods

Index	Null Hypothesis	Wald Test			
		F-statistic		Chi-square	
		Value	Prob.	Value	Prob.
S&P 500	$\alpha_{post}=\alpha_{pre}$, $\beta_{post}=\beta_{pre}$, $\gamma_{post}=\gamma_{pre}$	90.35393	0.0000	271.0618	0.0000
	$\alpha_{post}=\alpha_{pre}$	7.092409	0.0078	7.092409	0.0077
	$\beta_{post}=\beta_{pre}$	60.07866	0.0000	60.07866	0.0000
	$\gamma_{post}=\gamma_{pre}$	58.21242	0.0000	58.21242	0.0000
Nikkei 225	$\alpha_{post}=\alpha_{pre}$, $\beta_{post}=\beta_{pre}$, $\gamma_{post}=\gamma_{pre}$	89.87948	0.0000	269.6384	0.0000
	$\alpha_{post}=\alpha_{pre}$	10.13418	0.0015	10.13418	0.0015
	$\beta_{post}=\beta_{pre}$	29.90593	0.0000	29.90593	0.0000
	$\gamma_{post}=\gamma_{pre}$	211.6475	0.0000	211.6475	0.0000
HSI	$\alpha_{post}=\alpha_{pre}$, $\beta_{post}=\beta_{pre}$, $\gamma_{post}=\gamma_{pre}$	529.9476	0.0000	1589.843	0.0000
	$\alpha_{post}=\alpha_{pre}$	7.155842	0.0076	7.155842	0.0075
	$\beta_{post}=\beta_{pre}$	1399.044	0.0000	1399.044	0.0000
	$\gamma_{post}=\gamma_{pre}$	288.8309	0.0000	288.8309	0.0000
BSE Sensex	$\alpha_{post}=\alpha_{pre}$, $\beta_{post}=\beta_{pre}$, $\gamma_{post}=\gamma_{pre}$	3.021381	0.0291	9.064142	0.0285
	$\alpha_{post}=\alpha_{pre}$	3.685437	0.0553	3.685437	0.0549
	$\beta_{post}=\beta_{pre}$	4.888265	0.0274	4.888265	0.0270
	$\gamma_{post}=\gamma_{pre}$	2.561393	0.1099	2.561393	0.1095

Accordingly, it is quite obvious that the impact of information on volatility is much greater and less persistent post-futures. The introduction of futures trading leads to an increase in the flow rate of information to the underlying spot market. Although the spot market may be more volatile post-futures, the efficiency of the stock market is improved owing to the advent of futures trading.

Besides, the ApEn values of S&P 500, Nikkei 225, HSI and BSE Sensex pre-futures and post-futures were calculated while m=2, r=0.1*standard deviations of the u(i) data. The results indicated in Table 3 using the software of Matlab 7.0. For each distinct ApEn statistics of index, values of pre-futures were markedly different from any values of post-futures.

Table 3. The ApEn values of S&P 500, Nikkei 225, HSI and BSE Sensex

Index	Sample periods	ApEn
S&P 500	Pre-futures(1/03/1977—4/21/1982)	1.3395
	Post-futures(4/22/1982—12/31/1987)	1.6003
Nikkei 225	Pre-futures(1/04/1984—9/03/1986)	1.0241
	Post-futures(9/04/1986—12/29/1989)	1.3321
HSI	Pre-futures(1/04/1982—5/06/1986)	1.2715
	Post-futures(5/07/1986—12/31/1990)	1.5251
BSE Sensex	Pre-futures(7/01/1997—6/09/2000)	0.9663
	Post-futures(6/10/2000—12/31/2003)	1.1398

It is indicated that the ApEn values of indice become larger after the introduction of futures trading in both developed markets and emerging markets. Because larger ApEn values mean less old pattern persistence and larger new pattern stochastic, recent news plays a more vital role in today's price changes. On the basis of calculations that included the above theoretical analysis, I drew a preliminary conclusion that information efficiency of spot markets is improved with the development of index futures. It implies that stock index futures has significant and positive effect on information transmission through the underlying spot markets.

4. Discussion

In this paper, we aim to examine the effects of the introduction of futures trading on the underlying spot markets. Previous studies tend to inspect whether futures trading could stabilize or destabilize spot markets. However, few studies consider the relationship between information flows and volatility associated with the onset of futures trading. For this reason, it is necessary to analyze the process that futures trading could affect the underlying spot market volatility in terms of influencing the information transmission. Futures trading can increase the channels through which information is transmitted into prices of the underlying market. Examining the impact of futures trading on information efficiency of stock market depends on the link between information and volatility.

In order to better analyze this process of impacts, we use the GJR-GARCH model to decompose the volatility factors into four terms, i.e. ω is the long-term average value; $\alpha\varepsilon_{t-1}^2$ is the lagged error term relating to the impact of recent market-specific news; βh_{t-1} is the fitted and lagged variance term which reflects the impact of old news relating to days prior to the previous day; $\gamma I_{t-1}\varepsilon_{t-1}^2$ is the asymmetric response, which implies that volatility increases more after a negative shock than a positive one. Then, we calculate the ApEn values, and compare the changes of the ApEn values pre-futures and post-futures.

To empirically measure and estimate the effects of futures trading on volatility, we examine several stock indices which have been successfully introduced in many developed markets and emerging markets, such as S&P 500, Nikkei225, HSI and BSE Sensex. The outcome of detailed analysis can be summarized as follows. First, all the four coefficients are proved significantly different between post-futures and pre-futures by the Wald test. It implies that there exist effects of futures on the volatility of spot market. Second, the increase of α post-futures in most cases, implying that recent news which are attributable to market factors has a greater impact on the spot market following the onset of futures. Thus, information is being transmitted in prices more quickly since the onset of futures trading. Third, the fall of β post-futures suggests reduction in uncertainty regarding pervious news and less persistent of old information after the advent of futures trading. Finally, the asymmetry response, γ, proves that there exists leverage effect of the information arrival on the volatility. Besides, all the calculations of the ApEn values indicate that the ApEn values of indice become larger after the introduction of futures trading in both developed markets and emerging markets. It implies that recent news plays a more vital role in today's price changes. Hence, information efficiency of spot markets is improved with the development of index futures.

In conclusion, no matter whether futures trading could increase or decrease the volatility of the underlying spot markets, the efficiency of the stock market is improved owing to the introduction of futures trading. Futures trading can increase the channels through which information is transmitted into prices of the stock market. The investigations of this paper provide no empirical support for policy makers that attempts to curtail trading in pursuit of market stability. Hence, as one financial derivative, futures trading doesn't deserve the blame for market crash. From a policymaker perspective, the financial authorities who are hesitate to make a new attempt to the launch of stock index futures should firstly complete basic system and technical preparations for this, and then learn from the corresponding experiences of the mature markets and the emerging markets.

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References

Abhyanka, A., Copeland, L. S., & Wong, W. (1997). Uncovering nonlinear structure in real-time stock-market indexes: The S&P 500, the DAX, the Nikkei 225, and the FTSE-100. *Journal of Business & Economic Statistics, 15*(1), 1-14. http://dx.doi.org/10.1080/07350015.1997.10524681

Ang, J. S., & Cheng, Y. (2005). Financial innovations and market efficiency: The case for single stock futures. *Journal of Applied Finance, 15*(1), 38-51.

Antoniou, A., & Holmes, P. (1995). Futures trading, information and spot price volatility: Evidence for the FTSE-100 stock index futures contract using GARCH. *Journal of Banking & Finance, 19*(1), 117-129. http://dx.doi.org/10.1016/0378-4266(94)00059-C

Antoniou, A., Holmes, P., & Priestley, R. (1998). The effect of stock index futures trading on stock index volatility: An analysis of the asymmetric response of volatility to news. *The Journal of Futures Markets, 18*(2), 151-166. http://dx.doi.org/10.2469/dig.v28.n4.361

Bae, S. C., Kwon, T. H., & Park, J. W. (2004). Futures trading, spot market volatility, and market efficiency: The case of the Korean index futures markets. *The Journal of Futures Markets, 24*(12), 1195-1228. http://dx.doi.org/10.1002/fut.20135

Beer, J. D. (2009). Changes in the volatility level and structure of shares post single stock futures trading. *Corporate Ownership & Control, 7*(2), 296-311.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. http://dx.doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T., Engle, R. F., & Jeffrey, M. (1988). A capital asset pricing model with time-varying covariances. *The Journal of Political Economy, 96*, 116-131. http://www.jstor.org/stable/1830713

Brown-Hruska, S., & Kuserk, G. (1995). Volatility, volume, and the notion of balance in the S&P 500 cash and futures markets. *The Journal of Futures Markets, 15*(6), 677-689. http://dx.doi.org/10.1002/fut.3990150606

Chang, E. C., Cheng, J. W., & Pinegar, J. M. (1999). Does futures trading increase stock market volatility? The case of the Nikkei stock index futures markets. *Journal of Banking & Finance, 23*(5), 727-753. http://dx.doi.org/10.1016/S0378-4266(98)00069-7

Cont, R. (2001). Empirical properties of asset returns: Stylized facts and statistical issues. *Quantitative Finance, 1*, 223-236. http://dx.doi.org/10.1080/713665670

Cont, R., & Fonseca, J. D. (2002). Dynamics of implied volatility surfaces. *Quantitative Finance, 2*(1), 45-60. http://dx.doi.org/10.1088/1469-7688/2/1/304

Das, S. C., & Mishra, B. (2011). The effect of futures trading on the underlying volatility: Evidence from the Indian stock market. *Vilakshan: The XIMB Journal of Management, 7*(3), 99-110.

Debasish, S. S. (2009). Effect of futures trading on spot-price volatility: Evidence for NSE Nifty using GARCH. *The Journal of Risk Finance, 10*(1), 67-77. http://dx.doi.org/10.1108/15265940910924508

Edwards, F. R. (1988). Does futures trading increase stock market volatility? *Financial Analysts Journal, 1*, 63-69. http://dx.doi.org/10.2469/faj.v44.n1.63

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. Inflation. *Econometrica, 50*, 987-1008. http://dx.doi.org/10.2307/1912773

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance, 48*(5), 1749-1778. http://dx.doi.org/10.1111/j.1540-6261.1993.tb05127.x

Floros, C., & Vougas, D. V. (2008). The efficiency of Greek stock index futures market. *Managerial Finance, 34*(7), 498-519. http://dx.doi.org/10.1108/03074350810874451

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics, 19*(1), 3-29. http://dx.doi.org/10.1016/0304-405X(87)90026-2

Gahlot, R., & Datta, S. K. (2011). Impact of future trading on efficiency and volatility of the Indian stock market: A case of CNX 100. *Journal of Transnational Management, 16*(1), 43-57. http://dx.doi.org/10.1080/15475778.2011.550213

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801. http://dx.doi.org/10.1111/j.1540-6261.1993.tb05128.x

Lee, C. L., Stevenson, S., & Lee, M. L. (2014). Futures trading, spot price volatility and market efficiency: Evidence from European real estate securities futures. *The Journal of Real Estate Finance and Economics, 48*(2), 299-322. http://dx.doi.org/10.1007/s11146-012-9399-3

Mazouz, K., & Bowe, M. (2006). The volatility effect of futures trading: Evidence from LSE traded stocks listed as individual equity futures contracts on LIFFE. *International Review of Financial Analysis, 15*(1), 1-20. http://dx.doi.org/10.1016/j.irfa.2005.07.001

Mckenzie, M. D., Brailsford, T. J., & Faff, R. W. (2001). New insights into the impact of the introduction of futures trading on stock price volatility. *The Journal of Futures Markets, 21*(3), 237-255. http://dx.doi.org/10.2469/dig.v31.n3.937

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*, 347-370. http://dx.doi.org/10.2307/2938260

Shastri, K., Thirumalai, R. S., & Zutter, C. J. (2008). Information revelation in the futures markets: evidence from single stock futures. *The Journal of Futures Markets, 28*(4), 335-353. http://dx.doi.org/10.1002/fut.20313

Yang, J., Yang, Z., & Zhou, Y. (2012). Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China. *Journal of Futures Markets*, *32*(2), 99-121. http://dx.doi.org/10.1002/fut.20514