FACULTY OF BUSINESS AND LAW

School of

ACCOUNTING, ECONOMICS AND FINANCE

School Working Papers – Series 2004

SWP 2004/08

STRUCTURAL EFFECTS AND SPILLOVERS IN HSIF, HSI AND S&P500 VOLATILITY

Gerard Gannon*
Department of Accounting, Economics and Finance
Deakin University
Email: gerard@deakin.edu.au

and

Siu Pang Au-Yeung
Department of Finance
Faculty of Economics and Commerce
The University of Melbourne

Email elvis_ay@hotmail.com Gerard Gannon*

URL: http://www.deakin.edu.au/fac_buslaw/sch_aef/publications/default.htm

STRUCTURAL EFFECTS AND SPILLOVERS IN HSIF, HSI AND S&P500 VOLATILITY

Gerard Gannon*
Department of Accounting, Economics and Finance
Faculty of Business and law
Deakin University
Burwood Highway, Burwood
Victoria 3128
Australia
Fax (61 3) 92546283 Tel (61 3) 92546243
Email: gerard@deakin.edu.au

and

Siu Pang Au-Yeung
Department of Finance
Faculty of Economics and Commerce
The University of Melbourne
Grattan Street, Parkville
Victoria 3010
Australia
Email elvis_ay@hotmail.com Gerard Gannon*

Abstract

We adopt a BEKK-GARCH framework and employ a systematic approach to jointly examine structural breaks in the Hong Kong cash index and index futures volatility and volatility spillovers from the S&P 500 cash and futures. Multiple switching dummy variables are included in the variance equations to test for any structural changes in the autoregressive volatility structure due to the events that have taken place in the Hong Kong market. Abolishment of the up-tick rule, increase of initial margins and electronic trading of the Hang Seng Index Futures are found to have significant impact when U.S. market spillovers are excluded from a restricted model. Volatility spillovers from the US market are found to have a significant impact and account for some mis-specification in the restricted model.

* **Corresponding author**

KEY WORDS: Multivariate Volatility, Regulatory change, Volatility transmissions.

JEL G14

STRUCTURAL EFFECTS AND SPILLOVERS IN HSIF, HSI AND S&P500 VOLATILITY

Abstract

We adopt a BEKK-GARCH framework and employ a systematic approach to jointly examine structural breaks in the Hong Kong cash index and index futures volatility and volatility spillovers from the S&P 500 cash and futures. Multiple switching dummy variables are included in the variance equations to test for any structural changes in the autoregressive volatility structure due to the events that have taken place in the Hong Kong market. Abolishment of the up-tick rule, increase of initial margins and electronic trading of the Hang Seng Index Futures are found to have significant impact when U.S. market spillovers are excluded from a restricted model. Volatility spillovers from the US market are found to have a significant impact and account for some mis-specification in the restricted model.

KEY WORDS: Volatility transmissions, Regulatory change, Multivariate Volatility.

JEL code G14

1. INTRODUCTION

Modeling of international financial market spillovers in both return and volatility processes has attracted a large focus in recent years. The need for regulators, market makers, speculators and traders to understand the effects of overnight news transmission has fuelled much of this research. This area is still very much of interest as the results of past research are rather mixed and firm conclusions only drawn from research where the data analysis and modeling is unambiguous. We propose such a study in this paper where we are able to rely on data sampled from a stock and futures market that has well defined interventions and institutional links to overseas markets. The interventions are those that have been imposed in the Hong Kong markets. Information spillovers might be expected because of the direct link between the Hong Kong and U.S. currencies and non-overlapping trading time in these financial markets.

Restricted short selling was first allowed in the Hong Kong stock market in January1994 and the up-tick rule was eventually abolished on 25 March 1996. The objective is to provide more flexibility in stock trading by allowing short selling of stocks at times of downward market movements and hence boosts the short selling transactions. While relaxing short selling restrictions will increase the market efficiency, it may also influence the price discovery process between the futures and spot markets. Conversely, in response to the substantial increase in the volatility of Hang Seng Index (HSI) during the Asian Financial Crisis, the Hong Kong Futures Exchange (HKFE) raised the initial margins of Hang Seng Index Futures (HSIF) from HK$75,000 to HK$90,000 per contract, which represents a significant 20% increase, on 7 November 1997. The upward adjustment in initial margin also aimed at curbing stock market manipulation through the futures contracts. Moreover, with the objective of improving market transparency and efficiency, the trading of HSIF has migrated from an open outcry system to an electronic system, Hong Kong Automatic Trading System (HKATS) since 5 June 2000. All these market events were reported by Au-Yeung and Gannon (2003) to have a significant effect on the volatility structure of both index and futures returns. They found a strong unidirectional information flow from the futures to the spot index based on likelihood ratio tests, which is consistent with the documented evidence in other markets.

A natural extension would be to test if there exists volatility spillovers from other markets as the global financial market becomes more integrated. For instance, the US market, which has strong connection with the Hong Kong market owing to the linked exchange rate system, may play an important role on the inter-temporal relationship. The presence of strong volatility spillovers may alter or even diminish the effects of regulatory change on the HSI and HSIF return volatility. This may be the case if the volatility effect from the foreign markets leads the changes in the Hong Kong market.

Hamao, Masulis and Ng (1990) investigate price changes and volatility across major financial markets by employing GARCH-M models. They found significant volatility spillover effects from the US market (S&P 500) to the UK (FTSE 100) and Japanese market (Nikkei 225) using open-to-close returns. Karolyi (1995) adopted a multivariate GARCH model to test the returns and volatility transmissions between the US and Canadian markets and found time-varying cross market dependence between returns and volatilities of S&P 500 and TSE 300. Wei et al (1995) test the volatility spillover effect from the US and Japanese markets to the emerging Asian markets by using an univariate GARCH estimator. They find no significant volatility spillover effects using open-to-close returns. Liu and Pan (1997) employ a similar univariate GARCH model and do not find significant volatility spillover from both the US and Japanese markets.

Gannon and Choi (1998) used a structural volatility model to test for any volatility spillovers from S&P 500 index futures by employing intraday data and they found S&P 500 futures has a great impact on the volatility of HSI and HSIF. Recently, Ng (2000) tested the volatility spillover effects from the US and Japanese market to the Pacific-Basin markets by first modeling the conditional volatilities of the US and Japanese market returns with an asymmetric dynamic covariance (ADC) model. Employing weekly returns, she found no volatility spillover from the US market to Hong Kong market and that the effects decreased after the Hong Kong dollar was pegged to the US dollars in 1983. In order to test for the presence of any volatility spillover from the US market to the Hong Kong market we allow for the volatility spillover effect from the US market by including the most current return volatilities of S&P 500 and its futures into the model.

In this paper, we adopt a bi-variate GARCH framework to examine jointly these regulatory induced structural effects and U.S. market volatility spillover effects on HSI and HSIF open to close intra-day volatility. Switching dummy variables are included in the variance equations to test for any structural changes in return volatilities due to the market events. This is an innovative approach as we allow all volatility parameters to systematically adjust to each regime switch. The choice of the Hong Kong market is motivated by the occurrence of policy changes and market innovations before, during and after the eruption of the Asian Financial Crisis in 1997.

The paper is organized as follows. In section II we discuss the data and the volatility model specification is described in section III. In section IV we analyse the joint impact of the structural changes in the Hong Kong market and the impact of volatility spillovers on the intertemporal relationship. Section V concludes the paper.

2. MARKET STRUCTURE, DATA AND METHODOLOGY

2.1. Trading Information of HSI and HSIF

The HSI is a market capitalization-weighted index of 33 constituent stocks trading in the Hong Kong Stock Exchange (HKSE), which accounts for about 70% of the total market capitalization. The influence of each constituent stock on the index's performance is directly proportional to its relative market value. There are three trading sessions: the normal morning session is from 10:00a.m. to 12:30p.m., the extended morning session is from 12:30p.m. to 2:30p.m., the afternoon session starting at 2:30p.m., ending at 4:00p.m.. The HSIF is one of the most active trading derivative securities in the Asia-Pacific region with a contract multiplier of $50 on the index value. Its normal trading hours were from 10:00a.m to 12:30p.m and 2:30p.m. to 4:00p.m., before 20 November 1998. Since then, the trading hours have extended to 9:45p.m. to 12:30p.m., in the morning session and 2:30p.m. to 4:15p.m., in the afternoon session. The HSIF expires 1 day before the last business day of each month. There are numerous transaction costs in trading stocks. They include brokerage fee of 0.25% of the transaction value, transaction levy of 0.01% of the amount of consideration for every purchase and sale, transaction tariff of HK$0.50 for every purchase and sale and ad valorem stamp duty at the ratio of HK$1.125 for every HK$1000 or part thereof on the transaction value on both buyers and sellers. On the other hand, the cost of trading HSIF includes trading fees and levies of HK$11.50 per side per contract and a minimum commission of HK$60.[1] The initial margin is set at HK$47,750 at the time this paper is written which is equivalent to about 7.5% of each contract value, the initial margin is payable on the amount of gross position rather than net positions.[2] Therefore, the trading cost of HSIF is considerably less than that of stock transactions.

2.2 Data Collection

The sample period starts from 1st July 1994 and ends in 31st August 2001, which covers all the potential structural events in the market as described earlier. Daily opening and closing prices of the HSI and HSIF and daily trading volume for each HSIF contracts within the sample period are collected from Bloomberg and from the Hong Kong Stock Exchange Website.[3] Continuously compounded intra-day returns are generated from the open to close prices. The intra-day returns of the nearby (Spot month) HSIF contract is used as it has the highest trading volume.[4] The HSIF contracts are rolled over to the next month contract depending on the trading volume of relevant contracts so that the HSIF price series constructed is comprised of intra-day returns with the highest trading volume over the sample period.[5] In all, both HSI and HSIF price series and the HSIF volume series contain a total of 1,770 observations for the entire estimation period.

---

[1] The minimum commission is HK$100 for overnight trade.
[2] The initial margin is adjusted upon changes in volatility of the HSI.
[3] The daily closing price and trading volume of HSIF from 4th January 1999 onwards are collected from the Hong Kong Stock Exchange website. There exist a few missing values for the HSIF daily volume, we substitute them with the average of the volumes of the trading date before and after.
[4] As mentioned before, the futures market has closed 15 minutes later than the cash market since 20 November 1998, however, the asynchronous daily closing prices of index and futures should not have significant impact using daily data.
[5] In general, the trading activity of the HSIF contracts was usually reduced substantially three days to expiry before July 1997. Since then, the trading activity of the HSIF contracts was mostly switched to the next contract two days before its expiration date.

Numerous empirical evidence suggests that the price series of both index and index futures is not stationary and are stationary when they are first differenced. Augmented Dickey Fuller Tests reveal that levels of both HSI and HSIF open to open and close to close prices contain a unit root. However, the first difference of logged HSI and logged HSIF prices (close – open) is stationary, so that their continuous rate of return will be applied in the estimation process. Their daily continuous return is calculated as the formula below,

$$\textit{HSI daily continuous return} \quad R_{1,t} = \ln\left(P_{1,t}, c \big/ P_{1,t}, o\right) \tag{1}$$

$$\textit{HSIF daily continuous return} \quad R_{2,t} = \ln\left(P_{2,t,C} \big/ P_{2,t}, o\right) \tag{2}$$

$R_{1,t}$, $P_{1,t,c}$ and $P_{1,t,o}$ represent the intra-day continuously compounded return and daily close and open price of the HSI at time t, respectively. Similarly, $R_{2,t}$,$P_{2,t,\mathrm{c}}$ and $P_{2,t,\mathrm{o}}$ represent the intra-day continuously compounded return and daily closing and opening price of HSIF at time t, respectively. These returns series are further re-scaled up by 1000 prior to estimation so as to avoid possible truncation errors in volatility estimates.

The S&P 500 is an equity value weighted arithmetic index representing around 75 percent of New York Stock Exchange's (NYSE) equity capitalization. The S&P 500 Futures has contract listings in the March quarterly cycle. The S&P 500 futures series is constructed by rolling over the most active (current) contract to the next contract based on the trading volume so that it is comprised of price data with the highest trading volume. The trading hours for S&P 500 and S&P 500 futures under the Eastern Standard Time (EST) is 9:30a.m. to 4:00p.m. and 9:30a.m. to 4:15p.m., respectively, whereas the trading hours of HSI and HSIF is 9:00p.m.to 3:00a.m. and 8:45p.m.to 3:15a.m.(EST), respectively. To avoid any overlapping daily returns between the US market and the Hong Kong market, we employ open-to-close prices of the indexes and their futures. The open and close price data are collected from the Bloomberg system, which cover the identical period as in the structural events estimation.[6] The "intra-day" U.S. market returns for index and futures is calculated as the natural logarithm of the relative of daily close price to daily open price as defined in equations (1) and (2). Any missing returns of the Hong Kong market due to holidays or exchange closures on that day mean data across all markets is deleted for that day. Missing returns of the US market, because of market closures, are substituted with the U.S. market return from the previous trading day since no information is lost. We argue that owing to the time zone differential between the US market and the Hong Kong market, any revelation of information or shocks in the US market at time t will not reflect in the Hong Kong market until time t+1. The Hong Kong returns series and the US returns series are lined up so that the US returns always lead the Hong Kong returns. It means the US returns at time t-1 are matched with the Hong Kong returns at time t. This approach allows us to get the same number of data points employed in Au-Yeung and Gannon (2003) in the close-to-close return analysis of the market interventions.

3 MODEL SPECIFICATION

Lee and Ohk (1992) investigate the variation of return volatility after changes to the trading of the futures index in the Korean market by adopting a univariate switching GARCH model. They argue that a change of trading activity of individuals and institutional investors may be associated with a change in return volatilities and hence a noticeable difference in the arrival process of new information in the cash market. They further assert that there should be a significant difference in the

[6] There is a missing value for the opening price of HSI on 15th September 1995. In order to complete

autocorrelation structure of stock volatility around the time that stock index futures are listed on the stock index. In their modified GARCH model, an autoregressive structure is imposed on conditional variance, allowing volatility shocks to persist over time and captures structural one-time shift in regime using dummy variables. Chang and Gannon (2001) extended this procedure to multiple switch points in univariate GARCH models.

Based on the argument that any significant institutional events that impact on the stock or futures market may also alter their volatility structures, by varying the decay of the autocorrelation and the speed that information is transferred to the cash market, a bi-variate version of the switching GARCH model is applied. This allows us to consider regime shifts in volatilities of HSI and HSIF. In addition, the switching GARCH model is further extended to allow for multiple switching points in this analysis.

The effects of non-synchronous trading in the component stocks of HSI and bid-ask bounce in the HSIF return is avoided because of the use of the intra-day open/closing prices of a narrow-based HSI, it is therefore not necessary to model the index and futures returns as an autoregressive process. Preliminary estimation with an AR(1) returns equations did not generate any difference in conditional volatility estimates. Equation (3) shows that the returns are modeled by its mean return level only. To capture the second-order time dependence of both cash and futures returns, a bi-variate BEKK GARCH(1,1) model proposed by Engle and Kroner (1995) will be utilized. The model that governs the joint process is presented below.

$$R_t = \alpha + u_t \tag{3}$$

$$u_t | \Omega_{t-1} \sim N(0, H_t) \tag{4}$$

---

the series, we substitute it with the closing price from the previous trading day.

the return vector for the cash and futures series is given by $R_t = [R_{1,t}, R_{2,t}]$, the vector of the constant is defined by $\alpha = [\alpha_1, \alpha_2]$, the residual vector $u_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]$ is bi-variate and conditionally normally distributed, and the conditional covariance matrix is represented by H_t, where $\{H_t\} = h_{ij,t}\ for\, i, j = 1,2$. Ω_{t-1} is the set of information available at time t – 1. The conditional covariance matrix can be stated as follow:

$$H_t = C_0'C_0 + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + G_{11}'H_{t-1}G_{11} \tag{5}$$

As shown in equation (5) above, the parameter matrices for the variance equation are defined as C_0, which is restricted to be lower triangular and two unrestricted matrices A_{11} and G_{11}. Therefore the second moment can be represented by:

$$H_t = C_0'C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}, \varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}, \varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \tag{6}$$

The application of the BEKK-GARCH specification in our analysis is advantageous from the interaction of conditional variances and covariance of the two return series. The BEKK-GARCH model guarantees, by construction, that the covariance matrices in the system are positive definite. The equation (6) for H_t can be further expanded by matrix multiplication and it takes the following form:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1} \tag{7}$$

$$\begin{aligned} h_{12,t} &= c_{11}c_{21} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + g_{11}g_{12}h_{11,t-1} \\ &\quad + (g_{21}g_{12} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1} \end{aligned} \tag{8}$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + g_{12}^2 h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2 h_{22,t-1} \tag{9}$$

To test for any shift in the variance structure, following the approach of Chang and Gannon (2001), event dummy variables are included for the constant, lagged squared errors and lagged conditional variance in the variance equation (7) and (9).

To construct a switching GARCH model, the GARCH parameters are assumed to be different before and after the switching point. Therefore, the coefficient of the dummy variables measure the change in mean level and the autoregressive structure on conditional volatility after the events happen in the stock and futures market.

$$H_t = C_0' C_0 + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + G_{11}' H_{t-1} G_{11} + \sum_{i=1}^{k} \left[\Phi_{id} D_{it} + \Phi_{iq} \varepsilon_{t-1} \varepsilon_{t-1}' D_{it} + \Phi_{ip} H_{t-1} D_{it} \right] \qquad (10)$$

The equation (10) above shows a generalized multivariate switching GARCH model that allow for up to *k* switching points. The first half of the equation shows the specification of BEKK GARCH(1,1) model for the initial time segment. The second half of the equation characterizes a total of *k* switching dummy variables for volatility intercept and slope terms. Each of the *k* sets of dummy parameter estimates are successively added back to the first part of equation (10) so that at each of the *k* switch points the significance test of difference between the current and previous time segment parameters can be undertaken. In this way a sequence of tests of regime shift is undertaken. Φ_{id}, Φ_{ip}, Φ_{iq} represent the i^{th} matrix of switching dummy coefficients for intercept, lagged squared errors and lagged conditional variance respectively. In addition, the off diagonal terms in all these matrices of switching dummy coefficients are restricted to be zero so that no structural shift is allowed in the covariance equation as a consequence of the policy changes. Each dummy variable will have a value of 0 before the date of the occurrence of the event and a value of 1 from the event date onwards.

The six major structural changes throughout the sample period are listed below. The uptick rule, introduced in January 1994, was eventually abolished on 25 March 1996. This rule was reinstated on 7^{th} September 1998. The HKFE raised the initial margins of the HSIF from HK$75,000 to HK$90,000 per contract, a significant

20% increase, on November 1997. The margin was decreased by 14% on 30th November 1998. The HKSE and HKFE merged on 6th March 2000 and trading of the HSIF has migrated from an open outcry system to an electronic system HKATS since 5 June 2000. Initially, we estimate a model of 6 switching points, and reduce down to all combinations of 5, 4, 3, 2, 1 and zero switch points. Some models ended up with poor estimation results due to the switching points being too close and also there are insignificant structural changes. For example, the size of the subsequent HSIF margin decrease is lower than the initial increase with the decrease not significant but the margin increase significant. In the end, the final 3 switching points are chosen based on its highest log likelihood with full details reported in Au-Yeung and Gannon (2003).

In summary,

$$\begin{aligned} H_t &= C_0'C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}, \varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}, \varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \\ &+ \sum_{i=1}^{k} \left[\begin{bmatrix} d_{11} & 0 \\ 0 & d_{22} \end{bmatrix}_i D_{it} + \begin{bmatrix} q_{11} & 0 \\ 0 & q_{22} \end{bmatrix}_i \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} D_{it} + \begin{bmatrix} p_{11} & 0 \\ 0 & p_{22} \end{bmatrix}_i H_{t-1} D_{it} \right] \end{aligned} \tag{11}$$

where $$D_{it} = \begin{cases} 0 \text{ if } i = 0 \\ 1 \text{ if } i = 1, 2, \ldots, k \end{cases}$$

The notation D_{it} stated above represents the dummy variables for 3 significant different events:

D_{1t} ~ dummy variable for the removal of the uptick rule

D_{2t} ~ dummy variable for the increase of HSIF initial margins

D_{3t} ~ dummy variable for the trading of HSIF on HKATS

The significance of elements of dummy variables matrices will reveal the power of the switching GARCH model. If there is no change in the mean level and the autoregressive structure on conditional volatility after the k^{th} event, both diagonal elements of the dummy variable matrices will not be significantly different from zero. That is, the null hypothesis H_0: $\Phi_{id} = \Phi_{ip} = \Phi_{iq} = 0$. Alternatively, H_1: any elements of matrices are significantly different from zero. The reported estimation outputs are shown in Panel 1 in the Table of results.

We report the model with 3 most significant switching points then incorporate the U.S. volatility spillover effects into the 3 switch point model. The results for the joint switch point and volatility spillover model are reported in panel 2 of the table of results.

Below are three different measures of volatility of S&P 500 and S&P 500 futures:

SPUV/SPFUV	Unconditional volatility of S&P 500 index and futures based on the variance of intra-day returns of each trading day
SPCV1/SPFCV1	Conditional volatility of S&P 500 index and futures based on a univariate GARCH (1,1) model (see below)
SPCV2/SPFCV2	Conditional volatility of S&P 500 index and futures based on a BEKK- GARCH (1,1) model (see below)

The models employed for obtaining the conditional volatility of S&P 500 and S&P 500 futures returns are presented as follow:

Univariate GARCH (1,1) Model

$$r_{it} = \rho_0 + \theta WKD_t + \varepsilon_t \tag{12}$$

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

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{13}$$

BEKK-GARCH (1,1) Model

$$r_t = \omega + \delta WKD_t + u_t \tag{14}$$

where $u_t | \Omega_{t-1} \sim N(0, H_t)$

$$H_t = C_0' C_0 + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + G_{11}' H_{t-1} G_{11} \tag{15}$$

From equation (12) to (13), either S&P 500 (r_{St}) or S&P 500 futures (r_{Ft}) intra-day returns are modeled by a constant only in the first moment, whereas the conditional volatility is governed by a GARCH (1,1) structure. The dummy variable (WKD_t) is equal to 1 on Monday and 0 otherwise, so as to pick up the day-of-week effect. The most recent conditional volatilities (SPCV1/SPFCV1) are then incorporated into the respective variance equation of HSI and HSIF in the switching GARCH model. For the bi-variate model, equation (14) shows the S&P 500 and its futures returns are modeled with a constant only.[7] The intra-day return vector is denoted by $r_t = [r_{St,} r_{Ft}]$. The residual vector is given by $u_t = [\varepsilon_{St}, \varepsilon_{Ft}]$, with its corresponding conditional covariance matrix $\{H_t\} = h_{ij,t}$. The parameter vectors in the mean equation are defined as $\omega = [\omega_S, \omega_F]$ for the constant and $\delta = [\delta_S, \delta_F]$ for the coefficient of the dummy variable. With regard to the BEKK-GARCH (1,1) model in equation (15), all the matrices are defined in the same way as in equation (5). The conditional volatility of S&P 500 (SPCV2) and S&P 500 futures (SPFCV2) are then included into the respective equation of HSI and HSIF.

These alternative volatility measures are re-scaled prior to full spillover model estimation. Details of re-scaling are reported in the footnotes to the table of results.

[7] The VAR(1) model of S&P 500 and S&P 500 futures is found to be considerably lower, so the simple constant model is chosen.

The equation below illustrates the generalized switching GARCH model with the volatility spillover effect incorporated. To simplify the presentation, only the volatility spillover parameters are shown.

$$r_t = \eta + \lambda WKD_t + u_t \tag{16}$$

where $u_t \left| \Omega_{t-1} \right. \sim N(0, H_t)$

$$\{\text{Equation 11}\} + \begin{bmatrix} m_{11} & 0 \\ 0 & m_{22} \end{bmatrix} \begin{bmatrix} SPV_t \\ SPFV_t \end{bmatrix} \tag{17}$$

SPV_t and $SPFV_t$ denote various volatility measure for the S&P 500 Index and the S&P500 Futures specified above. The intra-day return vector for HSI (r_{1t}) and HSIF (r_{2t}) is denoted by $r_t = [r_{1t}, r_{2t}]$. The residual vector is given by $u_t = [\varepsilon_{1t}, \varepsilon_{2t}]$, with the corresponding conditional covariance matrix $\{H_t\} = h_{ij,t}$. The parameter vectors in the mean equation (16) are defined as $\eta = [\eta_1, \eta_2]$ for the constant and $\lambda = [\lambda_1, \lambda_2]$ for the dummy variable coefficient. With respect to the BEKK-GARCH (1,1) model in equation (17), all the matrices are defined in the same way as in equation (11), with an addition that the matrix of volatility spillovers is diagonal.

All the maximum likelihood estimations are optimized by the Berndt, Hall, Hall and Hausman (BHHH) algorithm.[8] From equations (3) to (10), the conditional log likelihood function $L(\theta)$ for a sample of T observations has the following form:

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta) \tag{18}$$

$$l_t(\theta) = -\log 2\pi - 1/2 \log \left| H_t(\theta) \right| - 1/2 \varepsilon_t^{'}(\theta) H_t^{-1}(\theta) \varepsilon_t(\theta) \tag{19}$$

[8] Marquardt maximum likelihood has also been applied, however, BHHH algorithm is found to have better performance.

θ denotes the vector of all the unknown parameters. Numerical maximization yields the maximum likelihood estimates with asymptotic standard errors.

4. VOLATILITY STRUCTURE WITH VOLATILITY SPILLOVER

Panel A of the table of results shows that the 3 switching points BEKK-GARCH(1,1) model fits the open-to-close returns of HSI and HSIF quite well. The output reveals there exists at least one significant switching dummy variable for each event. For the first switch point (removal of the uptick rule) all switch dummies are significant in both equations. The mean level of volatility increases for the HSI, the c_{11}, and decreases for the HSIF. The ARCH parameter, the a_{11}, increases (decreases) and the GARCH parameter, the g_{11}, decreases (increases), respectively. These latter effects imply that although the mean level of volatility increases (decreases) for the HSI (HSIF), volatility persistence defined as permanent shocks to the system dissipate quicker (take longer to die out) in the respective equations. For the second switch point (increase of HSIF initial margins) all switch dummies are significant in the HSIF equation but only the GARCH volatility parameter is significant in the HSI equation. This implies some increase in volatility persistence in the HSI equation but a higher mean level of volatility and a faster decay of volatility persistence (ARCH/GARCH parameters positive/negative respectively) in the HSIF equation. For the third switch point (electronic trading of HSIF) only the GARCH parameter in the HSI is significant and positive indicating some increase in volatility persistence relative to the period following the increase in HSIF margins. No dummy parameters are significant in the HSIF equation. This could reflect the fact that margins were subsequently decreased prior to automation so that the introduction of automation did not change the HSIF volatility structure from that experienced during the period of margin increase and decrease. However, the GARCH parameter (g_{22}) for the HSIF (second conditional variance equation) is marginally non-stationary with a value of 1.0142. Although roots in excess of one are not such a problem in the bi-variate case as they are in the univariate case, so that inference can be undertaken, there is some suggestion of mis-specification. An alternative explanation could be that mis-specification by failing to account for overnight news generates this perverse effect.

Panel B of the table illustrates the test results of volatility spillovers from the US market. Employing different volatility measures for the S&P 500 and S&P 500 futures intra-day returns, we find significant positive volatility spillover effects using the unconditional variance of S&P 500 only. There are no apparent individual significant volatility spillover effects from employing either conditional volatility effects for the S&P 500 index. There are no individual significant effects from the S&P 500 futures returns for all volatility measures. The log likelihoods with either sets of the univariate or bivariate generated measures of U.S. market conditional volatility included in the switching model are not significantly better than the log likelihood with effects excluded. However, the log likelihood with the unconditional U.S. volatility spillover effects included in the switching model is clearly significant at any reasonable level of significance. Based on a likelihood ratio test the calculated value is 15.53 with the 5% Chi-Squared(2) critical value 5.99. Comparing individual coefficient values across the included U.S. unconditional volatility model and that with the spillover effect excluded the following is apparent. The same dummy switch parameters are significant across the 2 models except the GARCH parameters in the HSI equation cease to be significant at the second switch point (increase in futures margin) and switch point three (automation of futures trading). At the same time the

S&P 500 cash market unconditional volatility is highly significant in the HSI equation. These results are to be expected if the direct effects of changes in the futures market trading mechanism do not affect volatility persistence in the index. However, the GARCH parameter (g_{22}) for the HSIF (second conditional variance equation) is now not marginally non-stationary with a value of 0.9781. Therefore, the volatility spillover effect from the US market does have an impact on the Hong Kong stock market and helps filter out spurious effects across the HSI and HSIF markets.

Not finding a robust volatility spillover effects from the US market is not uncommon in prior studies that employed conditional volatilities of the S&P 500 as the volatility spillover measure. It may stem from the fact that conditional volatilities of foreign markets from the univariate or even bi-variate GARCH models tend to be too smooth. This helps explain the reduced information effects diluting the correlation with the conditional volatilities of the domestic market.

5. CONCLUSION

We find the bi-variate BEKK-GARCH (1,1) model with 3 switching points is able to capture structural changes in the volatility of the HSI and HSIF. The significant events in the Hong Kong market were abolishment of the up-tick rule, increase in initial margins of the futures and electronic trading of the HSIF. Volatility spillover effects from the US market are also jointly examined with the switch point effects in this paper. We find no volatility spillover with the conditional volatilities of S&P 500 and S&P 500 futures, but significant spillover effects with the unconditional volatilities of S&P 500. This implies that the volatility spillover from the US market does play an important role on the inter-temporal relationship.

Bibliography

Au-Yeung, S.P. and G.L. Gannon, 2003, Regulatory change and structural effects in HSIF and HSI volatility, *Asia Pacific Futures Research Symposium Proceedings, Chigago Board of Trade, Shanghai February 2003*, forthcoming.

Chang, C.Y. and G.L. Gannon, 2001, Share Price Index Futures automated trading systems: micro structure effects, *Asia Pacific Futures Research Symposium, Chicago Board of Trade, Bangkok December, 2001.*

Engle, R.F. and K.F. Kroner, 1995, Multivariate Simultaneous Generalized ARCH, *Econometric Theory*, 11, 1, pp122-150.

Gannon, G.L. and D.F.S. Choi, 1998, Structural Models: Intra/Inter-day volatility transmission and spillover persistence of the HSI, HSIF and S&P500 futures, *International Review of Financial Analysis*, 7(1), 19-36.

Hamao, Y., Masulis, R.W. and V.K. Ng, 1990, Correlations in price changes and volatility across international stock market, *Review of Financial Studies*, 3(2), 281-307.

Karolyi, G.A., 1995, A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada, *Journal of Business and Economic Statistics*, 13(1), 11-25.

Lee, S.B. and K.Y. Ohk, 1992, Stock index futures listing and structural change in time-varying volatility, *Journal of Futures Markets*, 12(5), 493-509.

Liu, Y.A. and M.S. Pan, 1997, Mean and volatility spillover effects in the US and Pacific-Basin stock markets, *Multinational Finance Journal*, 1(1), 47-62.

Ng, A, 2000, Volatility spillover effects from Japan and the US to the Pacific-Basin, *Journal of International Money and Finance*, 19, 207-233.

Wei, K.C.J, Liu, Y.J., Yang, C.C. and G.S. Chaung, 1995, Volatility and price change spillover effects across the developed and emerging markets, *Pacific-Basin Finance Journal*, 3, 113-36.

TABLE OF RESULTS: Unrestricted BEKK-GARCH(1,1) Model with Volatility Spillover Effects

Volatility **Measure**	η_1 η_2	λ_1 λ_2	c_{11} c_{21}	 c_{22}	a_{11} a_{21}	a_{12} a_{22}	g_{11} g_{21}	g_{12} g_{22}	$d_{11(1)}$ $d_{22(1)}$ $(x10^{-3})$	$q_{11(1)}$ $q_{22(1)}$	$p_{11(1)}$ $p_{22(1)}$	$d_{11(2)}$ $d_{22(2)}$ $(x10^{-3})$	$q_{11(2)}$ $q_{22(2)}$	$p_{11(2)}$ $p_{22(2)}$	$d_{11(3)}$ $d_{22(3)}$ $(x10^{-3})$	$q_{11(3)}$ $q_{22(3)}$	$p_{11(3)}$ $p_{22(3)}$	m_{11}[a] m_{22}[b] $(x10^{-2})$	**Log** **Likelihood**
Panel A. 3 Switching Points (k=3) with No Volatility Spillover Effect																			
None	38.335	-38.334	0.0121		0.2378	0.2686	0.9131	-0.0831	0.1790	0.0304	-0.0521	-0.0557	-0.0070	0.0156	-0.1440	-0.0078	0.0276		3287.084
	(0.0000)	(0.0000)	(0.0001)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0014)	(0.0000)	(0.0000)	(0.5858)	(0.1749)	(0.0295)	(0.3783)	(0.4273)	(0.0216)		
	-36.341	-36.344	0.0116	0.0168	0.0009	0.0448	0.0554	1.0142	-0.4130	-0.0194	0.0454	0.5510	0.0108	-0.0262	-0.3650	-0.0068	0.0001		
	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.9825)	(0.2593)	(0.0001)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0014)	(0.0037)	(0.0000)	(0.1332)	(0.4997)	(0.9971)		
Panel B. 3 Switching Points (k=3) with Volatility Spillover Effect																			
SPUV/	30.989	-30.988	0.0053		0.2447	0.2778	0.9018	-0.0537	0.2590	0.0180	-0.0513	-0.1420	0.0054	0.0035	0.1700	-0.0129	0.0173	0.8640	3294.847
SPFUV	(0.4142)	(0.4145)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0207)	(0.0000)	(0.0065)	(0.0000)	(0.3590)	(0.4905)	(0.7635)	(0.5609)	(0.2481)	(0.3724)	(0.0019)	
	21.228	-21.226	0.0258	0.0160	-0.0009	0.0356	0.0693	0.9781	-0.8950	-0.0186	0.0657	0.6460	0.0144	-0.0281	-0.5350	-0.0112	0.0094	0.5022	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9848)	(0.4148)	(0.0001)	(0.0000)	(0.0000)	(0.0187)	(0.0000)	(0.0076)	(0.0599)	(0.0027)	(0.1208)	(0.3805)	(0.5961)	(0.1989)	
SPCV1/	-36.022	36.024	0.0111		0.2254	0.2640	0.9385	-0.0565	0.1980	0.0358	-0.0543	-0.1190	-0.0145	0.0213	-0.1000	0.0070	0.0102	0.0334	3289.005
SPFCV1	(0.2095)	(0.2094)	(0.0014)		(0.0000)	(0.0000)	(0.0000)	(0.0013)	(0.0000)	(0.0000)	(0.0000)	(0.0889)	(0.0000)	(0.0000)	(0.4451)	(0.5301)	(0.3332)	(0.1344)	
	63.506	-63.503	0.0146	0.0156	0.0204	0.0562	0.0288	0.9930	-0.3990	-0.0203	0.0418	0.4700	0.0153	-0.0268	-0.3300	-0.0081	0.0033	-0.0174	
	(0.0140)	(0.0140)	(0.0000)	(0.0000)	(0.5082)	(0.0002)	(0.0073)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0021)	(0.0000)	(0.0000)	(0.1285)	(0.3975)	(0.7703)	(0.5709)	
SPCV2/	91.995	-91.992	0.0115		0.2405	0.2679	0.9442	-0.0576	0.1700	0.0326	-0.0472	-0.0902	-0.0156	0.0204	-0.1170	0.0175	0.0006	0.3029	3287.963
SPFCV2	(0.0000)	(0.0000)	(0.0000)		(0.0000)	0.0000	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2104)	(0.0008)	(0.0001)	(0.2779)	(0.0709)	(0.9385)	(0.1420)	
	-123.462	123.466	0.0147	0.0120	0.0160	0.0499	0.0201	0.9973	-0.2910	-0.0168	0.0326	0.3060	0.0151	-0.0227	-0.2080	-0.0083	0.0014	-0.0967	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.6430)	(0.1645)	(0.0007)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0174)	(0.0014)	0.0000	(0.2199)	(0.3353)	(0.8767)	(0.7335)	

Note: The equation below represents the Unrestricted BEKK-GARCH (1,1) model with volatility spillover effects

$$H_t = C_0'C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}, \varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}, \varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$
$$+ \sum_{i=1}^{3} \left[\begin{bmatrix} d_{11} & 0 \\ 0 & d_{22} \end{bmatrix}_i D_{it} + \begin{bmatrix} q_{11} & 0 \\ 0 & q_{22} \end{bmatrix}_i \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} D_{it} + \begin{bmatrix} p_{11} & 0 \\ 0 & p_{22} \end{bmatrix}_i H_{t-1} D_{it} \right] + \begin{bmatrix} m_{11} & 0 \\ 0 & m_{22} \end{bmatrix} \begin{bmatrix} SPV_t \\ SPFV_t \end{bmatrix}$$

[a] SPUV is scaled by 100 and SPCV1 is scaled by 10.

[b] SPFUV is scaled by 100 and SPFCV1 is scaled by 10.

* The value in parentheses indicates the p-value given the asymptotic t distributed standard errors.