VOLATILITY LINKAGES BETWEEN HONG KONG FINANCIAL MARKETS

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Abstract

This paper examines the volatility linkages between three Hong Kong financial markets, namely the stock market, the quasi-government bond market and the HKD forward exchange market. To allow for structural shifts in the conditional variance process, a bivariate regime switching ARCH (SWARCH) model is specified for the investigation of volatility linkages. In summary, this paper finds the presence of regime shifts in the volatility process and evidences of volatility co-movement between Hong Kong financial markets. The expected duration for two financial markets to stay at a high-volatility state is between five to seven weeks. In particular, during crises like the Asian financial crisis, the duration can be as long as six months. This result can be useful to policy makers in the development of more effective policies when dealing with financial crises.

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* This is a preliminary and incomplete draft of the paper prepared for the 8th annual Australasian Macroeconomics Workshop, hosted by the Hong Kong Institute for Monetary Research, on September 22 and 23, 2003. We are grateful to seminar participants at the Hong Kong Institute for Monetary Research for many helpful suggestions and comments. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Hong Kong Monetary Authority. All remaining errors are ours.
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I. Introduction

The analysis of financial market volatility and the links between asset markets have gained growing interest in recent years, especially after the stock market crash in October 1987 and the Asian financial crisis in 1997-1998. Among the studies in the empirical and theoretical investigations of the relationship between asset markets, most are concentrated on the linkages across markets of the same types.[1] In many cases, these studies focus on how a shock in one market will affect returns and volatility in other geographically distinct markets. Within an economy, most studies concentrate on the volatility linkage between cash and futures markets, especially on the stock market. Yet there have been very few studies on understanding the volatility phenomenon and linkages between different financial markets, such as bond and foreign exchange markets, within an economy.[2] In this study, the volatility linkages between three Hong Kong financial markets, namely the stock market, the quasi-government bond market and the HKD forward exchange market, are examined.

There are several reasons for studying the volatility linkages between Hong Kong financial markets. The most apparent one is that the study on the volatility between different assets can provide useful information from a risk management perspective. The results derived can be used to improve or develop effective strategies for hedging or portfolio management against shocks emanating across markets. To policy makers, the results have implications for financial stability and risk monitoring. For instance, if volatility movements are highly synchronised across markets, a shock developed in one asset is likely to have destabilising impacts on the economy's financial system. Without understanding these linkages, the effectiveness of policy actions against any undesirable financial volatility may be affected.

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[1] For example, Lin et al. (1994) focus at equity markets, while Engle et al. (1990) and Fleming and Lopez (1999) concentrate at the foreign exchange market and the US Treasury market respectively.

[2] Examples like Fleming et al. (1998), Darbar and Deb (1999) for the US, and Ebrahim (2000) for Canada.

This paper contributes to the analysis of financial market volatility in two ways. First, it examines the volatility transmission across different asset classes rather than between markets of the same nature. Second, it allows for the possibility of structural shifts in the investigation of volatility linkage between markets with the specification of a regime switching ARCH (SWARCH) model.[3] The inclusion of regime switching is important for modeling volatility in Hong Kong financial markets as structural shifts in these markets are common in the last decade. A by-product of applying the SWARCH model is the derivation of transition probability between different volatility states. The result provides information to policy makers in gauging the expected duration of high financial market volatility due to extreme shock to the financial system.

The remainder of this paper is organised as follows. Section II discusses the model specification in details and introduces the regime switching ARCH models. In section III, the data and some preliminary analyses on the volatility of each financial market are examined. Empirical results on volatility linkages are presented and discussed in section IV. A conclusion is provided in the final section.

[3] As it turns out, the estimation of SWARCH model is extremely intensive in computation time and the issue of "positive" variance-covariance is not always guaranteed. In order to minimise the dimensionality problem and to keep the number of parameters tractable, only a 2-regime bivariate SWARCH model will be considered.

II. The Regime-Switching ARCH Model

While the family of ARCH and GARCH models has been widely applied to modeling variance, Lamoureux and Lastrapes (1990) show that these models may not be appropriate in the presence of structural breaks. As pointed out by Hamilton and Susmel (1994), ARCH models are inadequate when the data are characterised not much by persistent shocks but by structural shifts leading to switches in variance regimes. Cai (1994) and Hamilton and Susmel (1994) propose a regime switching ARCH or SWARCH model that is time variant and allows for the conditional volatility process to switch stochastically between a finite number of regimes. They demonstrate that this formulation leads to a significant reduction in the degree of volatility persistence compared to standard GARCH models.[4]

To illustrate the features of the SWARCH model, a univariate case is first considered. For any financial market, the return of an asset at time *t* is represented by y_t and the residual with respect to the information set Ω_{t-1} is denoted as ε_t. The process ε_t from a first-order autoregression for y_t under a SWARCH(*K*, *q*) model is specified as:

$$\begin{aligned}
& y_t = w_0 + w_1 y_{t-1} + \varepsilon_t \qquad\qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0,\, \sigma_t^2) \\
& \varepsilon_t = \sqrt{g_{s_t}}\, u_t \\
& u_t = h_t v_t \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (1) \\
& h_t^2 = c_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \qquad\qquad i = 1, 2, \ldots, q, \ and \ s_t = 1, 2, \ldots, K
\end{aligned}$$

where *q* is the number of ARCH terms, *K* is the number of regime states, and the g_{s_t} are scale parameters that capture the size of volatility in different regimes. Thus, the underlying ARCH variable u_{t-i}^2 is multiplied by the scale parameter g_1 when the process is in the regime represented by $s_t = 1$, multiplied by g_2 when $s_t = 2$, and so on. The scale parameter for the first state g_1 is normalised at unity with $g_{s_t} \geq 1$ for

[4] While Gray (1996) introduces the generalised regime-switching (GRS) model, in which the ARCH and GARCH parameters are regime-dependent, the incorporation of regime switches into the GARCH term introduces tremendous estimation problems, especially in a bivariate setting. In this study, the empirical analysis of regime switches is confined to the ARCH process only.

$s_t = 2, 3, \ldots, K$. The K-state regime switching is assumed to be described by a Markov process, where

$$\text{Prob}(s_t = j \mid s_{t-1} = i,\ s_{t-2} = k, \ldots,\ y_t, y_{t-1}, y_{t-2}, \ldots)$$
$$= \text{Prob}(s_t = j \mid s_{t-1} = i) = p_{ij}\,, \tag{2}$$

for $i,j,k = 1, 2, \ldots, K$. Under this specification, the transition probabilities, the p_{ij}'s, are constant. Under a two-regime states setting, for example, if the financial time series was at a high-volatility state in the last period (s_t = 2), the probability of changing to the low-volatility state (s_t = 1) is a fixed constant p_{21}. One of the byproducts of the maximum likelihood estimation is the "smoothed probabilities":

$$\text{Prob}(s_t \mid y_1, y_2, \ldots, y_T) \tag{3}$$

which provides information about the likelihood a volatility process is at a particular regime state at time t based on the full sample of observations.

There are several advantages in using the SWARCH model in modeling volatility. First, the SWARCH model incorporates the possibility of regime shifts or structural breaks in the conditional variance process in explaining the volatility persistence, a phenomenon that is commonly observed in the literature. Second, the SWARCH model can date the period of high volatility based on the smoothed probabilities. Thus, one can easily explore the question of whether periods of "high volatility" coincide across different financial markets. And finally the identification of breakpoints can also be used to "time" the effectiveness of policy changes on financial markets.[5]

Having said that, there is a limitation on the flexibility in the specification of the SWARCH model as the estimation is technically non-trivial and very time consuming. Thus, in this study, the application of the SWARCH model is restricted to pairs of financial markets only, each with one ARCH term in the conditional variance process and two volatility states. Under this bivariate AR(1) SWARCH(2,1) specification, the number of states is four. For instance, with the

[5] For a review of the SWARCH model, please refer to Ramchand and Susmel (1998), Susmel (2000), Edwards and Susmel (2001) and Edwards and Susmel (2002).

stock market and the quasi-government bond market in the system, the four states, s_t^*, are as follows:

s_t^* = 1: Stock market – low volatility, Quasi-gov't bond market – low volatility.

s_t^* = 2: Stock market – low volatility, Quasi-gov't bond market – high volatility.

s_t^* = 3: Stock market – high volatility, Quasi-gov't bond market – low volatility.

s_t^* = 4: Stock market – high volatility, Quasi-gov't bond market – high volatility.

The system can be written as:

$$y_t = A + B\, y_{t-1} + e_t,\quad e_t \mid \Omega_{t-1} \sim N(0, H_t) \qquad (4)$$

where $y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix}$ is a 2x1 vector of returns, $e_t = \begin{bmatrix} e_{1,t} \\ e_{2,t} \end{bmatrix}$ is a 2x1 vector of disturbances, which are assumed to follow a bivariate normal distribution with zero mean and a time varying conditional covariance matrix H_t. The time varying conditional covariance matrix H_t is specified as a constant correlation matrix where the diagonal elements follow a SWARCH(2,1) process. A = $\begin{bmatrix} w_{10} \\ w_{20} \end{bmatrix}$ is a 2x1 vector and B = $\begin{bmatrix} w_{11} & 0 \\ 0 & w_{22} \end{bmatrix}$ is a 2x2 matrix. The parameters of the bivariate AR(1) SWARCH(2,1) model are estimated using GAUSS by numerically maximising the likelihood function using the algorithm developed by BFGS, subject to the constraints that $g_1 = 1$, $g_2 \geq 1$, $\sum_{j=1}^{2} p_{ij} = 1$ for i = 1, 2 and $0 \leq p_{ij} \leq 1$ for i,j = 1, 2.[6]

[6] GAUSS programmes and most of the routines are obtained from websites of James Hamilton and Rauli Susmel.

III. The Data and Preliminary Analyses

The data consist of weekly figures for three types of assets in Hong Kong financial markets, namely the stock market (represented by the log differences (in percent) of the Hang Seng Index), the quasi-government bond market (the holding returns for 10-year Exchange Fund Notes) and the HKD forward exchange market (the log differences (in percent) of the 12-month HKD forward exchange rate).[7] The data set spans from January 1990 to 7 March 2003, except the quasi-government bond market that starts from November 1996.

Table 1 presents some descriptive statistics of the financial markets. The series are skewed and have fat-tails, as implied by the high kurtosis coefficients. The significant Jarque-Bera statistics indicate the distributions of the financial time series are not normal. The augmented Dickey-Fuller (ADF) unit root test is performed to check for stationarity before the estimation. The significant test statistics of all the series imply they are stationary. The Q statistic is the Ljung-Box test for autocorrelation up to 6 lags. The significant Q (6) and Q^2 (6) statistics provide evidences of serial correlation in the level and in the squared level respectively. This also suggests the presence of autoregressive conditional heteroskedasticity (ARCH) in all the series and the use of an AR(1) term in the specification of the conditional mean equation is justified.[8]

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[7] The approximation for the weekly holding period return for government bond is based on Shiller (1979). For bonds selling at or near par value, Shiller suggests an approximate expression for the *n*-period holding period return $H_t^{(n)}$, where $H_t^{(n)} = (R_t^{(n)} - \gamma_n R_{t+1}^{(n-1)})/(1-\gamma_n)$, $\gamma_n = \gamma(1-\gamma^{n-1})/(1-\gamma^n)$, $\gamma = 1/(1+\overline{R})$, $R_t^{(n)}$ is the yield to maturity and $\overline{R}$ is the mean value of the yield to maturity.

[8] For a general discussion of Hong Kong financial market volatility, please refer to Yu and Fung (2003).

Table 1: Summary of Statistics

	Stock Market (in % return)	**Quasi-government Bond Market** (in % return)	**Forward Market** (in % change)
Mean	0.16	0.20	0.00
Maximum	13.92	5.68	2.92
Minimum	-19.92	-8.91	-2.41
Std.Dev.	3.67	1.48	0.30
Skewness	-0.39	-0.81	1.60
Kurtosis	5.65	9.69	32.33
Jarque-Bera	222.14	662.62	25,391.34
ADF statistics	-25.89*	-17.72*	-28.00*
Q (6)	7.90	10.01^{+}	28.85*
Q^2 (6)	20.56*	28.34*	111.25*
Observations	700	336	700

Notes: * indicates significant at the 5% level. $^{+}$ indicates significance at the 10% level. The Jarque-Bera statistic has a χ^2 distribution with two degree of freedom under the null hypothesis of normally distributed errors. The critical value of χ^2 (2) at the 5% level is 5.99. The critical ADF value at the 5% level is –2.87. Q (6) and Q^2 (6) are the Ljung-Box statistics based on the levels and the squared levels of the time series respectively up to order 6. Both statistics are asymptotically distributed as χ^2 (6). The critical value of χ^2 (6) at the 5% and the 10% level is 12.59 and 10.64 respectively.

As a first step in the analysis, a simple AR(1) GARCH(1,1) model for each series is estimated and the results are presented in Table 2. The estimated coefficients of ARCH (α) and GARCH (β) effects are highly significant in each asset. The sum of ARCH and GARCH coefficients ($\alpha + \beta$) in each estimation is close to or larger than one, suggesting that shocks to the conditional variance are highly persistent. This means that shocks occurred in the distant past continue to have effects on the current conditional variance.

Table 2: Parameter Estimates and Specification Tests of Univariate AR(1) GARCH(1,1) Model

	Stock Market	Quasi-government Bond Market	Forward Exchange Market
w_0	0.303*	0.177*	-0.006
	(0.124)	(0.068)	(0.006)
w_1	0.021	0.058	-0.165*
	(0.039)	(0.074)	(0.080)
c_0	0.273	0.096	0.001
	(0.158)	(0.072)	(0.001)
α_1	0.078*	0.068*	0.493
	(0.031)	(0.034)	(0.303)
β_1	0.905*	0.890*	0.638*
	(0.035)	(0.051)	(0.114)
$\alpha_1 + \beta_1$	0.983	0.958	1.131
Log Likelihood	-1,860	-579	367
Q (6)	7.64	4.32	3.21
Q^2 (6)	2.17	0.85	1.21

Notes: Numbers in parentheses are standard errors. * indicates significance at the 5% level. Q (6) and Q^2 (6) are the Ljung-Box statistics based on the standardised residuals and the squared standardised residuals respectively up to order 6. Both statistics are asymptotically distributed as χ^2 (6). The critical value of χ^2 (6) at the 5% level is 12.59.

In the last decades, Hong Kong financial markets witnessed events such as the change over of sovereignty, the Asian financial crisis and the burst of the technology bubble. Thus, it is important to check whether financial market volatility may be characterised by structural shifts or extreme events leading to switches in variance regimes. To take the structural shifts into account, an AR(1) SWARCH(2,1) model for each series to identify periods of unusually high volatility is estimated. The results are presented in Table 3.

Table 3: Parameter Estimates and Specification Tests of Univariate AR(1) SWARCH(2,1) Model

	Stock Market	Quasi-government Bond Market	Forward Exchange Market
w_0	0.281*	-0.020*	-0.004
	(0.120)	(0.008)	(0.003)
w_1	0.018	0.027	-0.173*
	(0.048)	(0.060)	(0.034)
c_0	5.844*	0.014*	0.004*
	(0.600)	(0.002)	(0.001)
α_1	0.000	0.018	0.475*
	(0.067)	(0.064)	(0.114)
g_2	3.78*	11.34*	81.16*
	(0.46)	(2.58)	(18.64)
Log Likelihood	-1,854	118	448
Q (6)	7.24	5.34	6.06
Q^2 (6)	1.97	0.59	10.31

Notes: Numbers in parentheses are standard errors. * indicates significance at the 5% level. Q (6) and Q^2 (6) are the Ljung-Box statistics based on the standardised residuals and the squared standardised residuals respectively up to order 6. Both statistics are asymptotically distributed as χ^2 (6). The critical value of χ^2 (6) at the 5% level is 12.59.

Table 3 shows that the estimated ARCH parameters (α_1) for stock and quasi-government bond markets under the SWARCH model are insignificant. The finding is similar to Edwards and Susmel (2001) where the use of SWARCH model causes the ARCH effect to be reduced or disappeared. The estimated scale parameters for variance in state 2 (g_2), the high-volatility state, are all significantly different from unity. The fact that the ARCH parameters are smaller and sometimes insignificant and the scale parameters of high-volatility state are significant suggest the presence of structural break and the appropriate use of the SWARCH model in modeling Hong Kong financial market volatility. The insignificant Q(6) and Q^2(6) statistics also give further indication that the financial series are adequately modeled with no further serial correlation or ARCH effect.

Table 4 gives the estimated transition probabilities and the volatility persistence of each market. Focusing on the high-volatility state (s_t = 2), the most persistence one is the stock market which has the longest expected duration of 39 weeks, as compared to 7 or 8 weeks of other markets.

Table 4: Parameter Estimates of Transition Probabilities
Univariate AR(1) SWARCH(2,1) Model

s_t = 1: low volatility
s_t = 2: high volatility

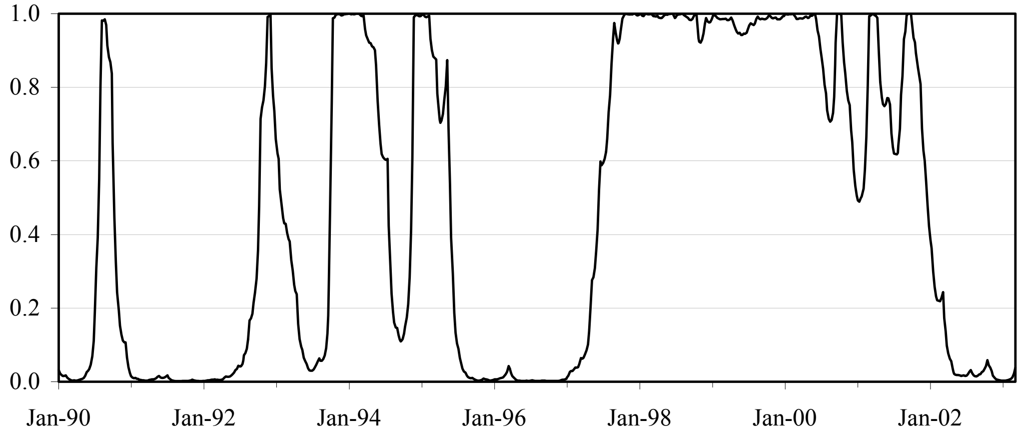
	Stock Market	**Quasi-government Bond Market**	**Forward Exchange Market**
$s_t = 1$	0.980	0.962	0.973
	(49 weeks)	(27 weeks)	(37 weeks)
$s_t = 2$	0.974	0.844	0.879
	(39 weeks)	(7 weeks)	(8 weeks)

Note: Figures in parentheses are measures of volatility-state persistence in number of weeks, which are calculated as $(1 - \text{transition probability})^{-1}$.

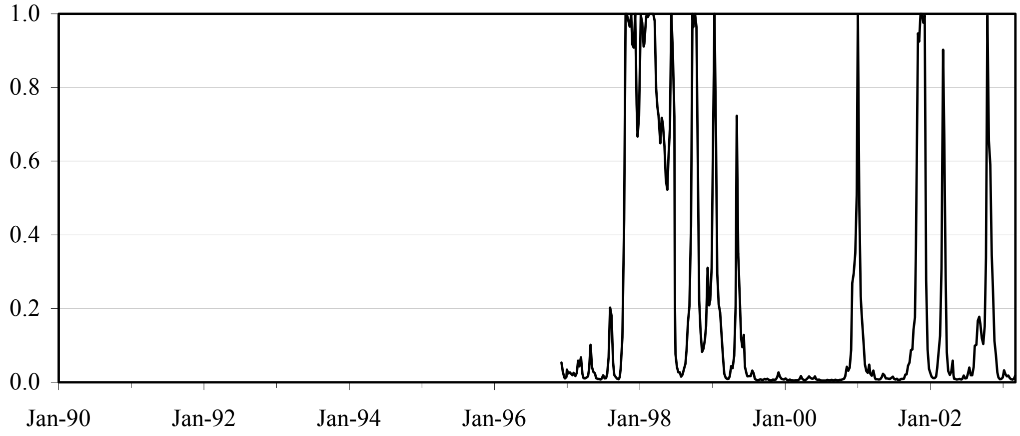
Chart 1 illustrates the smoothed probabilities of each financial market for the high-volatility state based on the univariate SWARCH model. From each panel in the chart, one can easily identify whether a high-volatility state coincides with each financial market during the same time period. Furthermore, the chart also provides early indication on which market is more sensitive to the news and shocks in the last decade.

Chart 1: Smoothed Probabilities at High-Volatility State

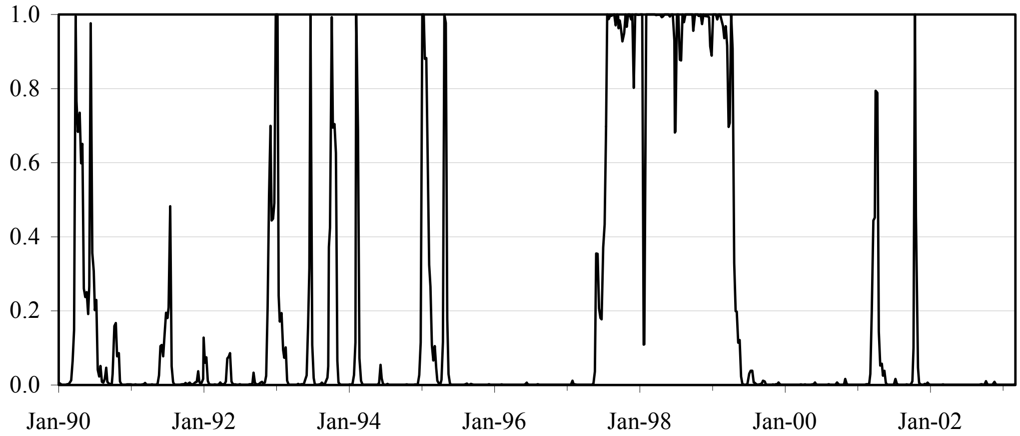
Stock Market



Quasi-government Bond Market



Forward Exchange Market



Note: Quasi-government bond series starts from November 1996.

From Chart 1, there is a close association for the appearance of high-volatility state in the three financial markets. In particular, the following observations from Chart 1 are worth noting:

- Stock and forward exchange markets were at a high-volatility state in late 1992 when the European Exchange Rate Mechanism (ERM) crisis surfaced.
- Stock and forward exchange markets exhibited sharp spikes in early 1995. This corresponds to the Mexican currency crisis.
- All three markets were at a high-volatility state from late 1997 onward, the period of the Asian financial crisis and the Russian-LTCM crisis. A closer examination reveals that stock and forward exchange markets were first to experience a shift to a high-volatility state from mid-1997.
- All three markets showed spikes in September 2001 when the US was under terrorist attack.

The graphs suggest that the high-volatility state of each financial market appears to occur at the same time. To examine the issue of volatility linkages between these markets, the univariate model is extended to a bivariate one in the next section.

IV. Volatility Linkages and Estimation Results

Estimation results from a bivariate AR(1) SWARCH(2,1) model are reported in Table 5. Diagnostic tests such as Q(6) and $Q^2(6)$ indicate that the data series are adequately modeled.

The scale parameters for volatility state two (g_2) are statistically significant in all markets for different pairs, suggesting that structural shifts need to be taken into account in modeling their volatility processes. As in the univariate case, the ARCH effect (α) in both stock and quasi-government bond markets disappears and only the estimated ARCH term of the forward exchange market is significant. As shown by the g_2 parameters, the volatility shift in the forward exchange market is the largest among all markets, with the variance at the high-volatility state (s_t = 2) over 80 times as large as that at the low-volatility state, compared to about ten times for the quasi-government bond market and three times for the stock market.

Table 5: Parameter Estimates of Bivariate AR(1) SWARCH(2,1) Model

	Stock – Quasi-government Bond	**Forward Exchange – Quasi-government Bond**	**Stock – Forward Exchange**
w_{10}	-0.112	-0.001	0.274*
	(0.718)	(0.004)	(0.119)
w_{11}	0.030*	0.082	0.017
	(0.076)	(0.071)	(0.040)
w_{20}	0.269*	0.267*	-0.004
	(0.065)	(0.062)	(0.003)
w_{22}	0.022	0.032	-0.173*
	(0.131)	(0.062)	(0.034)
c_{11}	7.310*	0.003*	5.863*
	(2.875)	(0.001)	(0.854)
c_{22}	0.741*	0.738*	0.004*
	(0.157)	(0.097)	(0.001)
α_{11}	0.000	0.535*	0.000
	(0.636)	(0.157)	(0.159)
α_{22}	0.029	0.026	0.471*
	(0.242)	(0.070)	(0.112)
$g_{2,1}$	2.937*	168.620*	3.771*
	(1.027)	(38.025)	(0.504)
$g_{2,2}$	9.633*	10.529*	81.385*
	(2.256)	(2.494)	(18.470)
Log likelihood	-1,472	-375	-1,408
$Q_1(6)$	4.43	3.38	7.27
$Q_2(6)$	5.87	5.36	6.07
$Q_1^2(6)$	1.86	0.66	1.97
$Q_2^2(6)$	0.63	0.66	10.28

Notes: Numbers in parentheses are standard errors. Standard errors are calculated from the inverse of the Hessian matrix. * indicates significance at the 5% level. Q (6) and Q^2 (6) are the Ljung-Box statistics based on the standardised residuals and the squared standardised residuals respectively up to order 6. Both statistics are asymptotically distributed as $\chi^2(6)$. The critical value of $\chi^2(6)$ at the 5% level is 12.59.

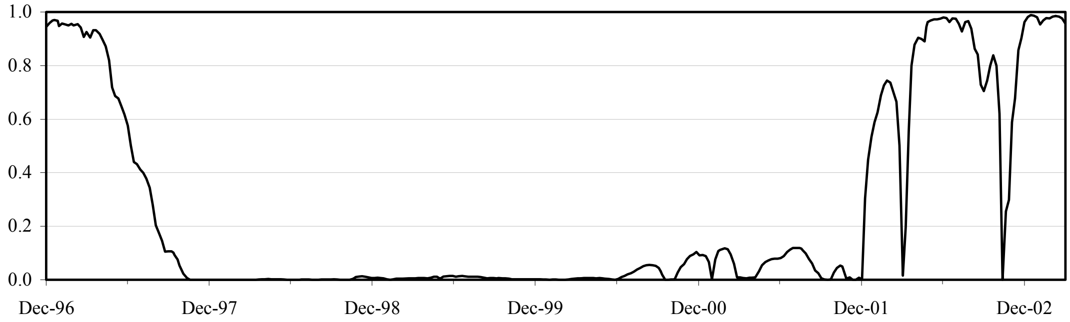
Charts 2 to 4 plot the smoothed probabilities of the four primitive volatility states (s_t^*) for the three market systems. The top panel is the smoothed probabilities when both markets are at a low-volatility state, whereas the bottom panel is the smoothed probabilities when both markets are at a high-volatility state.

In general, all market pairs started at a low-volatility state (top panel) and were jointly at a high-volatility state from early October 1997 onward (bottom panels). Except for some brief periods, the high-volatility condition lasted till early 1999. This clearly demonstrates that periods of "high volatility" coincide across different financial markets, suggesting that there are strong volatility linkages during crisis periods. After the 1997 – 98 crisis, the stock market remained at a high-volatility state from mid-1999 to 2000 while quasi-government bond and forward exchange markets were at a low-volatility state. All three markets shifted into a high-volatility state after the terrorist attack in the US in September 2001 but the disturbance was short-lived. Recently, except in some short-lived events, all market pairs had been at a low-volatility state since late 2002 (top panels). This shows that Hong Kong financial markets have regained their stability after events such as Asian and Russian financial crises, the burst of the technology bubble and the terrorist attack in the US.

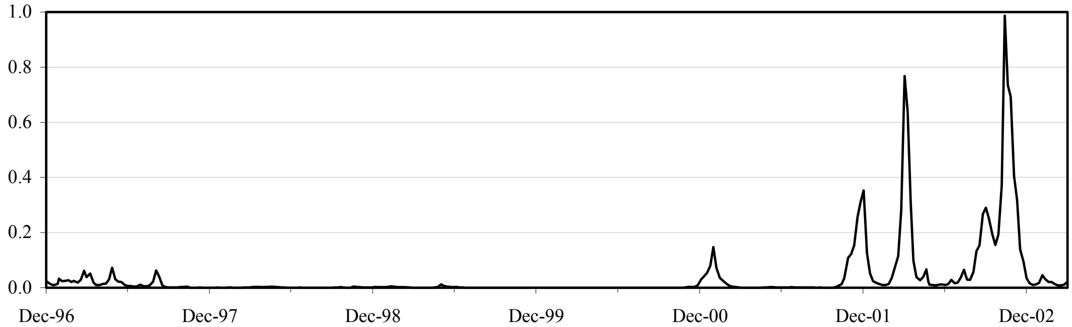
Another interesting feature of the SWARCH model is its ability to identify breakpoints and capture the reaction of different financial markets to news and events. For instance, from Chart 2, it is shown that stock market volatility shifted from a low-volatility state in early 1997 to a high-volatility state in mid-1997, while quasi-government bond market volatility remained at a low-volatility state. This may signal the sensitivity of the stock market to the change of sovereignty in July 1997, while the quasi-government bond market appeared to be insensitive. By October 1997, both markets responded to the Asian financial crisis and were at a high-volatility state.

Chart 2: Stock Market – Quasi-government Bond Market Volatility States

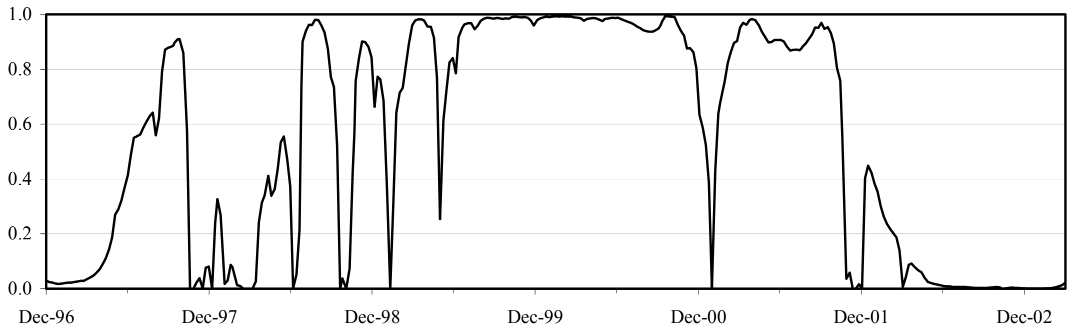
State 1: Stock Market - low volatility, Quasi-gov't Bond Market - low volatility



State 2: Stock Market - low volatility, Quasi-gov't Bond Market - high volatility



State 3: Stock Market - high volatility, Quasi-gov't Bond Market - low volatility



State 4: Stock Market - high volatility, Quasi-gov't Bond Market - high volatility

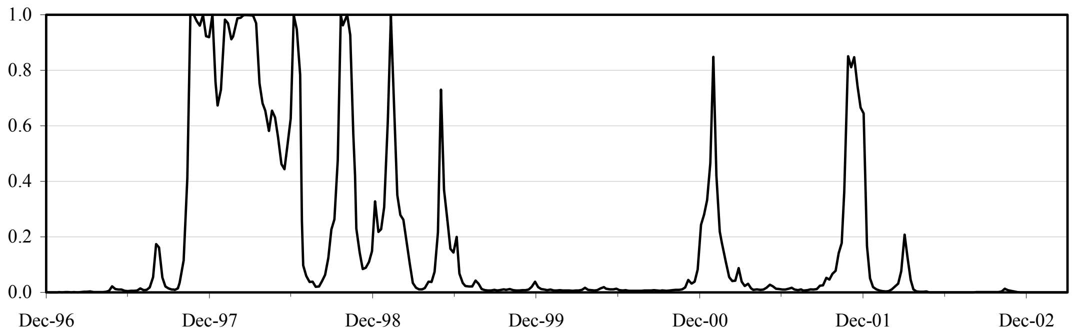
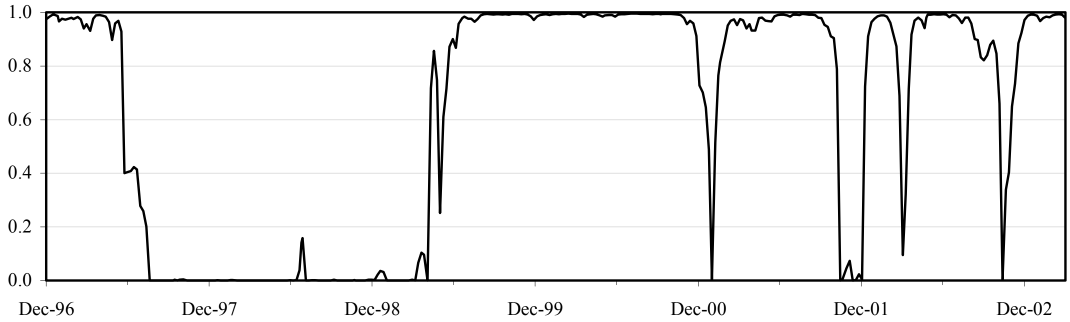
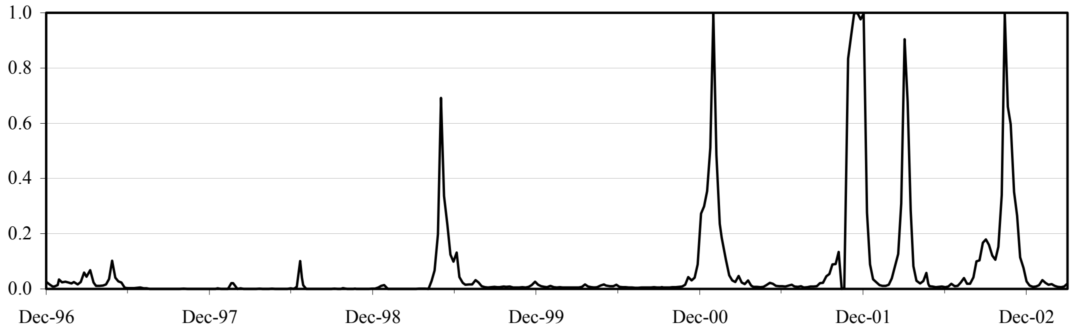


Chart 3: Quasi-government Bond Market – Forward Exchange Market Volatility States

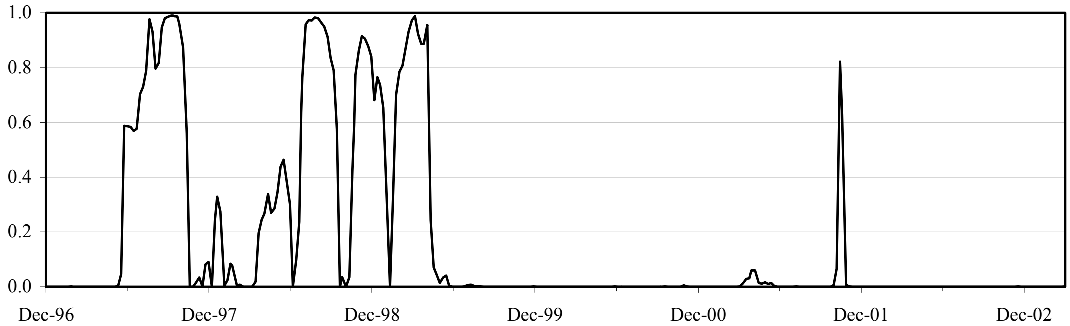
State 1: Forward Market - low volatility, Quasi-gov't Bond Market - low volatility



State 2: Forward Market - low volatility, Quasi-gov't Bond Market - high volatility



State 3: Forward Market - high volatility, Quasi-gov't Bond Market - low volatility



State 4: Forward Market - high volatility, Quasi-gov't Bond Market - high volatility

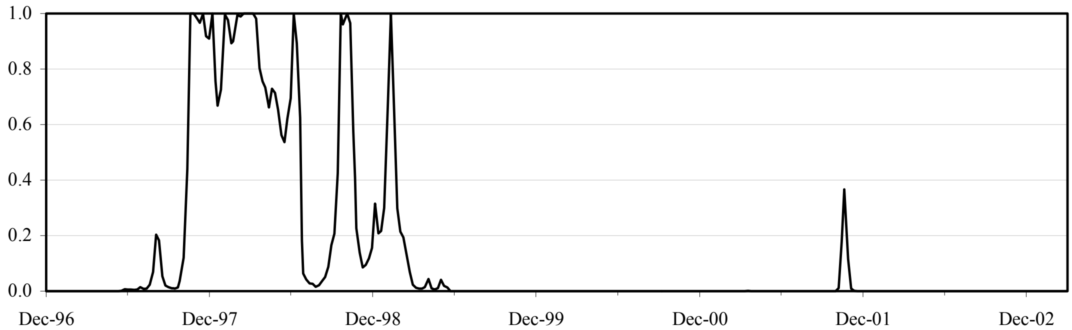
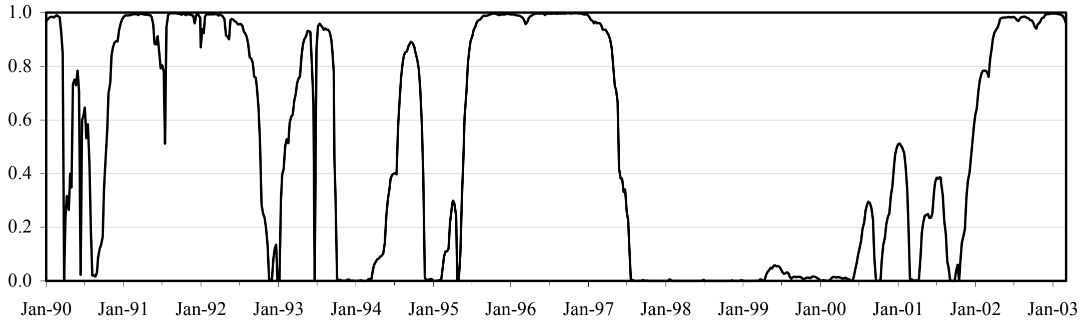
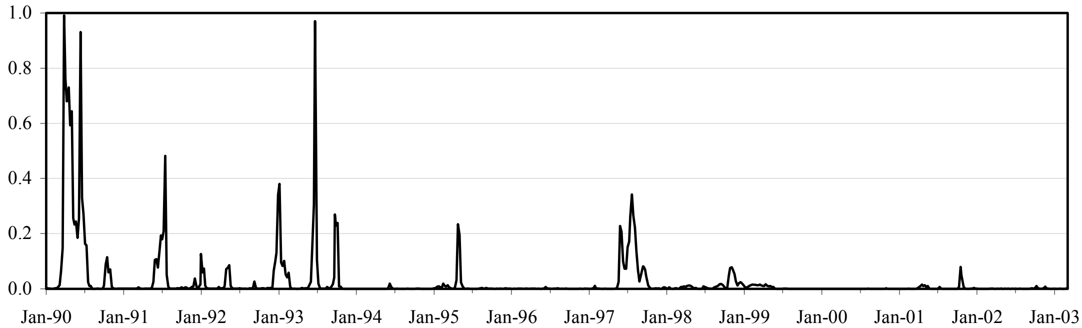


Chart 4: Stock Market – Forward Exchange Market Volatility States

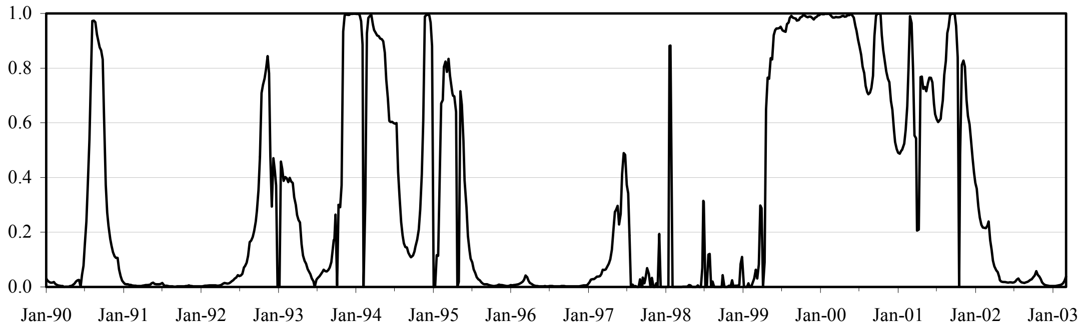
State 1: Stock Market - low volatility, Forward Exchange Market - low volatility



State 2: Stock Market - low volatility, Forward Exchange Market - high volatility



State 3: Stock Market - high volatility, Forward Exchange Market - low volatility



State 4: Stock Market - high volatility, Forward Exchange Market - high volatility

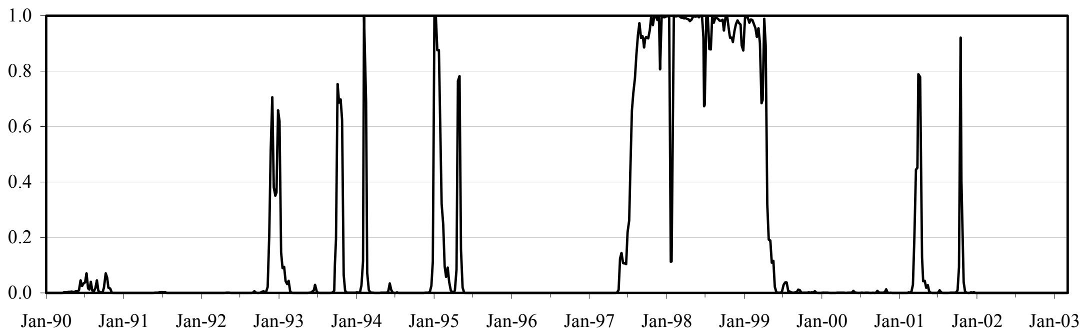


Table 6 gives the estimated transition probabilities of the three market systems when both markets start and remain at a particular volatility state. They show that, for most market pairs, the transition probability is quite high and the expected duration for the market pair to remain at the same volatility states can last for at least five weeks. For instance, the transition probability for both stock and quasi-government bond markets (first column) to be at the high-volatility state ($s_t^* = 4$) is 0.811. This translates into an expected duration (or volatility-state persistence) of 5 weeks (= $(1 - 0.811)^{-1}$). This means that, on average, stock and quasi-government bond markets are expected to start and remain at the high-volatility state for at least 5 weeks. One the other hand, for the stock and forward exchange market pair (third column), the transition probability for both markets to start at the high-volatility state and remain at the same state is only 0.856. The expected duration is 7 weeks (= $(1 - 0.856)^{-1}$). This indicates that when the market pair is at the high-volatility state, the expected duration of such volatility linkage across stock and forward exchange markets is longer than that of stock and quasi-government bond markets. Thus, the transition probability provides information to policy makers regarding the expected duration of volatility linkage across markets.

In summary, based on the parameter estimates in Table 6 and the smoothed probabilities graphs in Charts 2 to 4, the SWARCH model can provide additional information regarding volatility of financial time series, as well as in addressing the presence of regime shifts in the volatility process.

Table 6: Parameter Estimates of Transition Probabilities

s_t^* = 1: Market 1 – low volatility, Market 2 – low volatility.
s_t^* = 2: Market 1 – low volatility, Market 2 – high volatility.
s_t^* = 3: Market 1 – high volatility, Market 2 – low volatility.
s_t^* = 4: Market 1 – high volatility, Market 2 – high volatility.

	Stock – Quasi-government Bond	Forward Exchange – Quasi-government Bond	Stock – Forward Exchange
$s_t^* = 1$	0.944	0.948	0.953
	(18 weeks)	(19 weeks)	(21 weeks)
$s_t^* = 2$	0.809	0.814	0.861
	(5 weeks)	(6 weeks)	(7 weeks)
$s_t^* = 3$	0.946	0.930	0.948
	(19 weeks)	(14 weeks)	(19 weeks)
$s_t^* = 4$	0.811	0.799	0.856
	(5 weeks)	(5 weeks)	(7 weeks)

Note: Figures in parentheses are measures of volatility-state persistence in number of weeks, which are calculated as $(1 - \text{transition probability})^{-1}$.

V. Conclusion

The analysis in this paper provides an understanding on the issue of volatility linkages between three financial markets in Hong Kong, namely the stock market, the quasi-government bond market and the HKD forward exchange market. Such understanding is important to investment professionals from a risk diversification perspective as well as policy makers for their financial stability concern.

As structural shifts in the conditional variance process are common in many financial time series, the regime switching ARCH (SWARCH) model clearly demonstrates its usefulness in identifying the presence of such shifts in the volatility processes of financial markets. Based on a SWARCH model, the analysis in this paper finds evidences of volatility co-movement between financial markets, especially during crises like the Asian financial crisis. The expected duration for a pair of financial markets to stay at a high-volatility state is between five to seven weeks. For a shock in a magnitude as severe as the Asian financial crisis, the duration for these financial markets to stay at a high-volatility state can be as long as six months. This result can be useful to policy makers in gauging the possible duration of disruption in the financial system under a severe shock and in the development of more effective policies when dealing with financial crises.

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