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Volatility Switching and Regime Interdependence Between Information Technology Stocks 1995-2005

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Abstract

In this paper we adopt both univariate and bivariate SWARCH models to analyze volatility regime switching and regime interdependence for information technology (IT) stocks in Canada, France, Hong Kong, Japan, Taiwan, the United States and a composite Emerging Markets (EM) index. The results from the univariate SWARCH model suggest that during the Asian, Brazilian and Russian financial crises, prior to the IT bubble, different IT markets exhibited different switching behavior in response to the same crisis. However, during the IT bubble, when the fundamentals of the IT industry changed dramatically, all IT markets experienced the same volatility switching pattern and have since experienced similar volatility switching patterns. This result suggests that prior to the IT bubble country effects were more important for IT stocks, but the effect of the IT bubble has been to make industry effects more important than country effects in explaining the volatility switching behavior of IT stocks. The results from the bivariate SWARCH model indicate that the Hong Kong and French IT markets are independent of the U.S. IT market and while there is evidence of volatility regime dependence of the Canadian, Japanese, Taiwanese and EM IT markets on that of the U.S. IT market, none of these IT markets share a common volatility regime with the U.S. IT market.

Keywords: Volatility; Regime Switching; Interdependence; Information Technology

JEL Classification: F3; G12; G15

1. Introduction

The rapid growth and diffusion of information technology (IT) was a major driver of economic growth throughout the 1990s and, as such, has attracted much attention from analysts and investors alike. Oliner and Sichel (2000) estimated that developments in computer hardware, software and network infrastructure accounted for about two-thirds of the acceleration in labor productivity for the non-farm business sector in the United States (U.S.) between the first and second halves of the 1990s. By 1999-2000 a consensus was emerging that the IT revolution was responsible not only for productivity growth acceleration, but also for a stock market and wealth boom that were spreading benefits to those in the lower deciles of income distribution (Gordon, 2002, pp. 4-5). Gains in technology fueled the fastest growing companies in history through the second half of the 1990s. Between October 1998 and March 2000 the tech-focused NASDAQ stock market index more than tripled. Cisco Systems, then the world's most valuable company, traded at almost 200 times earnings. In 1990, Cisco Systems, Dell Computer and Microsoft had combined sales of $US2 billion; by 2000 their sales were $US80 billion (Berenson, 2001). Writing at the peak of the IT bubble, Gordon (2000, p. 49) stated: "The true enthusiasts treat the New Economy as a fundamental industrial revolution as great or greater in importance than the concurrence of inventions, particularly electricity and the internal combustion engine, which transformed the world at the turn of the last century".

However, what Gordon (2002, p. 1) termed "the miracle of U.S. economic performance between 1995 and mid-2000" that occurred on the back of the growth in the IT sector in the second half of the 1990s began to unravel when the NASDAQ fell by half between March and December 2000. In 2000 and 2001 it was reported that 784 IT companies went out of business and in those two years 143,440 workers in the IT industry in the U.S. lost their jobs (Maich, 2003). Profits of Yahoo, a company whose primary source of revenues is online advertising, collapsed from earnings of nearly $US300 million in 2000 to almost nothing in 2001. Yahoo's stock price slumped from a high of about $US 240 in early 2000 to $US 17 on March 9, 2001, the first anniversary of the 5000-level peak of the NASDAQ. Over the same period, IT stocks in countries other than the U.S also collapsed, focusing attention on the fact that the collapse in IT stocks was a global phenomenon.

Many researchers have examined interdependence, volatility transmission, and market integration among major national stock markets. Important studies include Jeon and von Furstenberg (1990), Hamao *et al*. (1990), Campbell and Hamao (1992), Longin and Solnik (1995), Hamori and Imamura (2000), Masih and Masih (2001) and Edwards and Susmel (2001) among others. A common finding in these studies is that co-movement across national stock markets has increased since the 1990s. This finding has resulted in growing interest in the importance of industry factors in explaining international return variation as investors consider alternative diversification strategies to reduce risk. Baca *et al.* (2000) reported that the importance of global industry factors in explaining international return variation increased in importance in the late 1990s. Cavaglia *et al.* (2000) and L'Her *et al.* (2002) found that industry factors had become more important than country factors in explaining variations in share returns in the late 1990s.

However, overall, as a subset of the literature on co-movements between national stock markets, there are relatively few studies that have examined industry-based stock market interdependence. Of the studies which do, Jorge and Iryna (2002) applied univariate T-GARCH models to examine whether price changes and volatility spillovers were generated from the U.S. or from the Asia-Pacific region, using stock data for the Telecommunications, Media and Technology (TMT) and non-TMT sectors from January 1990 to May 2001. Their findings suggested that the U.S. market plays an important role in determining price dynamics in Asia-Pacific stock markets for both the TMT and non-TMT sectors. They also found that Asia-Pacific stock markets have little or no effect on U.S. stock markets, especially for TMT stocks. Jeon and Jang (2004) used a vector autoregression (VAR) model to examine the interrelationship between the NASDAQ and KOSDAQ stock market indices for high-tech industries in South Korea as well as the relationship between the stock prices of South Korean and U.S. semiconductor firms, for the period July 1996 to February 2001. Their main finding was that unidirectional causation runs from the U.S. high-tech to the South Korean high-tech index.

To this point there is little research that analyzes the volatility of IT stocks. One study that does is an unpublished working paper by Ryan (2002). Ryan (2002) attempted to use a SWARCH model to identify regime switches in volatility and to analyze the volatility regime dependence of French IT stocks on U.S. IT stocks. However, his findings are suspect on econometric grounds because Ryan (2002) ignored both changing regime parameters and correlation parameters in the variance-covariance matrix of the bivariate SWARCH model. Given the important role the IT sector has played in the world economy since the mid-1990s as well as the interest it has attracted amongst investors, it is somewhat surprising that more research does not exist on co-movement between different IT markets. From the perspective of investors in IT stocks, it is interesting to examine co-movement between IT markets because if one IT market suffers a local shock, it is important to know whether other IT markets will be similarly affected.

In this paper we address this gap in the literature by applying both univariate regime switching ARCH (SWARCH) (Hamilton and Susmel, 1994) and bivariate SWARCH models (Edwards and Susmel, 2001, 2003) to analyze volatility regime switching and regime interdependence of IT stocks for Canada, France, Hong Kong, Japan, Taiwan, the United States and a composite Emerging Markets (EM) index.[1] Modeling volatility in IT markets with regime switching techniques is important because abrupt events in these markets have been common place over the past decade. Compared with traditional techniques of modeling volatility such as ARCH/GARCH models, one advantage of SWARCH models is that they allow stochastic regime shifts in the conditional volatility and assume that the transition between regimes is governed by a discrete state and hidden Markov process. Consequently the SWARCH model can avoid the misspecification problems of GARCH models when the volatility process is subject to abrupt changes (see Diebold, 1986; Hamilton and Susmel, 1994; Lamoureux and Lastrapes, 1990).

The remainder of the paper is organized as follows: Section 2 gives an overview of the markets and discusses the data and methodology. The empirical results are presented and analyzed in Section 3 and the final section contains some concluding remarks. Foreshadowing our main findings, the results from the univariate SWARCH model

[1] The Datastream Emerging Market index contains IT stocks from Columbia, China, Cyprus, Czech Republic, Hungary, India, Israel, Korea, Malaysia, Poland, South Africa, Taiwan, Thailand and Turkey.

confirms the presence of regime switching in the volatility of IT stock markets and further indicates the existence of three separate regimes for each IT stock market. We find that volatility switching patterns differ across stock markets in response to the Asian, Brazilian and Russian financial crises, but they had similar reactions to the formation and spread of the IT bubble that commenced in 1999. All markets switched to a high volatility regime in the period following the collapse of the IT bubble, while all stocks gradually switched to a low volatility regime as IT markets stabilized. We interpret our findings as suggesting that prior to the IT bubble in mid-1999 country effects were more important for IT stocks, but the effect of the IT bubble was to make industry effects more important than country effects for IT stocks. The results from the bivariate SWARCH model indicate that the Hong Kong and French IT markets are independent of the U.S. IT market and while there is evidence of volatility regime dependence of the Canadian, Japanese and Taiwanese IT markets as well as the EM index on that of the U.S. IT market, none of these IT markets share a common volatility regime with the U.S. IT market.

2. Overview of the Markets, Data and Methodology

The data consists of the EM composite IT index and the IT indices for the United States (US), Canada (CA), France (FR), Japan (JP), Taiwan (TW) and Hong Kong (HK) available in *Datastream*[2]. Table 1 provides an overview of the stock markets in the six countries with separate stock market indices. With the exception of Taiwan, each of these countries is classified by Standard and Poors (2004) as a developed market. The sample contains three of the major Asian markets, a major European market and the two major

[2] The choice of countries was dictated by data availability. *Datastream* does not provide IT indices for the other G7 countries, (UK, Germany and Italy). *Datastream* does provide IT indices for some emerging markets beginning in 2000, but this presents a short time span for these countries and several have missing observations.

North American markets. Based on both market capitalization and total value traded the United States and Japan are the two largest stock markets in the world, France is in the top five and Canada, Hong Kong and Taiwan are around the top 10. The United States, Canada and Japan are in the top 10 based on the number of listed domestic companies, while Hong Kong lies just outside the top 10. In terms of average company size, the United States and France are in the world's leading stock markets, but the others fall down the list, with Canada and Taiwan dropping out of the top 20 with smaller listed companies.

Insert Table 1

These countries also have substantial IT sectors. The Network Readiness Index (NRI) is a measure of the degree of preparation of a country to take advantage of IT developments. It consists of three components; namely, the IT environment, the readiness of key stakeholders to take advantage of advances in IT and the usage of IT products by key stakeholders. In the 2004-2005 NRI the United States ranked fifth, Hong Kong ranked seventh, Japan ranked eighth, Canada ranked tenth, Taiwan ranked fifteenth and France ranked twentieth out of 105 countries (World Economic Forum, 2005). These countries are also among the leading computer producing economies in the world. In 2000 the United States was the largest producer of computer hardware in the world with 26.1% of global share; Japan was the second largest with 16.3% of global share; Taiwan was fifth with 6.5% of global share and France fourteenth with 6.5% of global share (APEC, 2002).

Instead of using daily data as some previous studies have done (see e.g, Ryan, 2002) to address the problem of non-synchronous trading (Lo and MacKinlay, 1988) we use the weekly Wednesday stock price indices for the IT sector that are complied by *Datastream*. The data are for the period January 1995 to July 2005, which gives a total of 554 observations. To avoid exchange rate bias, all indices are expressed in US dollars. This follows the approach in several similar studies (see Edwards and Susmel, 2001; Geert *et al.,* 2005; Cappiello *et al.,* 2006 and Tai, 2007). The log of weekly returns:

$$r_t = 100(\ln p_t - \ln p_{t-1}) \tag{1}$$

is used where r_t is the weekly continuously compounded rate of return and p_t is the corresponding price index on date *t* for each of the IT stock price indices.

We employ a SWARCH model in our study because, in contrast to the standard ARCH/GARCH models, it enables the incorporation of regime shifts or structural breaks in the conditional variance process.[3] As discussed by Hamilton and Susmel (1994), during regime shifts the behavior of time series could change dramatically. Thus, both univariate and bivariate SWARCH models have to be used together to circumvent this problem. In this section, we first discuss the univariate SWARCH model used to analyze the volatility behavior for each IT market and then outline the bivariate SWARCH framework used to estimate volatility dependence between two series simultaneously.

[3] In addition to a model with variance switching, we also employed a model with mean switching and a model with simultaneous mean and variance switching. While we found evidence of variance switching, we found no evidence of mean switching or simultaneous mean and variance switching. Thus, we only report the model with variance switching. The results of the models with mean switching and simultaneous mean and variance switching are available upon request.

Univariate SWARCH Analysis

We first adopt the regime switching ARCH (SWARCH) model developed by Hamilton and Susmel (1994) to model the conditional variance for each of the return series. The settings of the SWARCH (K, q) for r_t are defined as follows:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \cdots + \phi_l r_{t-m} + \varepsilon_t \qquad \varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \qquad (2)$$

$$\varepsilon_t = \sqrt{g_{s_t}}\, u_t \qquad s_t = 1,2,\cdots K$$

$$u_t = \sqrt{h_t} \cdot v_t$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i u_{t-i}^2$$

where r_t is the return of an index at time *t* defined in Equation (1)*, q* is the number of ARCH terms, *K* is the number of regime states, Ω_{t-1} is the matrix of information available up to time *t-1*, v_t is an independent and identically-distributed (*i.i.d.)* sequence with zero mean and unit variance and $\{g_{s_t}\}$ ($s_t = 1,2,\cdots K$) are the scale changing regime parameters that capture the size of volatilities in different regimes. The underlying ARCH variable u_t is multiplied by the scale parameter $\sqrt{g_1}$ when the process is in the regime represented by s_t = 1, multiplied by $\sqrt{g_2}$ when s_t= 2 and so on. Thus, different regimes are measured by different scale variables g_{s_t}, thereby changing the conditional variance equation accordingly. The first regime of the scale parameter g_1 is normalized to be unity while $g_{s_t} \geq 1$ for s_t = 2, 3, … , *K*. Under a Gauss distribution, we have:

$$f(r_t \mid s_t, s_{t-1}, \cdots s_{t-q}, r_{t-1}, r_{t-2}, \cdots r_{t-q}) = \frac{\exp\left\{\dfrac{-(r_t - \phi_0 - \phi_1 r_{t-1} - \cdots - \phi_1 r_{t-m})^2}{2h_t(s_t, s_{t-1}, \cdots s_{t-q})}\right\}}{\sqrt{2\pi h_t}(s_t, s_{t-1}, \cdots s_{t-q})} \quad . \tag{3}$$

The conditional variance of ε_t is:

$$\begin{aligned} h_t\left(s_t, s_{t-1}, \cdots, s_{t-q}\right) &\equiv \mathrm{E}\left(\varepsilon_t^2 \,\middle|\, s_t, s_{t-1}, \cdots s_{t-q}, \varepsilon_{t-1}, \varepsilon_{t-2}, \cdots \varepsilon_{t-q}\right) \\ &= g_{s_t}\left\{a_0 + a_1 \cdot \left(\frac{\varepsilon_{t-1}^2}{g_{s_{t-1}}}\right) + a_2 \cdot \left(\frac{\varepsilon_{t-2}^2}{g_{s_{t-2}}}\right) + \cdots a_q \cdot \left(\frac{\varepsilon_{t-q}^2}{g_{s_{t-q}}}\right)\right\}. \end{aligned} \tag{4}$$

The *K*-state regime switching is assumed to follow a Markov process with probability:

$$\mathrm{Pr}ob(s_t = j \mid s_{t-1} = i, s_{t-2} = k, \cdots; r_t, r_{t-1}, r_{t-2,\cdots}) = \mathrm{Pr}ob(s_t = j \mid s_{t-1} = i) = p_{ij}$$

for *i, j, k = 1, 2, …, K.* (5)

At time *t-1* in Regime *i,* the stock market will change to Regime *j* with fixed probability p_{ij}. The conditional distribution for any future regime s_{t+1} given past regimes $s_0, s_1, \ldots s_t$, is independent of $s_0, s_1, \ldots, s_{t-1}$ as it is determined only by the present state s_t. The transition probabilities in a $(K \times K)$ matrix are defined such that:

$$P = \left[\, p_{ij} \,\right] \text{ where } \; p_{ij} \geq 0, \;\; i, j \geq 0, \;\; \sum_{j=1}^{K} p_{ij} = 1, \;\; i = 1, 2, \cdots \; . \tag{6}$$

All estimators can be obtained by maximizing the following log-likelihood function:

$$\psi = \sum_{t=1}^{T} \ln f(r_t | r_{t-1}, r_{t-2,\cdots})$$

subject to:

$$g_1 = 1, \ \sum_{j=1}^{K} p_{ij} = 1 \ \text{ for } \ i = 0,1,\cdots K, \text{ and } \ 0 \le p_{ij} \le 1 \ \text{ for } \ i, j = 0,1,\cdots, K. \tag{7}$$

Estimating the model gives the "smoothed probability" $prob(s_t | r_T, r_{T-1}, \cdots)$ that provides information on the likelihood that the index is in a particular volatility state at time *t,* based on the full sample of observations. This provides a useful tool to examine volatility switching evolution in each IT market. Initially, in the analysis, we do not impose any constraint on the transition probabilities in the estimation except $p_{ij} \ge 0$, $i, j \ge 0$, $\sum_{j=1}^{3} p_{ij} = 1$. However, the unrestricted *MLE* could fall into the boundary of $p_{ij} = 0$ and when this occurs the regularity conditions will be violated[4]. To address this issue, we set $p_{ij} = 0$ and treat this parameter as a known constant for calculating the second derivatives of the log-likelihood function. In addition, we also employ several randomly generated starting values in the estimation to check the consistency of the estimates and to reduce the possibility of attaining any local minimum.

Bivariate SWARCH Analysis

While univariate SWARCH analysis can offer some useful insights into the nature of volatility associated with different IT markets, it cannot be used to examine the interrelationship between volatility across markets. To address this issue, we adopt a

[4] In this case we can obtain the likelihood value, but we cannot obtain standard errors for the estimated coefficients.

multivariate SWARCH framework developed by Edwards and Susmel (2001, 2003) to test whether volatility is independent across IT markets. In principle, volatility could be independent across IT markets if the IT markets are isolated. If, however, these markets are driven by common factors, shocks will be transmitted rapidly across markets and volatility will not be independent across IT markets. In order to keep the number of parameters small enough to make the estimation tractable, we analyze pairs of markets. As the IT industry in the U.S. holds a leading position in the world, and its stock prices are closely monitored by investors globally, we examine whether volatility in each of the IT markets in the non-U.S. countries in the sample is dependent on the IT market in the U.S. More specifically, we test two null hypotheses; namely, the independent volatility regime hypothesis and the common volatility regime hypothesis. The independent volatility regime hypothesis states that the volatility regime of the non-U.S. IT market is independent of the volatility regime of the U.S. IT market. The common volatility regime hypothesis states that the IT market of each of the countries other than the U.S. in the sample shares a common volatility regime with the U.S. IT market.

As bivariate SWARCH analysis is extremely computationally intensive, in this study we restrict the SWARCH model to analyze only two volatility regimes (low volatility and high volatility) and one ARCH term in the conditional variance process (SWARCH(2,1)) . To construct the model, we use an AR (1) process to specify the conditional mean due to partial-price adjustment, limit-price policy, the existence of feedback trading and other forms of market friction (Kim and Rogers, 1995; Koutmos, 1998; Antoniou *et al*., 2005). With this bivariate AR(1)-SWARCH (2,1) specification, the total number of states is four;

namely, the low and high volatility regimes of U.S. matching against the low and high regimes of other markets respectively. Here, we use superscripts *x* and *y* to denote the U.S. and a non-U.S. market respectively. The four possible states, s_t^*, are defined as follows:

$s_t^* = 1$: low volatility in markets x and y,

$s_t^* = 2$: low volatility in market x but high volatility in market y,

$s_t^* = 3$: high volatility in market x but low volatility in market y, and

$s_t^* = 4$: high volatility in markets x and y.

This is a general regime specification encompassing a range of interactions between any volatility regime in the U.S. and any volatility regime in one of the other countries in the sample being studied. The switch between regimes is then governed by a 4x4 transition probability matrix $P^* = [p_{ij}^*]$ with each element defined as:

$$p_{ij}^* = \mathrm{Prob}(s_t^* = j \mid s_{t-1}^* = i), \qquad i, j = 1, 2, 3, 4. \tag{8}$$

The bivariate AR(1)-SWARCH(2,1) model can then be written as:

$$r_t = A + Br_{t-1} + e_t \qquad e_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{9}$$

where $H_t = \begin{bmatrix} h_t^x & h_t^{xy} \\ h_t^{yx} & h_t^y \end{bmatrix}$, $r_t = \begin{bmatrix} r_{x,t} \\ r_{y,t} \end{bmatrix}$ is a 2x1 vector of returns, $A = \begin{bmatrix} \varphi_{0x} \\ \varphi_{0y} \end{bmatrix}$ is 2x1 vector and $B = \begin{bmatrix} \varphi_{1x} & 0 \\ 0 & \varphi_{1y} \end{bmatrix}$ is 2x2 vector in conditional mean, and $e_t = \begin{bmatrix} e_{x,t} \\ e_{y,t} \end{bmatrix}$ is a 2x1 vector of disturbances assumed to follow a bivariate normal distribution with zero mean and a time varying conditional covariance matrix, H_t, which is regime dependent and specified as a constant correlation matrix where the diagonal elements h_t^x and h_t^y follow the univariate SWARCH (2,1) process as specified above. As there are too many parameters to be estimated in a bivariate regime switching model, we follow Edwards and Susmel (2001, 2003), Ang and Bekaert (2001) and Fong (2003) in imposing the restriction on the system that the correlations are equal within Regimes 1 and 2 and within Regimes 3 and 4. This keeps the estimation tractable and implies that correlations change only when any volatility regime in the U.S. IT market changes. This is a reasonable restriction to impose given the dominant influence of the U.S. IT industry on global IT stocks[5]. Based on this restriction, the covariance h_t^{yx} is specified as:

$$h_t^{yx} = \rho_t^x (h_t^x \cdot h_t^y)^{\frac{1}{2}} \quad . \tag{10}$$

In this study, we apply a two-step process to examine formally the volatility regime interdependence between each of the non-U.S. IT markets and the U.S. IT market. We first estimate the unrestricted bivariate AR(1)-SWARCH(2,1) model with the general transition probability matrix described in Equation (8), and thereafter test the independent volatility regime hypothesis. For those IT markets where the null hypothesis of independence is rejected, we examine the null hypothesis that there is a common volatility regime.

The rationale for the independent volatility regime hypothesis is straightforward. If the volatility regimes of *x* and *y* are independent, each transition probability in Equation (8)

[5] All estimations in this study are implemented using the OPTIMUM module of GAUSS with a combination of the BFGS numerical algorithm as described in Gill and Murray (1972).

will collapse into the product of two independent transition probabilities. Thus, the independent volatility regime hypothesis infers the following transition probability matrix:

$$P^* = \left[p_{ij}^* \right] \equiv \begin{bmatrix} p_{11}^x p_{11}^y & p_{11}^x p_{21}^y & p_{21}^x p_{11}^y & p_{21}^x p_{21}^y \\ p_{11}^x p_{12}^y & p_{11}^x p_{22}^y & p_{21}^x p_{12}^y & p_{21}^x p_{22}^y \\ p_{12}^x p_{11}^y & p_{12}^x p_{21}^y & p_{22}^x p_{11}^y & p_{22}^x p_{21}^y \\ p_{12}^x p_{12}^y & p_{12}^x p_{22}^y & p_{22}^x p_{12}^y & p_{22}^x p_{22}^y \end{bmatrix} \qquad i, j = 1,..4. \tag{11}$$

If the independent volatility regime hypothesis is rejected, we further examine the common volatility regime hypothesis between the IT market in the U.S. and the IT market in the other countries in the sample. Take p_{12}^* as an example; if the transition probability of Regime *i* to Regime *j* of the two markets is exactly the same, then we have:

$$p_{12}^* = \Pr ob(s_t^x = 1\, and\ s_t^y = 2 \mid s_{t-1}^x = 1\, and\ s_{t-1}^y = 1\ ) = 0\ . \tag{12}$$

Thus, the common volatility regime hypothesis implies that the transition probability matrix will become:

$$P^* = \begin{bmatrix} p_{11}^* & 0 & 0 & p_{41}^* \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ p_{14}^* & 0 & 0 & p_{44}^* \end{bmatrix}\ . \tag{13}$$

The independent volatility regime hypothesis can be investigated by employing the

Likelihood Ratio Test (LRT). Estimation of the unrestricted bivariate AR(1)-SWARCH(2,1) model is first conducted to obtain the corresponding log-likelihood function, $\log L_U$. A restricted model with transition probability matrix as in Equation (12) is then estimated, yielding the log-likelihood $\log L_R$. The null hypothesis of volatility regime independence can then be examined using the LRT statistic, $LR = -2(\log L_R - \log L_U)$. Under the null hypothesis, this statistic follows a chi-squared distribution with k degrees of freedom where k is given by the number of additional parameters estimated under the alternative hypothesis. Rejection of the hypothesis infers that the volatility regimes of the two markets are not independent. For those pairs where the null hypothesis of independence is rejected, we follow a similar procedure to test the null hypothesis of a common volatility regime.

3 Empirical Results

We plot the stock price indices in the IT sectors for each of the countries being studied in Figure 1. Figure 1 shows clearly that stock prices in the IT sector increased rapidly prior to 1999 and slumped sharply after 2001. Table 2 contains descriptive statistics for the weekly returns of the IT sectors for each of the countries in the sample. With the exception of Hong Kong, the returns are skewed to the left. Consistent with the literature, the kurtosis coefficients show that the distributions of the series have fat tails and the Jarque-Bera statistic suggests that each of the stock returns are not normally distributed. To examine serial correlation in the level and squared level of the stock returns, we applied the Ljung-Box (LB) test on both the returns series (LB(q)) and on the square of the return series ($\text{LB}^2(q)$) respectively, where q represents the number of lags included in the computation of the LB statistics. The significance of the LB^2 statistics at lag 5 and lag 10 infers the existence of strong serial correlation in the squared levels, consistent with the presence of time-varying volatility such as ARCH or GARCH effects in the return series.

Insert Figure 1 and Table 2 here

To begin with, we model the conditional volatility for each IT stock market by using the univariate SWARCH framework to examine the change effect in the variance regimes. The univariate SWARCH (3,1) model with three regimes and one autoregressive coefficient in the variance equation is the best specification based on the Akaike Information Criteria (AIC).[6] Table 3 presents the estimated results of the AR(1)-SWARCH(3,1) model for each country. The values of the log likelihood functions for the SWARCH(2,1), SWARCH(2,2) and SWARCH(3,2) models are also reported for reference. The Ljung-Box statistic for the residuals of the AR(1)-SWARCH(3,1) model indicates no serial correlation in either the residuals nor the squared residuals, inferring that the fitted model is appropriate.

Insert Table 3 here

As shown in Table 3, the estimated scale changing regime parameters for variances in Regime 2 (g2) and Regime 3 (g3) are significantly different from unity, suggesting that

[6] The AIC is calculated as a value of the likelihood function depending on *k* number of parameters in the model. For all IT markets except France, SWARCH (3,1) was selected as the best specification. For France, the AIC of SWARCH (3,1) is -1626.91, which is only marginally smaller than -1626.38 of SWARCH (2,1). As the SWARCH (3,1) model carries more information on volatility regimes than the SWARCH (2,1) model, we prefer SWARCH(3,1) for the French IT market here.

structural shifts have to be taken into account when modeling the volatility processes for all series. The results also indicate the existence of three separate volatility regimes: “low”, “medium” and “high” volatility regimes for each IT stock market. In addition, g2 and g3 provide useful information on the structural change in these markets. More specifically, they reveal volatility magnitude ratios of high volatility and medium volatility regimes respectively relative to a low volatility regime. These ratios vary greatly across markets. For example, for the U.S., the conditional variance in high (moderate) volatility regime is on average 7.67 (2.59) times of that in the low volatility regime. The corresponding ratios are 19.66 and 3.45 for Hong Kong. Thus, the relative strength of high volatility to low volatility regimes in the U.S. IT market is much smaller than that in the Hong Kong IT market. This implies that the IT stock market in Hong Kong is more volatile than that in the U.S. and that, consequently, a high volatility regime has a larger impact on the Hong Kong IT market than on the U.S. IT market.

In addition to providing the relative magnitudes of variances at different volatility regimes as discussed above, the SWARCH model can also be used to measure the proportion of time the market remains in a particular regime. The Ergodic probabilities ω1, ω2 and ω3 in Table 3 reflect this information. The low volatility regime dominates the IT markets in France, Hong Kong and the EM composite index for most of the period while the medium volatility regime dominates the IT markets for the U.S., Japan, Canada and Taiwan. The results also indicate that, although no market remains in the high volatility regime for most of the time, the IT market for Canada was highly volatile for 32.8% of the period being studied. Thus, investment risk for investors in the Canadian IT market has been sizeable.

The matrix of the transition probability of the SWARCH model is also reported in Table 3. For all markets, we find p_{11}, p_{22} and p_{33} is close to one, which implies that the volatility regime is very persistent. More importantly, our results show that transition probability $p_{13} = 0$ while $p_{23} \neq 0$ for all markets except Hong Kong.[7] This suggests that the high volatility state follows the medium volatility regime and that the market cannot jump to the high volatility regime directly from the low volatility regime.

A particularly attractive feature of the SWARCH model is that the estimates of the smoothed probability provide a useful means to study volatility regime shifts among different markets. Figure 2 plots the weekly stock return series in the first panel and plots the smoothed probability in the second through fourth panel in Regime 1 (low volatility), Regime 2 (moderate volatility) and Regime 3 (high volatility) respectively for the IT markets in each of the countries in the sample. We follow Hamilton's (1989) procedure for dating regime switches which classifies an observation as being in Regime *i* if the smoothed probability $prob(s_t = i | r_T, r_{T-1}, \cdots)$ is bigger than 0.5.

Insert Figure 2 here

Figure 2 provides a visual examination of the volatility switching patterns across markets. The volatility switching behavior in the U.S., Japanese and Canadian IT markets differs from that in Hong Kong and the EM composite index. Comparatively speaking, the markets of the latter group are more apt to shift between the three volatility regimes. One

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[7] For Hong Kong, we find p_{23} is bigger than p_{13}.

explanation for this phenomenon is that investors in developing markets are not as confident of market prospects relative to those in developed markets. It follows that their adjustments are responsive to a broader set of market information, i.e. any shock that disturbs index return parity conditions or the risk component in the local and international IT industries will lead them to adjust their portfolio allocation. In contrast, investors in the Canadian, Japanese and U.S. IT markets are more certain about market prospects and, thus, are not as likely to shuffle portfolios and this reduces volatility switching.

Figure 2 also provides a convenient instrument for tracking regime switching in different markets. It suggests that volatility switching in these IT markets reflects different responses to the major international financial crises over the period 1995 to 2005. Table 4 provides the periods of the three volatility regimes for each IT market based on the estimated smoothed probabilities, which is useful for comparing different volatility states across countries. During the Asian financial crisis, the IT markets of the U.S. and Canada remained in the medium volatility regime until August 19, 1998 and August 26 1998 respectively, while France remained in the low volatility regime until March 4, 1998, but the IT markets of Japan, Taiwan, Hong Kong and the EM composite index switched to a higher volatility regime during the same period. The IT markets of Japan and Hong Kong switched from the low volatility regime to the medium volatility regime on June 11 and August 6, 1997 respectively,[8] while Taiwan and the EM jumped from the medium volatility regime to the high volatility regime on June 4, 1997 and remained highly volatile until early February 1998. When the Russian financial crisis occurred in August 1998, the IT markets of the U.S, Canada, France and Hong Kong switched from the

[8] The Hong Kong IT market further shifted from a medium volatility regime to a high volatility regime on October 8, 1997.

medium volatility regime to the high-volatility regime on August 26, September 2, August 26 and August 12 of 1998, respectively. However, during this period, we do not find evidence of a shift in volatility regime for Japan, Taiwan or the EM. Our results show that the Brazil crisis, starting in early January 1999, had little impact in triggering the shift of volatility to a higher regime of all IT markets and the U.S. and Hong Kong even switched to a lower volatility regime in January 1999.[9] In short, we do not observe a high-volatility synchronization phenomena across countries during these financial crises. However, during the spread and burst of the IT bubble across the world, all markets became much volatile and switched to a higher volatility regime in late 1999 or early 2000 and remained turbulent for about two years. After the extremely volatile period in 2000 and 2001, apart for some temporary events, all markets have become less volatile, switching to the lower volatility regime gradually. In recent times these markets have not switched to a high volatility regime, implying that the markets have regained stability following the collapse of the IT bubble in 2001. Our results above suggest that prior to the IT bubble, country effects were more important for IT stocks but the effect of the IT bubble has been to make industry effects more important than country effects in explaining the volatility switching behavior of IT stocks.

Insert Table 4 here

The estimation of the bivariate SWARCH model for each of the countries reported in Table 5 contains the estimated SWARCH parameters, the estimated state-dependent correlation coefficients and the Likelihood Ratio Tests for the null hypothesis of volatility

[9] The U.S. IT market shifted from a high volatility regime to a medium volatility regime on January 13, 1999. The Hong Kong IT market shifted from a medium volatility regime to a low volatility regime on January 27, 1999.

regime independence and the null hypothesis of a common volatility regime for each country. As indicated in the table, the scale parameters of the volatilities in Regime 2 (g_{2x} and g_{2y}) are statistically significant in all markets, suggesting that structural shifts have to be taken into account when modeling their volatility processes. As shown in the table, for the U.S., when taking the regime shift in variance into account jointly, the variance in the high volatility regime is around three times that in the low volatility regime. For the other markets, the largest volatility shift in the IT market occurs in Hong Kong. Its variance in the high volatility regime is over eight times larger than that in the low volatility regime. The ARCH effect for the markets is small, with only the estimated ARCH terms for Taiwan and the EM composite index being statistically significant.

Table 5 here

The correlation coefficients ρ-lv and ρ-hv among the markets are highly significant. Interestingly, the correlations move in different directions when the U.S. shifts to a high volatility regime. For example, in the US-CA, US-JP, US-HK and US-EM relationships, the correlations become smaller when the U.S. IT market is in a low volatility regime than when the U.S. IT market is in a high volatility regime. However, the reverse is true for the US-FR and US-TW relationships. From a risk management perspective, the fact that correlations are smaller for the US IT market *vis-a-vis* France or *vis-a-vis* Taiwan when the US IT market moves to a high volatility regime is useful information because when the U.S. IT market is turbulent, investors could make use of this knowledge to reduce their investment risk by shifting their investments from the U.S. to France and/or Taiwan.

Figure 3 plots the smoothed probabilities of the four volatility states s_t^* described previously for six pairs of U.S. and non-US IT markets. In each case the first panel contains the probabilities for the first primitive state, s_t^*=1; that is, both markets are in the low volatility regime. The second panel contains probabilities for the second primitive state, s_t^* = 2, and so on. Integrating the first and second panels displays the smoothed probabilities in which the U.S. is in the low-volatility regime. Similarly, integrating panels 1 and 3 gives the smoothed probabilities in which the non-US markets are in the low volatility regime. As shown by the fourth panel for each pair of countries, although joint high volatility periods do not coincide exactly among different pairs, we observe that all pairs of IT markets were in State 4 (high-high volatility) in 2000 and 2001.

Of particular interest for each pair of countries as shown in Figure 3 are the first and last panels since the common volatility hypothesis implies that the low (high) volatility regime of one market could move with the other markets in the same low (high) volatility regime. As can be observed in Figure 3, the two states, s_t^*=1 and s_t^*=4, dominate the IT markets for most of sample period in each of the six pairs.[10] This result is suggestive that the volatility regime of these IT markets could be linked in the same direction.

Insert Figure 3 here

We applied the SWARCH specification with the transition probability matrix specified in Equation (11) to the data to examine the independent volatility regime hypothesis. As

[10] The proportion of time that the markets remain in a particular state is also reflected in the ergodic probabilities ω1, ω2 and ω3 and ω4 reported in Table 3.

shown in Table 5, the null hypothesis is rejected for the US-CA, US-JP, US-TW and US-EM pairs, but not for the US-FR and US-HK pairs. Thus, we conclude that the volatility regime of the IT markets in France and Hong Kong is independent of the volatility shifts in the U.S. IT market. Finally, we test the common volatility regime hypothesis for the US-CA, US-JP, US-TW and US-EM pairs. The results, which are reported in Table 5, indicate that the null hypothesis of a common volatility regime is rejected for each of these four pairs of countries.

4. Conclusions

In this paper we have analyzed the volatility regime switching and regime interdependence of a group of IT stock markets by using both univariate and bivariate SWARCH models. The results confirm the presence of a structural break in the volatility process and indicate the existence of three separate regimes for each IT market. We find that volatility switching patterns differ across markets. Of each of the markets, Hong Kong is the most volatile market in the sense that it has the largest variance magnitude ratios between high volatility and low volatility regimes as well as the most frequent shifts across the three regimes compared with other markets. The main finding from the univariate SWARCH model is that while the IT markets under consideration exhibited different responses to major international financial crises prior to the IT bubble of the late 1990s, they all had similar reactions to the formation and spread of the IT bubble and their volatility regime switching behavior has been similar in the period since the collapse of IT stocks. During the IT bubble all IT markets switched to a high volatility regime and since the IT bubble all markets have become less volatile, gradually switching to the lower volatility regime as the IT market has stabilized. This finding suggests that industry effects have become more important than country effects in explaining volatility shifting behavior in IT stocks since the formation and spread of the IT bubble in the late 1990s.

Based on our bivariate SWARCH analyses, there is strong evidence of volatility regime dependence of the Canadian, Japanese, Taiwanese and EM IT markets on that of the U.S. IT market although none of the IT markets in these countries share a common volatility regime with the U.S. IT market. Meanwhile, we found that the volatility regime of the French and Hong Kong IT markets is independent from that of the U.S. IT market. One limitation of our findings is that the bivariate SWARCH model adopted to examine markets interrelations can only capture the shift in ARCH terms. Further research is needed to develop a bivariate SWGARCH model that is able to capture possible shifts in both ARCH and GARCH terms, to analyze regime independence and correlations between IT markets. In this study we assume the conditional distribution is Gaussian. However, sometimes this cannot account for all the leptokurtosis in financial data. Thus, another avenue for further research might be to explore the use of more flexible distributional forms that can accommodate leptokurtosis in a parsimonious framework.

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Table 1: Key Indicators of Stock Markets in the Sample, 2003

	Canada	France	Hong Kong	Japan	Taiwan	United States
Market Capitalization [a]	893,950 (6th)[b]	1,355,643 (4th)	714,597 (9th)	3,040,665 (2nd)	379,023 (14th)	14,266,266 (1st)
Total Value Traded [a]	476,813 (12th)	995,376 (5th)	331,615 (15th)	2,272,989 (2nd)	592,012 (9th)	15,547,431 (1st)
Number of Listed Domestic Companies	3,578 (4th)	723 (14th)	1,029 (11th)	3,116 (6th)	669 (17th)	5,295 (2nd)
Average Company Size [a]	249.8 (36th)	1,875 (6th)	694.5 (18th)	975.8 (15th)	566.6 (24th)	2,694.3 (1st)

Notes: (a) Figures are in $US million.
(b) Figures in parenthesis are world rankings

Source: Standard and Poors (2004)

Table 2 Descriptive Statistics for Stock Returns of the IT Sectors

	US	CA	FR	JP	TW	HK	EM
Mean	0.218	0.018	0.107	0.018	0.200	0.160	0.219
Median	0.369	0.499	0.125	0.193	0.269	-0.072	0.245
Maximum	16.622	22.542	22.875	14.432	19.195	45.572	15.757
Minimum	-21.399	-38.371	-29.531	-18.467	-29.286	-34.958	-21.191
Std. Dev.	4.497	6.422	5.420	4.737	5.781	7.299	4.819
Skewness	-0.353	-0.691	-0.294	-0.038	-0.173	0.340	-0.275
Kurtosis	4.335	6.135	6.081	4.188	4.785	8.939	4.568
Jarque-Bera	52.400***	269.540***	225.863***	32.536***	75.898***	820.374***	63.408***
LB(5)	4.785	17.087***	7.577	6.192	4.518	18.882***	11.106**
LB(10)	23.079***	23.958***	13.487	9.601	8.080	23.814***	13.874 ***
$LB^2(5)$	69.547***	63.620***	75.385***	76.347***	87.654***	188.460***	115.010***
$LB^2(10)$	123.100***	130.120***	134.990***	120.630***	94.373***	229.250***	131.380***

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. The Jarque-Bera statistic has a χ^2 distribution with two degrees of freedom under the null hypothesis of normally distributed errors. LB (5) and LB (10) are the Ljung-Box statistics based on the levels of the time series up to the 5th and 10^{th} order. LB^2 (5) and LB^2 (10) are the Ljung-Box statistics based on the squared levels. Both statistics on the levels and squared levels are asymptotically distributed as $\chi^2(5)$ and $\chi^2(10)$ respectively.

Table 3 Estimates of the Univariate AR (1)-SWARCH (3, 1) Models

Market	US	CA	FR	JP
φ0	0.357 (0.159)***	0.421(0.184)***	0.321(0.165)*	0.028(0.241)
φ1	-0.063 (0.043)	0.021(0.043)	0.035(0.042)	0.019 (0.045)
a0	5.432(0.839)***	5.288(1.070)***	8.869(0.869)***	5.048(0.982)***
a1	0.000 (0.038)	0.000(0.040)	0.000(0.066)	0.019(0.038)
g2	2.585 (0.459)***	2.967(0.664)***	3.106(0.928)***	3.764(0.732)***
g3	7.671 (1.666)***	14.776(3.344)***	7.872(1.509)***	8.614(2.027)***
ω1	0.371	0.278	0.634	0.298
ω2	0.426	0.394	0.126	0.502
ω3	0.203	0.328	0.240	0.200
Log-likelihood	-1559.802	-1712.368	-1616.905	-1584.214
Transition Probabilities Matrix	$\begin{bmatrix} 0.996 & 0.004 & 0.000 \\ 0.004 & 0.985 & 0.011 \\ 0.000 & 0.023 & 0.977 \end{bmatrix}$	$\begin{bmatrix} 0.995 & 0.005 & 0.000 \\ 0.003 & 0.983 & 0.014 \\ 0.000 & 0.016 & 0.984 \end{bmatrix}$	$\begin{bmatrix} 0.994 & 0.006 & 0.000 \\ 0.000 & 0.918 & 0.082 \\ 0.015 & 0.028 & 0.957 \end{bmatrix}$	$\begin{bmatrix} 0.987 & 0.013 & 0.000 \\ 0.007 & 0.988 & 0.005 \\ 0.000 & 0.012 & 0.988 \end{bmatrix}$
LB(5)	1.341	8.449	3.687	2.585
LB(10)	10.048	13.090	7.314	7.389
LBS(5)	9.575	0.957	5.844	4.679
LBS(10)	10.439	3.390	8.371	8.493
L-21	-1569.639	-1721.340	-1619.377	-1592.301
L-22	-1568.638	-1718.734	-1619.377	-1589.603
L-32	-1565.639	-1716.697	-1616.905	-1606.731

Market	TW	HK	EM
φ0	0.300(0.203)	0.092(0.312)	0.258(0.170)
φ1	0.084 (0.046)*	0.005(0.038)	0.105(0.046)***
a0	8.212(1.725)***	12.603(2.494)***	8.561(1.040)***
a1	0.032(0.050)	0.000(0.047)	0.053(0.059)
g2	3.401(0.735)***	3.445(0.722)***	2.023(0.421)***
g3	12.316(4.706)***	19.663(3.670)***	6.742(1.987)***
ω1	0.232	0.477	0.542
ω2	0.660	0.406	0.308
ω3	0.108	0.117	0.148
Log-likelihood	-1704.353	-1762.076	-1592.813
Transition Probabilities Matrix	$\begin{bmatrix} 0.963 & 0.037 & 0.000 \\ 0.013 & 0.973 & 0.014 \\ 0.000 & 0.087 & 0.913 \end{bmatrix}$	$\begin{bmatrix} 0.946 & 0.000 & 0.054 \\ 0.000 & 0.914 & 0.086 \\ 0.063 & 0.025 & 0.912 \end{bmatrix}$	$\begin{bmatrix} 0.996 & 0.004 & 0.000 \\ 0.008 & 0.947 & 0.045 \\ 0.000 & 0.094 & 0.906 \end{bmatrix}$
LB(5)	2.028	9.414	5.907
LB(10)	7.229	12.695	9.463
LBS(5)	1.387	4.769	4.805
LBS(10)	3.400	6.147	7.449
L-21	-1713.343	-1769.953	-1597.093
L-22	-1711.277	-1769.886	-1596.130
L-32	-1704.353	-1765.181	-1592.728

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. g2 and g3 are scale parameters that capture the size of volatility in regime2 and regime 1. ω1, ω2 and ω3 are ergodic probability of regime 1, 2 and 3; L-21, L-22 and L-32 are the log-likelihood values for the SWARCH (2, 1), SWARCH (2, 2) and SWARCH (3,2) models respectively. The Jarque-Bera statistic has a χ^2 distribution with two degrees of freedom under the null hypothesis of normally distributed errors. LB (5) and LB (10) are the Ljung-Box statistics based on the levels of the time series up to the fifth and tenth order. LB^2 (5) and LB^2 (10) are the Ljung-Box statistics based on the squared levels. Both statistics on the levels and squared levels are asymptotically distributed as $\chi^2(5)$ and $\chi^2(10)$ respectively.

Table 4 The periods of three volatility regimes for IT markets from January 1995 to July 2005

	Low volatility regime	Medium volatility regime	High volatility regime
US	08/27/2003-07/27/2005	01/04/1995-08/19/1998 01/13/1999-03/08/2000 12/26/2001-06/12/2002 02/05/2003-08/20/2003	08/26/1998-01/06/1999 03/15/2000-12/19/2001 06/19/2002-01/29/2003
CA	01/04/1995-06/19/1996	06/26/1996-08/26/1998 03/17/1999-10/06/1999 03/05/2003-12/17/2003 07/21/2004-07/27/2005	09/02/1998-03/10/1999 10/13/1999-02/26/2003 12/24/2003-07/14/2004
FR	01/04/1995-03/04/1998 04/07/1999-10/27/1999 04/02/2003-07/27/2005	03/11/1998-08/19/1998 11/03/1999-12/01/1999 07/05/2000-09/13/2000 12/26/2001-06/12/2002	08/26/1998-03/11/1999 12/08/1999-06/28/2000 09/20/2000-12/19/2001 06/19/2002-03/26/2003
JP	10/18/1995-06/04/1997 10/13/2004-07/27/2005	01/04/1995-10/11/1995 06/11/1997-06/09/1999 01/16/2002-10/06/2004	06/16/1999-01/09/2002
TW	07/24/1996-02/12/1997 07/30/2003-03/10/2004 11/10/2004-07/27/2005	01/04/1995-07/17/1996 02/19/1997-05/28/1997 02/11/1998-09/20/2000 01/24/2001-/09/12/2001 10/17/2001-07/23/2003 03/17/2004-11/03/2004	06/04/1997-/02/04/1998 09/27/2000-01/17/2001 09/19/2001-10/10/2001
HK	04/05/1995-01/10/1996 04/03/1996-09/18/1996 10/30/1996-02/05/1997 04/02/1997-07/30/1997 01/27/1999-03/24/1999 01/09/2002-07/31/2002 11/13/2002-06/25/2003 09/17/2003-07/27/2005	01/04/1995-03/29/1995 01/17/1996-03/27/1996 09/25/1996-10/23/1996 02/12/1997-03/26/1997 08/06/1997-10/01/1997 02/18/1998-08/05/1998 10/28/1998-01/20/1999 03/31/1999-10/27/1999 05/17/2000-01/02/2002 08/07/2002-11/06/2002 07/02/2003-09/10/2003	10/08/1997-02/11/1998 08/12/1998-10/21/1998 11/03/1999-05/10/2000
EM	01/04/1995-04/16/1997 07/23/2003-07/27/2005	04/23/1997/05/28/1997 08/27/1997-10/08-1997 02/18/1998-01/19/2000 05/10/2000-09/13/2000 02/14/2001-09/05/2001 01/30/2002-09/04/2002 11/13/2002-07/16/2003	06/04/1997-08/20/1997 10/15/1997-02/11/1998 01/26/2000-05/03/2000 09/20/2000-02/07/2001 09/12/2001-01/23/2002 09/11/2002-11/06/2002

Table 5 Estimates of the Bivariate AR (1)-SWARCH (2, 1) Models

Non-US Market	CA	FR	JP
φ_{0x}	0.512(0.165)***	0.252(0.158)	0.471 (0.156)***
φ_{1x}	-0.087 (0.036)***	-0.055(0.038)	-0.133 (0.041)***
a_{0x}	11.305(0.994)***	6.960(0.999)***	10.885(0.939)***
a_{1x}	0.010(0.031)	0.046(0.034)	0.000 (0.041)
g_{2x}	3.141(0.440)***	3.604(0.552)***	3.429(0.448)***
φ_{0y}	0.461(0.178)***	0.247(0.174)	-0.012(0.043)
φ_{1y}	-0.023(0.041)	-0.030(0.045)	-0.004(0.034)
a_{0y}	12.985(1.398)***	9.686(1.158)***	9.155 (0.918)***
a_{1y}	0.017(0.063)	0.018(0.050)	0.025(0.046)
g_{2y}	6.348(0.846)***	5.363(0.711)***	3.668(0.451)***
ρ-lv	0.606(0.061)***	0.725(0.077)***	0.380(0.128)***
ρ-hv	0.739(0.055)***	0.580(0.063)***	0.482(0.111)***
ω1	0.646	0.350	0.609
ω2	0.096	0.025	0.146
ω3	0.032	0.249	0.038
ω4	0.227	0.376	0.207
Log Likelihood SWARCH	-3138.8	-3073.3	-3103.0
Log Likelihood-Independent regime	-3144.8	-3075.1	-3134.5
LR-Independent regime(p-value)	0.000	0.165	0.000
Log Likelihood-Common regime	-3145.7	/	-3117.6
LR-Common regime(p-value)	0.000	/	0.000

Table 5 (continued) Estimates of the Bivariate AR (1)-SWARCH (2, 1) Models

Non-US Market	TW	HK	EM
φ_{0x}	0.276(0.159)*	0.342(0.181)*	0.507(0.169)***
φ_{1x}	-0.079(0.041)**	-0.114(0.043)***	-0.137(0.041)***
a_{0x}	6.025(0.801)***	12.572(1.096)***	10.827(1.138)***
a_{1x}	0.039(0.034)	0.050(0.047)	0.000(0.065)
g_{2x}	3.992(0.603)***	3.312(0.632)***	3.559(0.483)***
φ_{0y}	0.320(0.194)*	0.112(0.284)	0.379(0.206)*
φ_{1y}	0.061(0.043)	-0.035(0.049)	0.067(0.044)
a_{0y}	8.831(1.538)***	15.214(1.740)***	9.027(1.228)***
a_{1y}	0.121(0.060)**	0.130(0.093)	0.116(0.062)*
g_{2y}	4.908(0.846)***	8.828(1.470)***	3.963(0.691)***
ρ-lv	0.530(0.139)***	0.421(0.130)***	0.344(0.161)**
ρ-hv	0.400(0.112)***	0.458(0.222)**	0.545(0.103)***
ω1	0.292	0.634	0.590
ω2	0.053	0.167	0.120
ω3	0.174	0.110	0.042
ω4	0.480	0.088	0.248
Log Likelihood SWARCH	-3229.4	-3292.7	-3108.8
Log Likelihood-Independent regime	-3236.7	-3294.0	-3115.8
LR-Independent regime(p-value)	0.000	0.457	0.003
Log Likelihood-Common regime	-3237.6	/	-3116.3
LR-Common regime(p-value)	0.000	/	0.010

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. Subscripts *x* and *y* denote the U.S. and a non-US country respectively. g2 is a scale parameter that capture the size of volatility regime 2. ρ-lv and ρ-hv denote the correlation between the US and non-US markets when the US market is in a low volatility and high volatility regime respectively. ω1, ω2, ω3 and ω4 are ergodic probability for states 1, 2, 3 and 4, respectively. The Jarque-Bera statistic has a χ^2 distribution with two degrees of freedom under the null hypothesis of normally distributed errors. LB (5) and LB (10) are the Ljung-Box statistics based on the levels of the time series up to the 5th and 10^{th} order. LB^2 (5) and LB^2 (10) are the Ljung-Box statistics based on the squared levels. Both statistics on the levels and squared levels are asymptotically distributed as $\chi^2(5)$ and $\chi^2(10)$ respectively.

Figure 1 Stock Price Indices of IT sectors

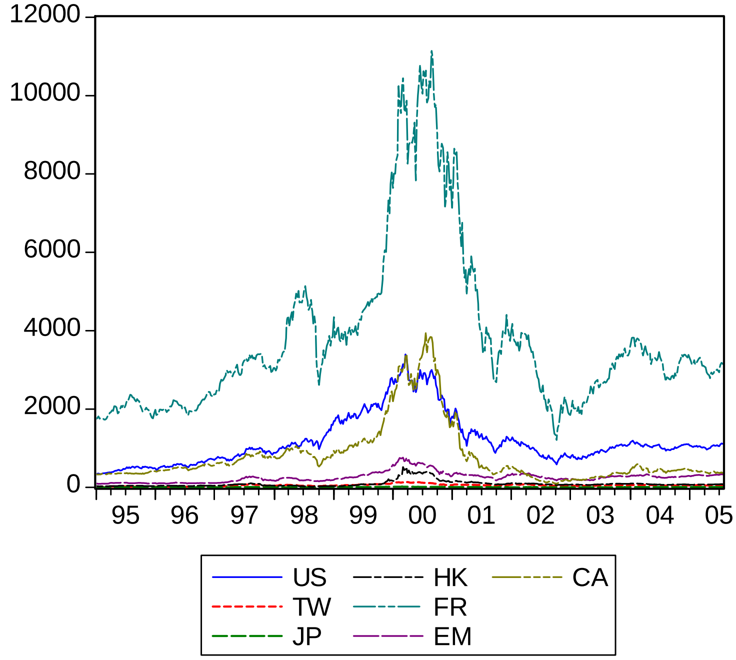
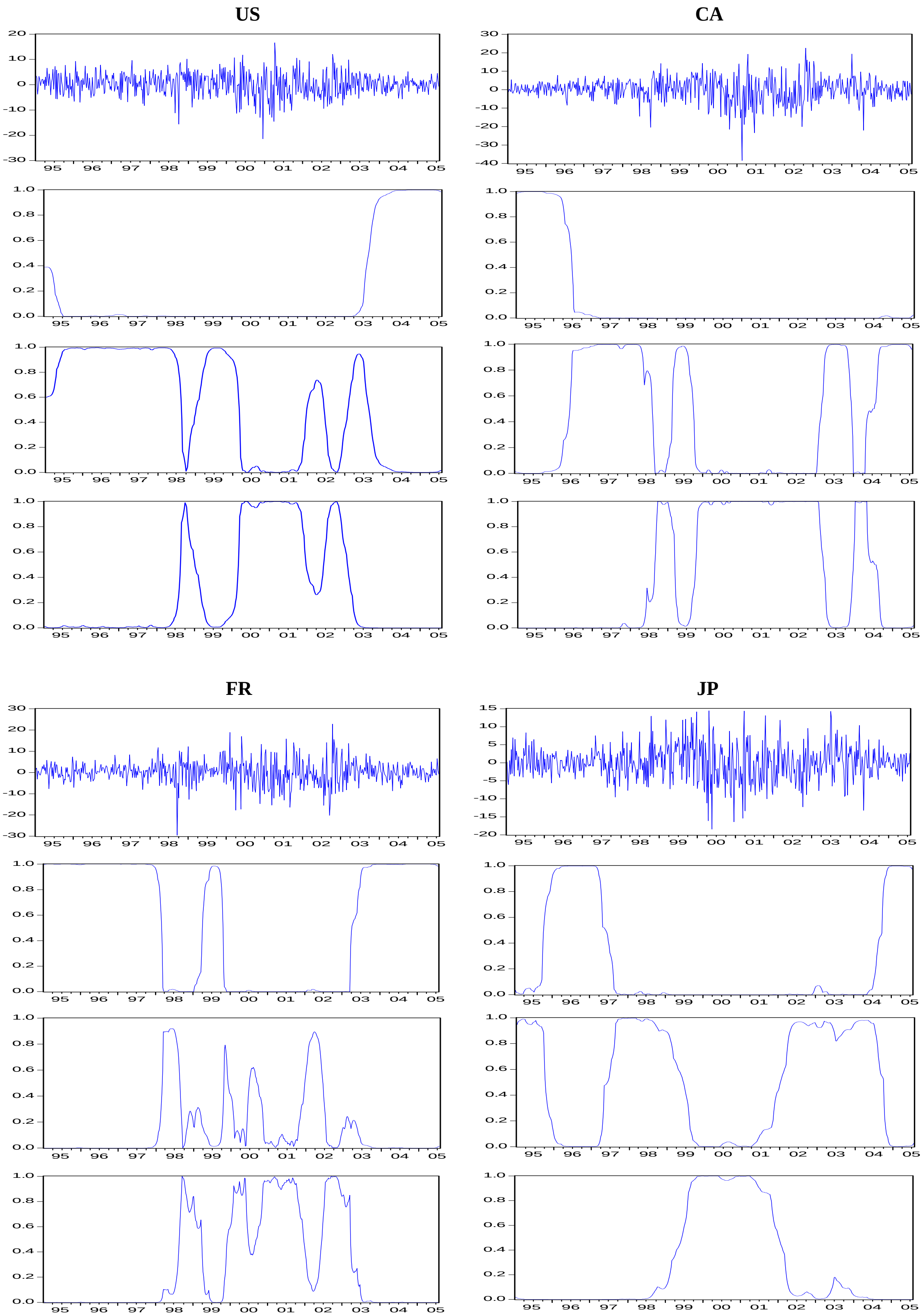
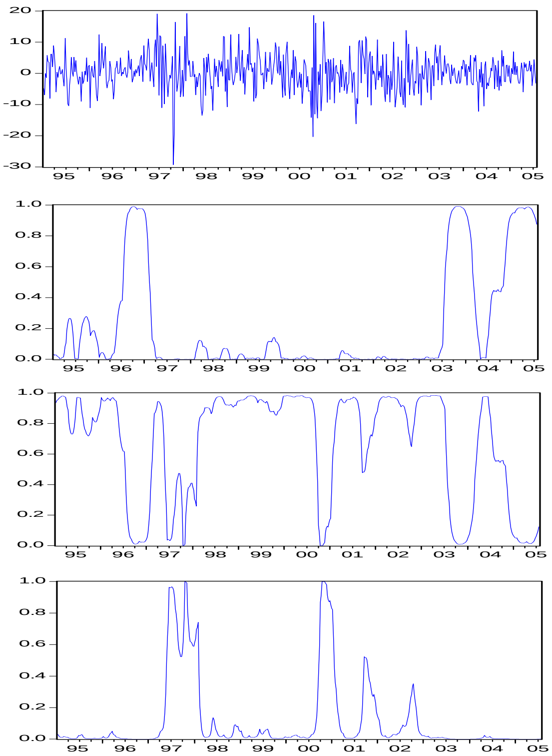


Figure 2 AR(1)-SWARCH (3,1) Estimates



TW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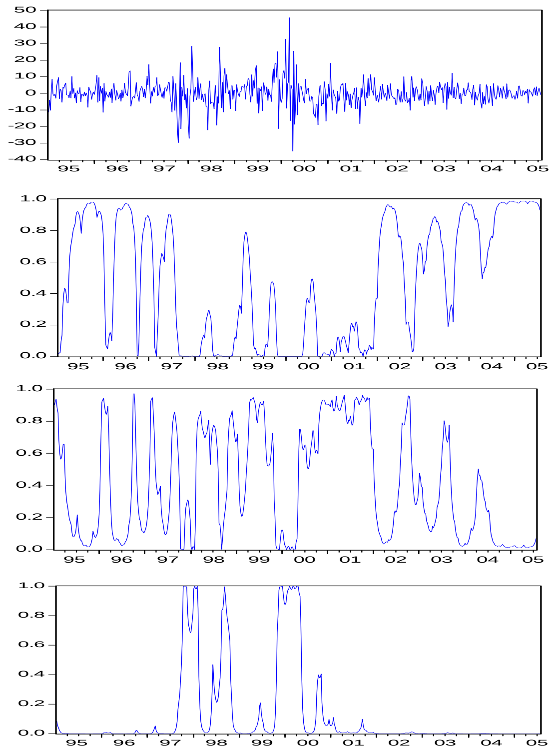
HK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EM

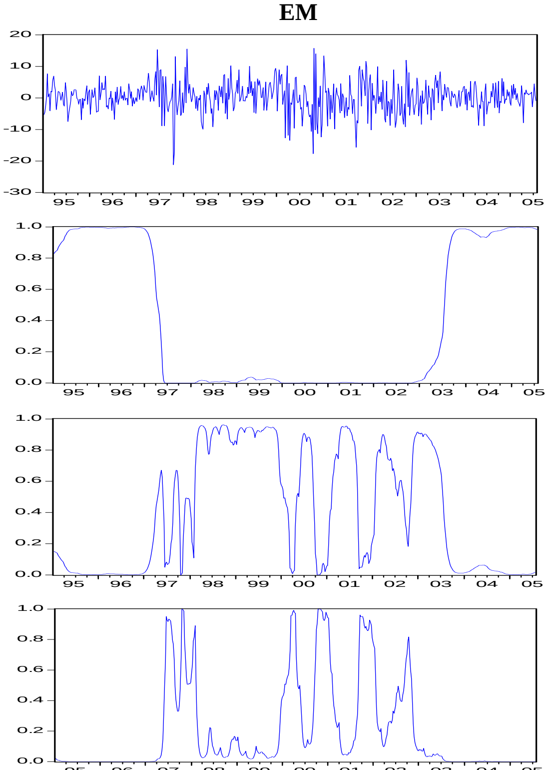
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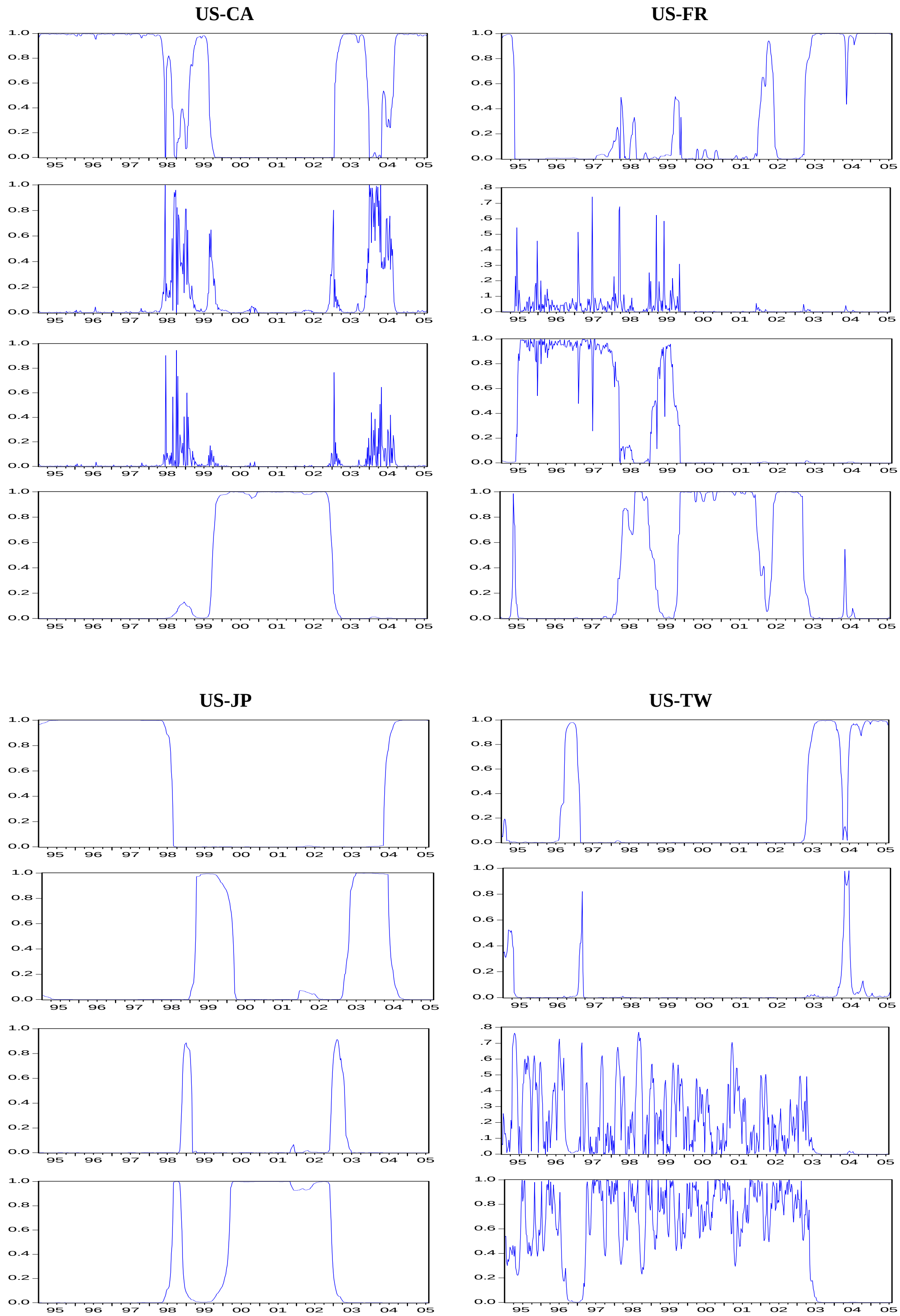
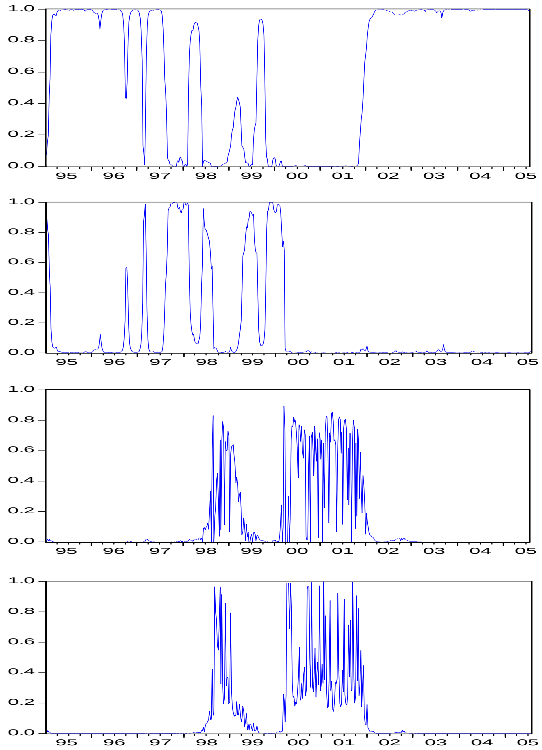
Figure 3. Bivariate AR(1)-SWARCH(2, 1) Volatility Regimes



US-HK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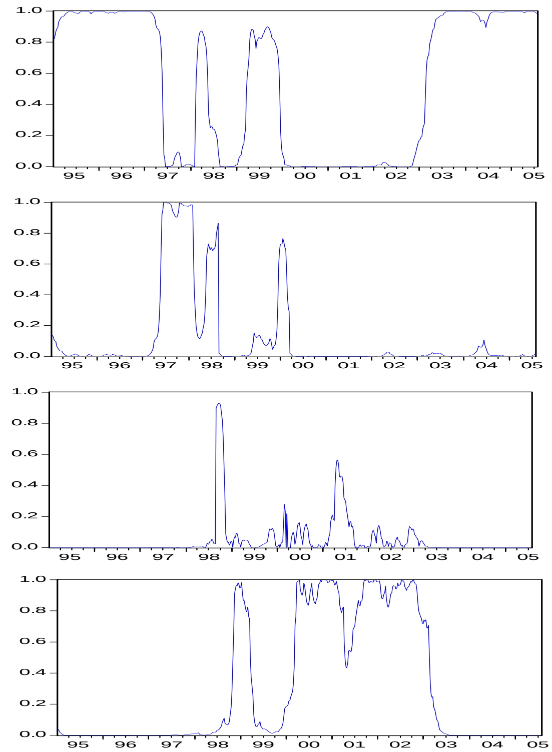
US-EM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