



# Asymmetrical reaction to US stock-return news: evidence from major stock markets based on a double-threshold model

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## Abstract

This paper examines the hypothesis that both stock returns and volatility are asymmetrical functions of past information from the US market. By employing a double-threshold GARCH model to investigate six major index-return series, we find strong evidence supporting the asymmetrical hypothesis of stock returns. Specifically, negative news from the US market will cause a larger decline in a national stock return than an equal magnitude of good news. This holds true for the volatility series. The variance appears to be more volatile when bad news impacts the market than when good news does.

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*JEL classification:* C15; C22; C51

*Keywords:* Asymmetry; Threshold GARCH; Volatility; MCMC methods

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## 1. Introduction

As a result of increasing globalization and market integration, a substantial amount of research has been devoted to the investigation of intermarket linkages among national stock indexes. Empirical studies of the relationship among international stock returns can be broadly categorized into two areas: (i) investigation of common factors that affect cross-country stock returns and variances and (ii) examination of the co-movements of national stock returns and volatility spillovers.

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The main concern of the first approach to studying international market integration is a search for common factors in each market. Jeon and Chiang (1991) and Kasa (1992), by employing Johansen's (1988, 1991) cointegration tests, show evidence to support the existence of a common stochastic trend in a system formed by the major global stock exchanges. Engle and Susmel (1993) report that national stock markets are linked through their second moments. More recent evidence presented by Arshanspalli, Doukas, and Lang (1997) suggests that a common ARCH-feature is displayed in groups formed by the United States, Europe, the Pacific Rim, and the corresponding world industry-return series. By emphasizing economic fundamentals, Campbell and Hamao (1992) find that variables such as dividend yields (positively) and domestic short-term interest rates (negatively) are helpful in forecasting stock returns in the US and Japanese markets. However, the evidence reported by Karolyi and Stulz (1996) indicates that US macroeconomic announcements, shocks to the yen/dollar exchange rate and Treasury bill returns, and industry effects have no measurable influence on US and Japanese return correlations. Rather, only big shocks to major market indices produce a positive and persistent impact on the return correlation.

The second approach emphasizes the co-movements of stock returns and explores the dynamics of return covariances. On the basis of multi-market analysis, significant cross correlations have been found in studies by Koch and Koch (1991), Koutmos and Booth (1995), and Kim and Rogers (1995). Their findings indicate that national stock returns are significantly correlated and that linkages among international stock markets have grown more interdependent over time. Moreover, Ross (1989) argues that market volatility is related to the information flow, suggesting that information from one stock market can be incorporated into the volatility process of another stock market. By utilizing the evolution of conditional variance, Hamao, Masulis, and Ng (1990), Theodossiou and Lee (1997), Chiang and Chiang (1996), Chiang (1998) and Martens and Poon (2001) find supporting evidence for volatility spillovers among major stock markets.

Our analysis of financial market integration takes the second route. The goal of this paper is to contribute to the literature on transmitting stock return news from the United States to Japan as well as to several European markets by considering an asymmetrical effect. In particular, we analyze index-return asymmetries by linking conditional mean to asymmetries in the conditional variance since bad news in stock returns tend to cause higher volatility in stock returns.<sup>1</sup>

This study extends the existing literature in at least two ways. First, traditional studies focus on correlations on cross markets that are located in proximate geographic areas. Our causality tests show that the US index plays a role in price leadership across global markets. This is consistent with fact that the US market has long been the center of financial transactions as well as the most influential producer of information. Modern technological advancements and computerized trading systems have greatly facilitated the transfer of information from market to market. As a result, investors tend to react more to news from the US market than from other markets (Becker, Finnerty, & Friedman, 1995; Eun & Shim, 1989; Masih & Masih, 2001).

Second, instead of employing an AR-EGARCH (Koutmos, 1999) or EAR-TGARCH model (Koutmos & Booth, 1995), we include both autoregressive and cross-asset returns in our mean equation. Moreover, we are also interested in examining the possibility of an asymmetrical effect

on volatility in reaction to news emerging from the US market. To capture these features, we propose a double-threshold autoregressive GARCH model (DTAR-GARCH), with the latter estimated by a Bayesian method. Rather than focusing on past stock-return information contained in the autocorrelation term (Amihud and Mendelson, 1987; Damodaran, 1993; Koutmos, 1997, 1998; Sentana & Wadhvani, 1992), we address past information derived from a dominant capital market and analyze asymmetries in returns and variances. Our findings provide a new avenue for processing information in a multi-market framework and shed some light on asymmetrical effects on international asset returns.

The remainder of the paper proceeds as follows. Section 2 describes the data used in this study and presents some statistical properties of stock returns in a standard GARCH(1,1) specification. Section 3 provides the rationale and procedures for using a Bayesian estimation of a DTAR-GARCH model. Section 4 presents the estimated results and compares the findings with existing literature. Section 5 contains concluding remarks.

## 2. The data and basic statistics

### 2.1. Data sample

The data consist of daily closing values for seven stock indices from January 1, 1985, through November 14, 2001. The data include the CAC 40 (France), Dax 30 (Germany), FTSE 100 (United Kingdom), Nikkei 225 Index (Japan), Swiss Market Price (Switzerland), Toronto SE 300 (Canada), and S&P 500 Index (United States). The shorter observations for France and Switzerland are constrained by the availability of data. All data were taken from *Data Stream International*. Following the conventional approach, daily stock-return series are generated by taking the logarithmic difference of the daily stock-index times 100. That is,  $R_t = 100 \cdot (\log P_t - \log P_{t-1})$ .

### 2.2. Basic statistics

To provide a general understanding of the nature of each market return, summary statistics of daily returns are presented in Table 1. The statistics include stock-index returns for mean ( $\mu$ ), standard deviation ( $\sigma$ ), skewness ( $S$ ), excess kurtosis ( $\kappa$ ), and Liung-Box  $Q(10)$  values for both returns and squared returns. The statistics in Table 1 indicate that the US stock market has performed best, with the highest returns and relatively low standard deviations. Canada and four European stock returns perform very similarly. However, the Japanese market appears to show a negative return and the largest standard deviation. The unfavorable Japanese stock returns are attributable to the fact that the Japanese market has been experiencing a bear market since 1989, aggravated by the Asian financial crisis of 1997. Another characteristic of the stock-return series shown in Table 1 is a high value of kurtosis. This suggests that, for these markets, big shocks of either sign are more likely to be present and that the stock-return series may not be normally distributed. Independence of the stock-index returns is less satisfactory, as seen in the rejection of the absence of first-order autocorrelation for the daily data. The existence of autocorrelation may result from nonsynchronous trading of the stocks that make up the index.

Table 1  
Summary statistics of daily stock-market returns

Statistics	UK	Canada	Germany	Japan	France	Switzerland	US
$\mu$	0.0328	0.0253	0.0408	-0.0031	0.0300	0.0415	0.0436
$\sigma$	0.9965	0.8621	1.3223	1.3672	1.2813	1.0956	1.0494
$S$	-0.9823*	-1.3526*	-0.7312*	-0.1397*	-0.4254*	-0.7421*	-2.6656*
$\kappa$	13.3836*	20.4124*	7.7928*	9.1184*	5.1063*	8.9559*	56.5461*
LB(10)	47.3576*	75.5450*	28.1951*	39.1088*	16.0123	21.4340*	44.9256*
LB <sup>2</sup> (10)	2058.37*	1371.25*	913.38*	466.25*	1174.21*	604.99*	2137.53*
$N$	4401	4401	4401	4401	3743	3488	4401

Notes.  $\mu$  and  $\sigma$  are the sample mean and standard deviations;  $S$  and  $\kappa$  are skewness and excess kurtosis; LB(10) and LB<sup>2</sup>(10) are Ljung-Box statistics testing for autocorrelation in the level of returns and the squared returns up to the 10th lag. The choice of 10 lags will provide statistics based on two weeks' trading. The time period covered is from 1/1/1985 to 11/14/2001 for 4401 observations, although France and Switzerland have shorter observation periods due to a lack of data availability.

\* Denotes significance at least at the 5% level.

It could also be due to market friction, producing a partial adjustment process. Next, statistics on the LB<sup>2</sup>(10) are very large, indicating high dependency on the squared returns as well as on the volatility of clustering phenomenon.

### 2.3. Causality tests

It is important to note that stock markets in different countries operate in different time zones with different opening and closing times. Our focal point in this study is not designed to investigate the impact of instantaneous stock news deriving from high frequency data, which can be highlighted by the intra-day or tic-tac data. Rather, our intention is simply to examine the effect of market closing information flowing from the US market to other major trading markets. This is based to some extent on the fact that New York City market operations (the S&P 500 Index) are the last to close among the global exchanges under investigation. Closing news in the US market at day  $(t - 1)$  will have information content that allows investors sufficient time to analyze market momentum and form optimal portfolio decisions in the subsequent Japanese and European market trading day.<sup>2</sup>

For instance, let us write  $p_t^{\text{uk}}$  and  $p_{t+m}^{\text{us}}$  as daily closing prices of FTSE 100 (United Kingdom) and S&P 500 (United States) indexes, respectively, where  $m$  ( $m = 5$  hours) is the time difference of market closed between New York and London stock exchanges. Then, the time sequence for the UK and US stock prices can be written as  $\{p_t^{\text{uk}}, p_{t+m}^{\text{us}}, p_{t+1}^{\text{uk}}, p_{t+m+1}^{\text{us}}, \dots\}$ . Correspondingly, the time sequence of stock returns involving the United Kingdom and the United States is  $\{R_t^{\text{uk}}, R_{t+m}^{\text{us}}, R_{t+1}^{\text{uk}}, R_{t+m+1}^{\text{us}}, \dots\}$ . The question is whether the information set  $\{R_{t-1}^{\text{uk}}, R_{t+m-1}^{\text{us}}\}$  makes significant contributions on  $R_t^{\text{uk}}$ .<sup>3</sup> Expressing this notion for the countries under investigation, we write:

$$R_t^i = \phi_0 + \phi_1 R_{t-1}^i + \psi_1 R_{t+m-1}^j + \varepsilon_t \quad (1)$$

where  $R_t^i$  and  $R_t^j$  are stock returns from countries  $i$  ( $i$ : Canada, France, Germany, Japan, Switzerland, and the United Kingdom) and  $j$  (the United States), respectively:  $\phi_0$ ,  $\phi_1$ , and  $\psi_1$  are constant parameters;  $\varepsilon_t$  is a random error term;  $m$  is the time difference in market closings between the  $i$  and  $j$  markets. The causal relationship, in the vein of the Granger test, can be examined by testing the restriction of  $\psi_1 = 0$  (as shown in Table 2) or equivalently by checking the significance of the  $F$ -statistics. Since a causality test is sensitive to the lag length for both lagged dependent and incremental variables, both optimal lag and one-period lag specifications are used to test the causal sequence. Appendix A contains the results of the Granger test. The  $F$ -statistics show consistently that the causal relationships have been dominated by information running from the US market into the international markets, although a minor feedback is found from the German and Japanese markets. On the basis of this statistical information, even with some overlapping between  $R_{t-1}^i$  and  $R_{t-1}^j$ , both  $R_{t-1}^i$  and  $R_{t+m-1}^j$  information sets are shown to contribute to explaining  $R_t^i$ , and the evidence shows that US stock news has played a major role in explaining international stock returns.

To follow the conventional approach and to provide a basis of comparison, we start with a model, as shown in Eq. (1), that includes only an autoregressive term and a lagged cross-asset return as arguments in the mean equation.<sup>4</sup> To incorporate conditional variance into the system, we follow Bollerslev, Chou, and Kroner (1992) by employing a GARCH(1,1) process as:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1}, \quad (2)$$

where  $h_t$  is the conditional variance;  $\alpha_0$ ,  $\alpha_1$ , and  $\beta$  are unknown parameters; and  $\varepsilon_t$  is a random error term. Estimates of Eqs. (1) and (2) are presented in Table 2, which contains the posterior means together with standard deviations of  $(\phi_0, \phi_1, \psi_1, \alpha_0, \alpha_1, \beta)$ . The evidence shows that, with the exceptions of Japan and Switzerland, the autoregressive terms are highly significant.

Consistent with findings in the literature (Koutmos, 1998), the coefficients of the autocorrelations for Canadian, French, and German terms are positive. However, a negative sign is found in the estimated equation for the United Kingdom, Japan, and Switzerland, although only the coefficient for the United Kingdom is significant. With respect to cross-asset returns, the hypothesis of independence in stock-index returns from the US market is uniformly rejected. The estimates of the coefficients are in the range of 0.300–0.435. The significance of the US news variable is consistent with the findings derived from the causality test. In further checking the variance equation, all the coefficients in the GARCH(1,1) model are significant, indicating that stock volatilities are characterized by a heteroscedastic process. Note that the average variance being measured by  $\alpha_0/(1 - \alpha_1 - \beta_1)$  shows that Japan has the highest average variance, significantly higher than other markets.

It is important to verify the adequacy of a fitted GARCH model. This can be done by examining the series of standardized residuals,  $\{\tilde{\varepsilon}_t\}$ , where  $\tilde{\varepsilon}_t = \hat{\varepsilon}_t/\sqrt{\hat{h}_t}$ . In particular, we calculate the Liung-Box statistics for the series of  $\tilde{\varepsilon}_t$  and  $\tilde{\varepsilon}_t^2$ , respectively, to check the adequacy of the mean equation as well as the validity of the volatility equation. The Liung-Box statistics of the series for standardized errors and squared errors, respectively, up to the 10th lag (two weeks) are reported in the last two rows of Table 2. Although these statistics have been reduced significantly as compared with those shown in Table 1, inadequacy is found in GARCH models for Canadian, French, and German markets. This indicates that some sort of non-linear specification may be

Table 2  
Parameter estimates for the GARCH(1, 1) model

Coefficient	UK	Canada	Germany	Japan	France	Switzerland
$\phi_0$	0.0312* (0.0121)	0.0055 (0.0070)	0.0402* (0.0161)	0.0295* (0.0148)	0.0261 (0.0165)	0.0553* (0.0151)
$\phi_1$	-0.0341* (0.0162)	0.2068* (0.0121)	0.0566* (0.0159)	-0.0164 (0.0158)	0.0513* (0.0165)	-0.0153 (0.0191)
$\psi_1$	0.3001* (0.0153)	0.4350* (0.0068)	0.3260* (0.0213)	0.3724* (0.0156)	0.3961* (0.0190)	0.3197* (0.0192)
$\alpha_0$	0.0215* (0.0047)	0.0061* (0.0011)	0.0610* (0.0090)	0.0194* (0.0013)	0.0515* (0.0102)	0.1014* (0.0136)
$\alpha_1$	0.08411* (0.0106)	0.1010* (0.0085)	0.1109* (0.0117)	0.0988* (0.0024)	0.0959* (0.0092)	0.1484* (0.0165)
$\beta_1$	0.8930* (0.0145)	0.8867* (0.0085)	0.8559* (0.0137)	0.8946* (0.0020)	0.8687* (0.0140)	0.7597* (0.0242)
$\alpha_0/1 - \alpha_1 - \beta_1$	0.9773	0.4480	1.7887	3.3310	1.4461	1.1066
LB(10)	14.2257	19.5984*	41.1755*	9.6277	45.7839*	9.9322
LB <sup>2</sup> (10)	6.5124	10.9002	2.4807	4.3210	9.7634	0.9424

Notes. The estimated equations are as follows:

$$R_t^i = \phi_0 + \phi_1 R_{t-1}^i + \psi_1 R_{t+m-1}^j + \varepsilon_t \quad \text{and} \quad h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1}$$

The numbers in parentheses are posterior standard deviations.

\* Indicates statistical significance at least at the 5% level.

necessary to be included in the variance equation. In addition, even though the system in Eqs. (1) and (2) provides a framework to describe the daily asset-return behavior in a GARCH(1,1) process, the estimated coefficients are fixed and fail to reflect the asymmetrical nature of market news. Moreover, a precise lagged length of the news variable that arrives in each market has not been detected. To examine whether the  $(t - 1)$  day stock-return news from the US market will produce asymmetrical effects on the mean and variance equations with an appropriate time lag, we construct a threshold GARCH model characterizing regime switching, which we shall discuss next.

### 3. The double-threshold GARCH model

#### 3.1. The model representation

The model we developed here is a double TAR-GARCH model, which is a generalization of the double-threshold ARCH model proposed by Li and Li (1996) and Chen (1998). This model is characterized by several non-linear factors commonly observed in practice, such as asymmetry in declining and rising patterns of a process. Our approach is to use piecewise linear models to obtain a better approximation of the conditional mean and conditional volatility equations. The two-regime model is specified as:

$$R_t^i = \begin{cases} \phi_0^{(1)} + \phi_1^{(1)} R_{t-1}^i + \psi_1^{(1)} R_{t+m-d}^j + \varepsilon_t & \text{if } R_{t+m-d}^j \leq r \\ \phi_0^{(2)} + \phi_1^{(2)} R_{t-1}^i + \psi_1^{(2)} R_{t+m-d}^j + \varepsilon_t & \text{if } R_{t+m-d}^j > r \end{cases} \quad (3)$$

$$h_t = \begin{cases} \alpha_0^{(1)} + \alpha_1^{(1)} \varepsilon_{t-1}^2 + \beta_1^{(1)} h_{t-1} & \text{if } R_{t+m-d}^j \leq r \\ \alpha_0^{(2)} + \alpha_1^{(2)} \varepsilon_{t-1}^2 + \beta_1^{(2)} h_{t-1} & \text{if } R_{t+m-d}^j > r \end{cases} \quad (4)$$

where  $m$  is the time difference between the  $i$  and  $j$  markets;  $\varepsilon_t$  is a normal random error variable, conditional on the information available at time  $(t - 1)$ , with mean zero and variance  $h_t$ ;  $\phi_0^{(1)}, \phi_1^{(1)}, \psi_1^{(1)}, \alpha_0^{(1)}, \alpha_1^{(1)}, \beta_1^{(1)}, \phi_0^{(2)}, \phi_1^{(2)}, \psi_1^{(2)}, \alpha_0^{(2)}, \alpha_1^{(2)}, \beta_1^{(2)}, r$  and  $d$  are unknown parameters. The positive integer  $d$  is commonly referred to as a delay (or threshold lag) and  $r$  is a threshold value. The threshold variable in our model is an exogenous variable,  $R_{t+m-d}^j$ , rather than an autoregression term, as that of  $R_{t-1}^i$  in Li and Li (1996) or in Koutmos (1998). To recall,  $R_t^i$  is the return of a market index and  $R_{t+m-d}^j$  is the lagged return of the US S&P 500 index. According to the model specification, the dynamic structure of the mean equation is still dependent on an autocorrelation term and ‘lagged’ US market return; the variance equation follows a GARCH(1,1) process.<sup>5</sup> However, the model is divided into two different regimes in response to bad news ( $R_{t+m-d}^j \leq r$ ) and good news ( $R_{t+m-d}^j > r$ ) in order to capture the mean and volatility asymmetries.

#### 3.2. Estimation procedures

Classical estimation of parameters in the threshold class of models is usually done by a least-squares or a maximum-likelihood method with  $r$  and  $d$  prefixed. Estimates of  $r$  and  $d$  are

usually determined by using information criteria such as AIC and BIC (Tsay, 1998; Shen & Chiang, 1999). The shortcoming of the sampling approach is that by fixing  $r$  and  $d$  in advance, before estimating other parameters by least squares, the uncertainty of  $r$  and  $d$  cannot be taken into account when performing statistical inference for other parameters. Moreover, the choices of  $r$  and  $d$  are likely to be dependent on the criteria we choose for model comparison. To alleviate the problems arising from predetermining  $r$  and  $d$ , we adopt a Bayesian approach, which allows us to estimate  $r$  and  $d$  as well as other parameters simultaneously.<sup>6</sup> Specifically, we can generate approximated samples from the posterior distribution of unknown parameters, including  $d$  and  $r$ , via Markov chain Monte Carlo (MCMC) methods (Chen, 1998; Chen & So, 2003; Chib & Greenberg, 1995). The estimation procedures of Bayesian analysis are outlined as follows:

**Step 1.** Choose the prior distribution  $p(\Theta)$ , given by:

$$p(\Theta) \propto I(\alpha_0^{(1)} > 0, \alpha_1^{(1)} + \beta_1^{(1)} < 1) \cdot I(\alpha_0^{(2)} > 0, \alpha_1^{(2)} + \beta_1^{(2)} < 1) \cdot I(a < r < b),$$

where  $\Theta = (\phi_0^{(1)}, \phi_1^{(1)}, \psi_1^{(1)}, \alpha_0^{(1)}, \alpha_1^{(1)}, \beta_1^{(1)}, \phi_0^{(2)}, \phi_1^{(2)}, \psi_1^{(2)}, \alpha_0^{(2)}, \alpha_1^{(2)}, \beta_1^{(2)}, r, d)'$ ;  $I(\cdot)$  the indicator function that  $I(A) = 1$  if the event  $A$  is true;  $a$  and  $b$  are 25 and 75 percentiles of the threshold variables  $R_{t+m}^j$ , respectively.

**Step 2.** Sample iteratively from  $p(\Theta|Y)$  to generate a posterior sample  $\Theta^1, \dots, \Theta^N$ , where  $N$  is set at 20,000. The sampling is done in six blocks, including  $(\phi_0^{(1)}, \phi_1^{(1)}, \psi_1^{(1)})$ ,  $(\alpha_0^{(1)}, \alpha_1^{(1)}, \beta_1^{(1)})$ ,  $(\phi_0^{(2)}, \phi_1^{(2)}, \psi_1^{(2)})$ ,  $(\alpha_0^{(2)}, \alpha_1^{(2)}, \beta_1^{(2)})$ ,  $r$ , and  $d$ .

**Step 3.** Form  $\hat{\Theta}$ , the point estimate of  $\Theta$ , except  $d$ , as the sample mean of the posterior sample:

$$\hat{\Theta} = \frac{1}{N - M} \sum_{k=M+1}^N \Theta^k,$$

where  $M = 10,000$  is the number of burn-in iterations to attain convergence. As  $d$  is a discrete variable, it can be estimated as the value occurring most frequently in the posterior sample. Details of the above procedures are presented in the Appendix B.

#### 4. The estimated results

The Bayesian estimates of the equation system of Eqs. (3) and (4) for the six stock markets are reported in Table 3. The parameters are the corresponding values of posterior means, while the  $d$  values (the third row from the bottom) are the posterior modes. The numbers in parentheses are the posterior standard deviations of the unknown parameters. The estimations are divided into two regimes based on the threshold variable  $r$  for each market, which is in the range from  $-0.3389$  to  $-0.3901$ , with an average value of  $-0.37$ .<sup>7</sup> An interesting point from our estimation is that the dividing line between good news and bad news is not located at zero; rather it depends on the threshold value. In the case of the United Kingdom, the result indicates that any previous-day loss greater than  $-0.3389\%$  in the US stock market is considered to be bad news. A minor loss, such as  $-0.1\%$ , does not seem to constitute a significant enough threat to make investors shift their portfolios. Moreover, our evidence shows that the information used

Table 3  
Bayesian estimates for a double TAR-GARCH model

Coefficients	UK	Canada	Germany	Japan	France	Switzerland
$\phi_0^{(1)}$	0.1684* (0.0445)	0.1482* (0.0210)	-0.3942* (0.0330)	0.2096* (0.0415)	-0.3256* (0.0384)	0.2186* (0.0644)
$\phi_1^{(1)}$	-0.0780* (0.0320)	0.2042* (0.0252)	0.0166* (0.0310)	0.0619** (0.0325)	0.0104 (0.0342)	-0.0179* (0.0438)
$\psi_1^{(1)}$	0.4493* (0.0409)	0.6352* (0.0149)	0.4705* (0.0347)	0.4874* (0.0270)	0.4131* (0.0354)	0.5310* (0.0570)
$\phi_0^{(2)}$	0.0339* (0.0176)	0.0373* (0.0093)	0.1944* (0.0174)	0.0636* (0.0199)	0.1417* (0.0193)	0.0936* (0.0186)
$\phi_1^{(2)}$	-0.0137 (0.0190)	0.1854* (0.0135)	0.0062 (0.0186)	-0.0419* (0.0181)	0.0058 (0.0195)	-0.0120 (0.0204)
$\psi_1^{(2)}$	0.2521* (0.0245)	0.4012* (0.0132)	0.2655* (0.0209)	0.2533* (0.0270)	0.3852* (0.0221)	0.2119* (0.0269)
$\alpha_0^{(1)}$	0.0808* (0.0149)	0.0259* (0.0047)	0.2312* (0.0338)	0.0930* (0.0173)	0.2170* (0.0451)	0.3107* (0.0386)
$\alpha_1^{(1)}$	0.1061* (0.0170)	0.1109* (0.0206)	0.1880* (0.0224)	0.1307* (0.0160)	0.1848* (0.0300)	0.2810* (0.0386)
$\beta_1^{(1)}$	0.8802* (0.0215)	0.8826* (0.0216)	0.7872* (0.0295)	0.8627* (0.0170)	0.7860* (0.0390)	0.6930* (0.0438)
$\alpha_0^{(2)}$	0.0174* (0.0067)	0.0040* (0.0016)	0.0360* (0.0129)	0.0038 (0.0030)	0.0782* (0.0226)	0.0799* (0.0147)
$\alpha_1^{(2)}$	0.0606* (0.0108)	0.0967* (0.0121)	0.0979* (0.0115)	0.0924* (0.0096)	0.0697* (0.0113)	0.0920* (0.0155)
$\beta_1^{(2)}$	0.8820* (0.0172)	0.8675* (0.0164)	0.8307* (0.0196)	0.8934* (0.0099)	0.8181* (0.0283)	0.7262* (0.0286)
$r$	-0.3389* (0.0586)	-0.3854* (0.0144)	-0.3490* (0.0112)	-0.3819* (0.0252)	-0.3788* (0.0133)	-0.3901* (0.0146)
$d$	1	1	2	1	2	1
$\alpha_0^{(1)}/1 - \alpha_1^{(1)} - \beta_1^{(1)}$	7.4849	5.3332	11.1520	20.4596	9.2973	15.4685
$\alpha_0^{(2)}/1 - \alpha_1^{(2)} - \beta_1^{(2)}$	0.3034	0.1105	0.4985	0.2209	0.6923	0.4371

Notes. The numbers in parentheses are posterior standard deviations.

\* Indicate statistical significance at the 5% levels.

\*\* indicate statistical significance at the 10% levels.

by investors is not necessarily restricted to the lag of one day. In the cases of the German and French markets, the highest frequency of  $d$  occurred at lag two among lags  $\{1, 2, 3, 4\}$ .<sup>8</sup> This finding is consistent with the meteor-shower hypothesis in that innovations are transmitted from one market to others (Ito, Engle, & Lin, 1992).

As may be seen from Table 3, the Bayesian analysis of each stock-index return in reacting to US market news exhibits different behavior. The estimated coefficients obtained from regime 1 (bad news) are much larger than those appearing in regime 2 (good news), displaying a strong asymmetrical effect. Specifically, with the exception of Japan, the coefficients of  $\phi_1^{(1)}$  and  $\phi_1^{(2)}$  for Canada, Germany, and France consistently show a positive correlation, while the coefficients for the United Kingdom and Switzerland are negative. These results are similar to our earlier analysis in Table 2. Despite the sign of the coefficients, the sensitivity of stock returns in response to past information is much more profound in regime 1 than in regime 2.

The asymmetrical effect is more apparent and consistent in the coefficients of cross-asset returns. This can be seen from the estimated mean equation in that the pricing behavior is dominated by the element of  $\psi_1^{(1)}$  in regime 1 and  $\psi_1^{(2)}$  in regime 2. The statistics show not only that the estimated coefficients for both  $\psi_1^{(1)}$  and  $\psi_1^{(2)}$  are positive, but also that they are highly significant. Moreover, the magnitude of the estimated coefficients for each market is uniformly greater in regime 1 than in regime 2. If we compare the coefficients  $\psi_1^{(1)}$  and  $\psi_1^{(2)}$  in Table 3 with in  $\psi_1$  Table 2, the coefficient  $\psi_1$  of is clearly underestimated when  $R_{t+m-d}^j \leq r$ , and appears to be overestimated when  $R_{t+m-d}^j > r$  if the data fail to be discriminated by a threshold value. The threshold model here certainly helps us explain the fact that bad news (regime 1) originating in the US market produces a much more profound impact on current stock returns than does good news (regime 2).

In all markets, coefficients on a GARCH(1,1) specification are highly significant, supporting the phenomenon of volatility clustering. An examination of the coefficients describing the volatility process reveals that the asymmetrical effect is also present in the variance equations. This can be seen from the constant component of the variance  $\alpha_0^{(1)}$  versus  $\alpha_0^{(2)}$ . In addition, the value of the average variance in regime 1 ( $\alpha_0^{(1)}/1 - \alpha_1^{(1)} - \beta_1^{(1)}$ ) is much larger than that in regime 2 ( $\alpha_0^{(2)}/1 - \alpha_1^{(2)} - \beta_1^{(2)}$ ), exhibiting an asymmetrical reaction to bad news versus good news. This asymmetrical behavior displayed in the conditional variance may be attributable to the leverage effect—bad news developed in the US market gives rise to downward pressure on domestic stock prices, leading to an increase in the debt/equity ratio and therefore to risk (Bekaert & Wu, 2000).<sup>9</sup>

One way to see whether the difference in the two regimes is statistically significant is to use the reversible-jump, Markov chain, Monte Carlo method (Green, 1995) to engage the Bayesian model selection between GARCH and TAR-GARCH models. This model selection procedure is equivalent to testing whether the asymmetrical-volatility effect is significant. The main idea is to compute the posterior probabilities  $p(M_1|Y)$  and  $p(M_2|Y)$  using MCMC methods, where  $M_1$  and  $M_2$  denote GARCH and TAR-GARCH models. Both probabilities add up to one. The larger the posterior probability, the more preferable is the designated model. We can insert a reversible-jump step to allow jumps from  $M_1$  to  $M_2$  and  $M_2$  to  $M_1$  with the acceptance probabilities  $\min\{1, p\}$  and  $\min\{1, p^{-1}\}$  where

$$p = \frac{p(Y|M_2, \Theta_2)p(\Theta_2|M_2)q_2(\Theta_1)}{p(Y|M_1, \Theta_1)p(\Theta_1|M_1)q_1(\Theta_2)}, \quad (5)$$

where  $\Theta_1$  and  $\Theta_2$  are GARCH and TAR-GARCH parameters and  $q_1(\Theta_2)$  and  $q_2(\Theta_1)$  are two multivariate normal kernels to facilitate the jumps. Specifically, if we consider jumping from  $M_1$  to  $M_2$ , we draw  $\Theta_2$  from  $q_1(\Theta_2)$  and accept the jump to  $M_2$  with the probability  $\min\{1, p\}$ . For the jump from  $M_2$  to  $M_1$ , we draw  $\Theta_1$  from the kernel  $q_2(\Theta_1)$  and determine the acceptance by  $\min\{1, p^{-1}\}$ . Upon convergence, the proportion of time staying in a model provides an estimate of posterior probability.

Using 10 market indices from 1985 to 2001, which contain the same data range used in this study, So, Chen, and Chen (2003) find that the asymmetrical volatility effect is highly evident in the equity markets of the United Kingdom, Canada, Germany, the United States, Japan, Hong Kong, Singapore, Korea, and Taiwan. In fact, all the posterior probabilities of a threshold GARCH model are close to one.<sup>10</sup> Therefore, we can conclude that the observed differences in the parameters of the two regimes are statistically significant in the Bayesian perspective.

## 5. Summary and concluding remarks

In this paper, we investigate financial market integration by exploring the dynamic behavior of daily stock-index returns of six advanced capital markets. Conforming to well-established empirical regularities—stock-index returns present some degree of persistence and are greatly influenced by international capital markets—the volatility evolution process appears to be described well by an GARCH(1,1) specification. By employing a double-threshold regression GARCH model to examine the nature of market integration, we find significant asymmetrical behavior in both mean and variance equations. Whatever the news developed in the US market, consistent with a meteor-shower hypothesis, this information is transmitted to each national market, causing domestic stock prices to move in the same direction. However, the evidence clearly shows that, conforming to risk-aversion behavior, the price movement is much larger when bad news impacts the market than when good news does. In addition to this, the variance equation presents an asymmetrical phenomenon: the variance appears to be more volatile when a significant negative return is released from the US market than when a positive one does. This can be attributable to the leverage effect—a decline in stock prices leads to a higher debt/equity ratio and hence to a higher risk.

## Notes

1. Studies in the form of weighted-innovation models accounting for asymmetrical effect between positive and negative shocks of stock returns include exponential GARCH (Koutmos & Booth, 1995; Nelson, 1991) and threshold autoregressive GARCH models (Glosten, Jagannathan, & Runkle 1993, henceforth, GJR; Chiang & Doong, 2001; Engle & Ng, 1993). In examining nine developed stock-market indexes, Koutmos (1998) presents a model to investigate the asymmetrical effects and finds that asymmetries in the conditional mean are linked to asymmetries in the conditional variance since the faster adjustment of prices to negative returns gives rise to higher volatility during down markets.

2. As will be seen in our empirical estimation, the time lag involving news spreading from the United States to other markets will be determined by the data through empirical simulation. However, if the US and Japanese markets display a correlation on the same calendar day with the data, it will reflect a Japanese lead of approximately 17 hours in real time as noted by Koch and Koch (1991).
3. We are indebted to C. W. Granger for his insightful suggestion and discussion to reformulate the model specification in this section.
4. LeBaron (1992) and Koutmos (1998) specify only one lag for the autoregressive parameter. Baillie and DeGennaro (1990) find a longer lag in the autocorrelation parameter.
5. As indicated by an anonymous referee as well as Hamao et al. (1990) and Chiang and Chiang (1996), the volatility spillovers from the United States to other stock markets may be added to enhance the predictability of the conditional variance. To follow this line of approach, it is necessary to add a U.S. volatility proxy in the two variance equations. However, we believe that part of the spillover effect observed in the literature can be explained by volatility asymmetry. Here, we just focus on a simple specification that highlights the impact of news asymmetry and allows us to compare the models such as Li and Li (1996) and Koutmos (1998). Undoubtedly, simultaneous modeling of volatility spillover and asymmetry is a fruitful direction for further research.
6. The discussion of Bayesian analysis and its comparison with sampling theory can be found in Greene (2000, pp. 402–412).
7. It is possible to present multiple regimes with different threshold values. In particular, when the number of changes (regimes) is known, the MCMC methods can be applied in a straightforward manner. However, in practice, it is not easy to decide the numbers of regimes having a particular economic meaning. Moreover, the computation can be very cumbersome. In our study, dividing the data into two regimes allows us to examine the asymmetrical phenomenon.
8. In implementing the MCMC methods, we employ  $d = 1, 2, 3$  and  $4$ . The result shows that  $d = 2$  has the highest frequency for France and Germany, rejecting the efficient market hypothesis.
9. Empirical tests for leverage effect can be found in Cheung and Ng (1992), while Bekaert and Wu (2000) have addressed the leverage effect and volatility feedback effect to explain the dynamics of asymmetric volatility.
10. The details of the jumping scheme, including how to construct  $q_1(\Theta_2)$  and  $q_2(\Theta_1)$ , and evidence, can be found in So et al. (2003).

## Acknowledgments

The authors would like to thank Professors C. W. J. Granger, Jay Choi, Wessel Marquering, C. W. Li, W. K. Li, and an anonymous referee for their useful comments and suggestions. The authors assume full responsibility for the analysis and the remaining errors. The research supports from Austin fund, Drexel University, National Science Council, and Feng Chia University are gratefully acknowledged.

**Appendix A. Causality tests for stock returns in global markets**

Causal direction	<i>F</i> -Test	Level of significance	Causal direction	<i>F</i> -Test	Level of significance
<b>A. Optimal lagged model</b>					
US → UK	164.84	0.001	UK → US	0.46	0.631
US → CA	1351.32	0.001	CA → US	1.70	0.182
US → GM	359.31	0.001	GM → US	3.14	0.043
US → JP	160.47	0.001	JP → US	2.42	0.088
US → FR	292.39	0.001	FR → US	0.69	0.498
US → SW	103.95	0.001	SW → US	2.42	0.089
<b>B. One-period lagged model</b>					
US → UK	488.47	0.001	UK → US	3.08	0.631
US → CA	3872.55	0.001	CA → US	2.53	0.182
US → GM	494.67	0.001	GM → US	3.96	0.046
US → JP	483.75	0.001	JP → US	9.23	0.002
US → FR	478.10	0.001	FR → US	0.31	0.570
US → SW	306.25	0.001	SW → US	2.57	0.109

*Notes.* In panel A, different optimal lags are used to predict autocorrelation and cross-asset return variables:  $F(3,4387)$  is used to test whether the United States causes international stocks, and  $F(2,4387)$  is used to test whether international stock returns cause US stocks returns. In panel B, one order lag is used.  $F(1,4390)$  is the *F*-statistic with degrees of freedom of (1,4390).

**Appendix B. Bayesian estimation of the double-threshold model**

The system of the double-threshold GARCH model in the text is given by:

$$R_t^i = \begin{cases} \phi_0^{(1)} + \phi_1^{(1)} R_{t-1}^i + \psi_1^{(1)} R_{t+m-d}^j + \varepsilon_t & \text{if } R_{t+m-d}^j \leq r \\ \phi_0^{(2)} + \phi_1^{(2)} R_{t-1}^i + \psi_1^{(2)} R_{t+m-d}^j + \varepsilon_t & \text{if } R_{t+m-d}^j > r \end{cases}$$

$$h_t = \begin{cases} \alpha_0^{(1)} + \alpha_1^{(1)} \varepsilon_{t-1}^2 + \beta_1^{(1)} h_{t-1} & \text{if } R_{t+m-d}^j \leq r \\ \alpha_0^{(2)} + \alpha_1^{(2)} \varepsilon_{t-1}^2 + \beta_1^{(2)} h_{t-1} & \text{if } R_{t+m-d}^j > r \end{cases}$$

where the distribution of  $\varepsilon_t$  is conditional on information up to time  $t - 1$  is  $N(0, h_t)$ . Let  $\pi_k$  be the time index of the  $k$ th smallest observation of  $\{R_1^j, \dots, R_n^j\}$ . Using the time index, we write the likelihood function as:

$$p(Y|\Theta) \propto \prod_{t=2}^n (2\pi h_t)^{-1/2} \exp \left\{ -\frac{1}{2} \sum_{k=1}^s \frac{1}{h_t} (R_{\pi_k}^i - \phi_0^{(1)} - \phi_1^{(1)} R_{\pi_{k-1}}^i - \psi_1^{(1)} R_{\pi_{k-1}}^j)^2 \right\}$$

$$\times \exp \left\{ -\frac{1}{2} \sum_{k=s+1}^{n-1} \frac{1}{h_t} (R_{\pi_k}^i - \phi_0^{(2)} - \phi_1^{(2)} R_{\pi_{k-1}}^i - \psi_1^{(2)} R_{\pi_{k-1}}^j)^2 \right\},$$

where  $p(Y|\Theta)$  is the likelihood function in the sampling process for all observations. Given the parameters being divided into two different regimes by the threshold variable,  $r$ ;  $s$  satisfies the restriction  $R_{\pi_s-d}^j \leq r < R_{\pi_s-d+1}^j$ . We define  $Y = (R_{\pi_1}^i, R_{\pi_2}^i \dots, R_{\pi_n}^i)'$ , the unknown parameters

$$\Theta = (\phi_0^{(1)}, \phi_1^{(1)}, \psi_1^{(1)}, \alpha_0^{(1)}, \alpha_1^{(1)}, \beta_1^{(1)}, \phi_0^{(2)}, \phi_1^{(2)}, \psi_1^{(2)}, \alpha_0^{(2)}, \alpha_1^{(2)}, \beta_1^{(2)}, r, d)'$$

To perform the Bayesian analysis of the double TAR-GARCH model, we choose the following prior distribution for  $\Theta$ :

$$p(\Theta) \propto I(\alpha_0^{(1)} > 0, \alpha_1^{(1)} + \beta_1^{(1)} < 1) \cdot I(\alpha_0^{(2)} > 0, \alpha_1^{(2)} + \beta_1^{(2)} < 1) \cdot I(a < r < b),$$

where  $I(\cdot)$  is the indicator function that  $I(A) = 1$  if the event  $A$  is true and  $a$  and  $b$  are 25 and 75 percentiles of the threshold variables  $R_t^j$ , respectively. The posterior distribution  $p(\Theta|Y)$  is then given by the Bayesian rule as:

$$p(\Theta|Y) \propto p(Y|\Theta) \cdot p(\Theta).$$

We generate an approximated sample  $\Theta^{M+1}, \dots, \Theta^N$  from the posterior distribution by using MCMC methods, where  $M$  is the number of ‘burn-in’ iterations for convergence and  $N$  is the total number of iterations. In our study,  $M = 10,000$  and  $N = 20,000$ . The sampling is done in six blocks:

- (1) Sample  $(\phi_0^{(1)}, \phi_1^{(1)}, \psi_1^{(1)})$  from  $p(\phi_0^{(1)}, \phi_1^{(1)}, \psi_1^{(1)}|Y, \Theta_{-(\phi_0^{(1)}, \phi_1^{(1)}, \psi_1^{(1)})})$ ,
- (2) Sample  $(\alpha_0^{(1)}, \alpha_1^{(1)}, \beta_1^{(1)})$  from  $p(\alpha_0^{(1)}, \alpha_1^{(1)}, \beta_1^{(1)}|Y, \Theta_{-(\alpha_0^{(1)}, \alpha_1^{(1)}, \beta_1^{(1)})})$ ,
- (3) Sample  $(\phi_0^{(2)}, \phi_1^{(2)}, \psi_1^{(2)})$  from  $p(\phi_0^{(2)}, \phi_1^{(2)}, \psi_1^{(2)}|Y, \Theta_{-(\phi_0^{(2)}, \phi_1^{(2)}, \psi_1^{(2)})})$ ,
- (4) Sample  $(\alpha_0^{(2)}, \alpha_1^{(2)}, \beta_1^{(2)})$ , from  $p(\alpha_0^{(2)}, \alpha_1^{(2)}, \beta_1^{(2)}|Y, \Theta_{-(\alpha_0^{(2)}, \alpha_1^{(2)}, \beta_1^{(2)})})$ ,
- (5) Sample  $r$  from  $p(r | \Theta_{-r})$ ,
- (6) Sample  $d$  from  $p(d | \Theta_{-d})$ ,

where  $\Theta_{-x}$  represents the vector  $\Theta$  without the parameter  $x$ . Point estimates of any function of the unknown parameter, say  $f(\Theta)$ , can then be obtained as the sample mean of the posterior sample. Thus, the point estimate of  $\hat{\Theta}$  is given by:

$$\hat{\Theta} = \frac{1}{N - M} \sum_{k=M+1}^N \Theta^k.$$

With respect to the estimated  $d$ , it is the value occurring most frequently in the posterior sample. Full details on how to implement the MCMC methods can be found in Chib and Greenberg (1995), Chen (1998), and Chen and So (2003).

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