New Evidence on Asymmetric Return-Volume Dependence and Extreme Movements

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*Corresponding author. We are very grateful to an anonymous referee and an associate editor for very valuable comments and suggestions. Our appreciation also goes to seminar participants at the 2017 Asia Global Workshop, Hong Kong University. We have no relevant or material financial interests that relate to the research described in this paper to disclose. Remaining errors are our own.

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Abstract

This paper examines the return-volume dependence structure across six major international stock markets using a dependence-switching copula model. The model allows the return-volume dependence to switch between positive and negative dependence regimes. The empirical results indicate that the return-volume (tail) dependence is asymmetric under the negative and positive dependence regimes, respectively. Next, there is a larger return-volume (tail) dependence for downward price ticks than for upward price ticks when trading volumes are large for most countries, supporting the view of heterogeneous investors with short-sale constraints and negative skewness in returns. Finally, both the intensity of information flow and liquidity trading are important driving forces of the time-varying, return-volume dependence.

Keywords: dependence-switching copula, tail dependence, return-volume dependence, liquidity, information flow.

JEL: C32, C51, G12, G15

1. Introduction

Stock returns and trading volumes are contemporaneously correlated as suggested by the Mixture Distribution Hypothesis (Epps and Epps, 1976; Tauchen and Pitts, 1983). In the bivariate mixture mode of Tauchen and Pitts (1983), a rise in the intensity of information flow increases both the mean and the variance of volume, as well as the variance of return. This in turn affects the dependence of return and volume. As for the relationship between stock returns and volumes, four different market statuses are observed: rising returns/rising volumes, falling returns/falling volumes, rising returns/falling volumes, and falling returns/rising volumes.[1] The first

[1] Rising volumes mean volumes rise relative to trend since volumes are detrended using the

(last) two market statuses are referred to as the positive (negative) return-volume dependence regime since returns and volumes move in the same direction (in different directions). Besides, the dependence of returns and volumes switches between positive and negative dependence regimes over time.

The above-mentioned four different market statuses are also implied by a model with heterogeneous investors and short-sale constraints (Chen et al, 2001; Hong and Stern, 2003). Stock markets, under normal conditions, mainly reflect the positive private information from optimistic investors since pessimistic investors will not actively participate in the market due to short-sale constraints. The arrival of positive (negative) public information causes the rise (fall) of returns and volumes. However, pessimistic investors will actively participate in the market when markets decline, and hence accumulated hidden information tends to come out. Markets mainly reflect the private information of pessimistic investors in such a case. Negative (Positive) public information causes the fall (rise) in returns and the rise (fall) in volumes.[2]

Empirical investigation of the return-volume dependence in stock markets is an interesting research topic in financial economics (Ying, 1966; Epps, 1975; Tauchen and Pitts, 1983; Karpoff 1987). Several empirical models have been applied, such as linear regression models with a dummy variable to control positive and negative returns (Jain and Joh, 1988; Assogbavi et al., 1995), GARCH-type models (Lamoureux and Lastrapes, 1990; Gallant et al., 1992; Andersen, 1996; Chen et al., 2001), Hamilton's regime-switching models (Chen, 2012), and copula models (Ning and Wirjanto, 2009). However, none of these approaches are able to estimate the dependence structure of returns and volumes under the above-mentioned four

Hodrick-Prescott filter.

[2] Facing positive public information in such a case, investors may decide to hold their stocks and wait for price to go down again. This results in the rise in returns and the fall in volumes.

different market conditions.[3] Furthermore, they fail to examine whether the (tail) dependences between falling returns/rising volumes and rising returns/falling volumes under the negative dependence regime are asymmetric. Nor are they, except Ning and Wirjanto (2009), able to examine the hypothesis of asymmetric (tail) dependence under different return-volume dependence regimes. However, these pieces of information are important to investors.

This paper examines the dependence structure between stock returns and trading volumes by applying a dependence-switching copula model in which the unknown state variable switches between positive and negative return-volume dependence regimes. The paper makes three contributions to existing literature. First, our model is flexible since it allows the dependence between returns and volumes to switch between positive and negative dependence regimes. Hence, we are able to discuss the dependence structure of returns and volumes under different market conditions and to examine whether the symmetric hypothesis holds for dependence and tail dependence under different dependence regimes. Second, the unknown state variable influences parameters in both marginal distributions and copula functions. Instead of applying a two-step method, we estimate marginal distributions and copula parameters simultaneously, and hence our estimates are free from the criticism of efficiency loss. Third, we empirically investigate market driving forces that account for the time-varying, return-volume dependence.

Using daily data from 01/03/2000 to 12/31/2016 for six developed stock markets, several important results are obtained. First, the duration is much longer for the positive return-volume dependence regime than the negative dependence regime, and

[3] Most existing literature do not apply the copula approach to examine the relationship between returns and volumes and assume that innovations follow a symmetric multivariate normal or Student-t distribution. Hence, they fail to examine the hypothesis of symmetric dependence of returns and volume (Patton, 2006; Garcia and Tsafack, 2011).

the volatilities of returns and volumes increase under the negative dependence regime. Second, dependence and tail dependence of stock returns and volumes are asymmetric regardless of the dependence regime being positive or negative. Third, return-volume (tail) dependence is significantly larger for downward price ticks than for upward price ticks for most countries when volumes are high relative to trend. This finding supports the view of heterogeneous investors with short-sale constraints and negative skewness in returns (Hong and Stein, 2003; Chen et al., 2001).[4] Finally, both the intensity of information flow and liquidity trading are important in driving the time-varying, return-volume dependence; this result agrees with Andersen (1996), Tauchen and Pitts (1983) and Li and Wu (2006).

In related literature, Ning and Wirjanto (2009) is the first paper to examine the return–volume dependence using a copula approach. They adopt a mixture of the Clayton, the survival Clayton and the Frank copulas and estimate their models by a conventional two-step estimation method.[5] There are three restrictions in Ning and Wirjanto (2009). First, their copula functions only allow them to consider the two different market statuses under the positive or negative return-volume dependence regime.[6] Second, their mixture copulas fail to capture the fact that return-volume dependence switches between positive and negative dependence regimes. Finally, the adoption of a two-step approach in estimation leads their estimates to suffer the criticism of efficiency loss (Rodriguez, 2007). Besides, Ning and Wirjanto (2009) focus on East Asian stock markets instead of major stock markets.

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[4] Hong and Stein (2003) provide a theory based on heterogeneous investors to explain that returns will be negatively skewed conditional on high trading volumes when the heterogeneous opinions among investors are large. See section 3.3 for more details.

[5] The two-step procedure has a cost in terms of efficiency loss since the estimation errors in the first stage result in efficiency loss in the second stage estimation.

[6] Ning and Wirjanto (2009) find asymmetric return-volume (tail) dependence under the positive dependence regime but no (tail) dependence under the negative dependence regime. Their results indicate that market booms are associated with high trading volumes but market stress has no significant relationship with volumes. Our results under the positive dependence regime are consistent with theirs.

Wang et al. (2013) develop a dependence-switching copula model allowing for a state-varying dependence and then apply it to examine dynamic dependence between currency and stock markets. Our paper differs from Wang et al. (2013) in four ways. First, we investigate the dependence structure of returns and volumes for stock markets rather than the dependence structure between stock and currency markets. Second, their mixture copula is a weighted average of two copulas under a specific dependence regime, and the weight is assumed to be 0.5. However, we allow the weight to be determined by data. Third, although our dependence–switching copula model is similar to theirs, our estimation method is not. Wang et al. (2013) apply a two-step method suggested by Li (2005) in which the unknown state variable appearing in the mean and variance of the marginal model is measured by observed interest differentials. The marginal distribution is then estimated in the first step, and copula parameters, given the specified copula functions, are estimated in the second step.[7] Instead of applying a two-step method, we estimate parameters in marginal models and the copula functions simultaneously. Finally, we investigate the market driving forces that account for the time-varying, return-volume dependence; these driving forces are not examined in Wang et al. (2013).

The organization of the paper is given as follows. We briefly discuss the dependence-switching model and describe the one-step estimation method in Section 2. The data and empirical results are discussed in Section 3, in which we explore parameter estimates and examine the symmetric hypothesis of dependence and tail dependence of returns and volumes. In Section 4, we identify market driving forces affecting the time-varying, return-volume dependence. Finally, conclusions are given

[7] Wang et al. (2013) proxy the unobservable state with an instrument and estimate the parameters in marginal models with the quasi-maximum likelihood estimation method proposed by Bollerslev and Wooldridge (1992) at the first step. The copula parameters are obtained at the second step by fitting the dependence switching copula to the estimated residuals obtained from the marginal models.

in Section 5.

2. The dependence-switching copula model

Copulas provide a powerful approach to examine the dependence structure of two variables (Hu, 2006; Patton, 2006). A copula is a multivariate cumulative distribution function whose marginal distributions are uniform on the interval [0,1]. A bivariate joint cumulative distribution function (F) of two variables can be decomposed into two marginal cumulative distribution functions (F_1 and F_2) and a copula cumulative distribution function (C) that completely describes the dependence structure between the two series (Sklar, 1959). In order to remove serial correlations and heteroscedasticity from the data, we pre-whiten returns and volumes by estimating an AR(1)-GARCH(1,1) model using the Gaussian Quasi-Maximum Likelihood method (McNeil and Frey, 2000; Bee et al., 2016). Let X_1 and X_2 be the stock return and volume, respectively. The AR(1)-GARCH(1,1) model is specified as follows:

$$X_{i,t} = \mu_i + \alpha_i X_{i,t-1} + \varepsilon_{i,t}, \quad i = 1,2,$$

$$h_{i,t} = \beta_{i,0} + \beta_{i,1}\varepsilon^2_{i,t-1} + \beta_{i,2}h_{i,t-1}.$$

Following Rodriguez (2007), the residual $\varepsilon_{i,t}$ has been assumed to have a standard normal distribution.[8] Let $\eta_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}$, where $\eta_{i,t}$ follows a distribution with zero mean and unit variance. The cumulative distribution function of η_1 and η_2 is

$$F(\eta_1, \eta_2; \delta_1, \delta_2, \theta_c) = C(F_1(\eta_1; \delta_1), F_2(\eta_2; \delta_2); \theta_c), \tag{1}$$

[8] The usefulness of the standardized Student's t distribution is also well documented in the literature, especially when dealing with heavy-tailed, high-frequency data of financial returns. We also assume the standardized Student's t distribution for residuals in the AR(1)-GARCH(1) model. Although the results in Tables 3 and 4 are not qualitatively affected by this change, the log likelihood value decreases for all countries except for CAN. This indicates that using the standardized t-distribution for residuals in the AR(1)-GARCH(1) model does not improve the model’s fit. Estimation results are available upon request from the authors.

where $F_k(\eta_k;\delta_k)$, k=1,2, is the marginal cumulative distribution function of η_k; δ_k and θ_c are the parameter sets of $F_k(\eta_k;\delta_k)$ and C, respectively.[9]

Assuming that all cumulative distribution functions are differentiable, the bivariate joint density is then given by

$$f(\eta_1,\eta_2;\delta_1,\delta_2,\theta_c) = c(u_1,u_2;\theta_c)\cdot\prod_{k=1}^{2} f_k(\eta_k;\delta_k)\,, \qquad (2)$$

where $f(\eta_1,\eta_2;\delta_1,\delta_2,\theta_c) = \partial F^2(\eta_1,\eta_2;\delta_1,\delta_2,\theta_c)/\partial\eta_1\partial\eta_2$ is the joint density of η_1 and η_2; u_k is the "probability integral transform" of η_k based on $F_k(\eta_k;\delta_k)$, k=1,2; $c\left(u_1,u_2;\theta_c\right) = \partial C^2(u_1,u_2;\theta_c)\big/\partial u_1\partial u_2$ is the copula density function; and $f_k(\eta_k;\delta_k)$ is the marginal density of η_k, k=1,2. The bivariate joint density of η_1 and η_2 is the product of the copula density and the two marginal densities.

Conventional copula functions such as Clayton, survival Clayton and Gumble copulas are able to model either the positive or negative return-volume dependence. They are not able to capture the coexistence of positive and negative return-volume dependences simultaneously. However, the return-volume dependence in stock markets includes the positive (negative) dependence regime with volumes and returns moving in the same (opposite) direction. Moreover, the dependence is positive sometimes and negative other times, and it switches between them frequently during a specific sample period. It is therefore not appropriate to apply a conventional copula model to investigate the return-volume dependence in stock markets.

To capture the above dependence switching, we propose a dependence-switching copula model in which the unobserved state variable affects copula functions and marginal models simultaneously (Wang et al, 2013). Consider the following

[9] η_1 and η_2 are pre-whitened stock returns and volumes. We apply pre-whitened data to estimate the parameters in marginal models and copula functions simultaneously.

state-varying copula:

$$C^{S_t}(u_1,u_2;\theta_c^1,\theta_c^0)=\begin{cases}C^1(u_1,u_2;\theta_c^1), & \text{if } S_t=1\\ C^0(u_1,u_2;\theta_c^0), & \text{if } S_t=0\end{cases},$$

where S_t is an unobserved state variable and $C^1(u_1,u_2;\theta_c^1)$ and $C^0(u_1,u_2;\theta_c^0)$ are two mixed copulas with positive and negative dependence structures, respectively. The above two copula functions mix the Clayton copula (C^C) with the survival Clayton copula (C^{SC}):[10]

$$C^1(u_1,u_2;\theta_c^1)=w_1C^C(u_1,u_2;\alpha_1)+(1-w_1)C^{SC}(u_1,u_2;\alpha_2), \tag{3}$$

$$C^0(u_1,u_2;\theta_c^0)=w_2C^C(1-u_1,u_2;\alpha_3)+(1-w_2)C^{SC}(1-u_1,u_2;\alpha_4), \tag{4}$$

where $\theta_c^1=(\alpha_1,\alpha_2,w_1)$, $\theta_c^0=(\alpha_3,\alpha_4,w_2)$, $C^C(u,v;\alpha)=(u^{-\alpha}+v^{-\alpha}-1)^{-1/\alpha}$, $C^{SC}(u,v;\alpha)=u+v-1+C^C(1-u,1-v;\alpha)$, and $\alpha\in(0,\infty)$. After estimating the shape parameter, α_i, we can transform it to obtain Kendall's τ_i, the correlation coefficient ρ_i and the tail dependence φ_i with $\tau_i=\alpha_i/(2+\alpha_i)$, $\rho_i=\sin(\pi*\tau_i/2)$, and $\varphi_i=0.5*2^{-1/\alpha_i}$, for $i=1,2,3,4$.[11]

ρ_2 (ρ_3) measures the dependence of high returns and high (low) volumes, and ρ_1 (ρ_4) measures the dependence of low returns and low (high) volumes as indicated in Figure 1. They are dependence measures under normal market conditions. φ_2 (φ_3) measures the dependence of extremely high returns with extremely high (low) volumes, and φ_1 (φ_4) measures the dependence of extremely low returns with

[10] The Gumbel copula could alternatively be employed, but it does not fit well according to model selection criteria such as the Akaike (Bayes) information criterion and the log-likelihood function value.

[11] Measuring dependence between two variables with the Pearson correlation coefficient is not appropriate when extreme values exist in data. In such a case our correlation coefficient is a better measure of the dependence between returns and volumes. The detailed derivation of tail dependence under different market status is given in the appendix.

extremely low (high) volumes.[12] They measure the return-volume dependence under extreme market conditions and may be different from those under normal market conditions (Gallant et al., 1992; Marsh and Wagner, 2004; Ning and Wirijanto, 2009). However, few existing studies estimate dependences at extremes. Our (tail) dependence estimates provide further insights on the relationship between stock returns and trading volumes since none of the existing literature estimate the return-volume dependence structure under four different market conditions.

The unobserved state variable S_t follows a two-state Markov chain with a transition probability matrix:

$$P = \begin{bmatrix} p_{00} & 1-p_{00} \\ 1-p_{11} & p_{11} \end{bmatrix},$$

where $p_{ij} = \Pr\left[S_t = j \mid S_{t-1} = i\right]$ for i,j=0,1. The state variable (S_t) switches between the negative dependence regime (S_t =0) and the positive dependence regime (S_t =1). The bivariate density function of the above model is expressed as

$$\begin{aligned} & f(\eta_1, \eta_2; \delta_1^1, \delta_1^0, \delta_2^1, \delta_2^0, \theta_c^1, \theta_c^0) \\ & = \left\{ \sum_{j=0}^{1} \Pr(S_t = j) c^j(u_1, u_2; \theta_c^j) \right\} \prod_{k=1}^{2} \left\{ \sum_{j=0}^{1} \Pr(S_t = j) f_k(\eta_k; \delta_k^j, S_t = j) \right\}, \end{aligned} \tag{5}$$

where $c^j(\cdot)$ is the copula under regime j and θ_c^j is its parameter set. δ_k^j is the parameter set of the marginal density under regime j for return (k=1) and volume (k=2).

The log-likelihood function of (5) is

$$L(\Theta) = L_c(\psi_1) + \sum_{k=1}^{2} L_k(\psi_{2,k}), \tag{6}$$

where $\Theta = (\theta_c^1,\ \theta_c^0,\ \delta_1^1,\ \delta_1^0,\ \delta_2^1,\ \delta_2^0,\ p_{11},\ \mathrm{p}_{00})$; $L_c(\psi_1)$ and $L_k(\psi_{2,k})$ are the log

[12] In other words, the tail dependence φ_2 is the probability of having an extremely high return (volume) conditional on high volumes (returns).

of the copula density and the marginal density of X_k, respectively. These two densities are given as follows:

$$L_c(\psi_1) = \log[\Pr(S_t = 1)c^1\left(u_1, u_2; \theta_c^1\right) + (1 - \Pr(S_t = 1))c^0\left(u_1, u_2; \theta_c^0\right)],$$

$$L_k(\psi_{2,k}) = \log[\Pr(S_t = 1) f_k(\eta_k; \delta_k^1, S_t = 1) + (1 - \Pr(S_t = 1)) f_k(\eta_k; \delta_k^0, S_t = 0)],$$

where $\psi_1 = (\theta_c^1, \theta_c^0, p_{11}, p_{00})$ and $\psi_{2,k} = (\delta_k^1, \delta_k^0, p_{11}, p_{00})$.

Since the state variable influences both the marginal distribution and the copula function, the IFM method proposed by Joe and Xu (1996) cannot be applied.[13] This paper estimates the parameters in marginal models and copula functions simultaneously. The marginal models are specified as follows:

$$\eta_{i,t} = \mu_i^{S_t} + \sigma_i^{S_t} v_{i,t}^{S_t}, \quad i = 1,\ 2, \quad v_{i,t}^{S_t} \sim N(0,1),$$

where $\mu_i^{S_t}$ and $\sigma_i^{S_t}$ denote the drift and the volatility, respectively, of $\eta_{i,t}$ under the negative (S_t =0) or positive (S_t =1) dependence regime; the $v_{i,t}^{S_t}$s are residuals that are normally distributed with zero mean and a unit variance.[14]

Following the Canonical Maximum Likelihood (CML) approach, this paper transforms the standardized residuals into a uniform distribution with the following empirical marginal cumulative distribution function:[15]

$$\hat{F}_i(\omega) = \frac{1}{T+1} \sum_{t=1}^{T} I(\hat{v}_{i,t}^{S_t} \le \omega), \tag{7}$$

[13] Due to there not being any prior theory about volumes and price changes, it is difficult to proxy the unobservable state variable with the instruments proposed by Li (2005) and Wang et al. (2013).

[14] The technical sophistication of one-step estimation lies in its allowing of the state variable to influence parameters in both marginal distributions and a copula function. The large number of parameters makes it difficult to find the numerical maximum of the likelihood function (Patton, 2004, 2006). Although the standardized t-distribution for $v_{i,t}^{S_t}$ may fit the data better, it raises the number of parameters to be estimated by four. This significantly increase the difficulty of finding convergence in estimation for some countries. Therefore, our assumption of a normal distribution for $v_{i,t}^{S_t}$ is an outcome of the trade-off between estimation cost and the feasibility of model specification.

[15] The CML approach points out that transforming standardized residuals based on an empirical CDF will always result in a uniform distribution asymptotically regardless of the specification of marginal models.

where $\mathrm{I}(\cdot)$ is an indicator function that is one if $\hat{v}_{i,t}^{S_t} \le \omega$ and is zero otherwise. This paper then obtains the cumulative probability for each observation of $\hat{v}_{i,t}^{S_t}$ and denotes it by $\hat{u}_{i,j}^{S_t} = \hat{F}_k(\hat{v}_{i,j}^{S_t})$, i=1, 2, $j = 1, 2, ..., T$, $S_t = 0,1$.

Since the dependence structure follows a Markov-switching process, we apply Hamilton's filtered system to transform the log-likelihood function of the model as follows:

$$L(\Theta) = \log\left(\hat{\xi}'_{t|t-1}\lambda_t\right),$$

$$\hat{\xi}_{t|t} = \left(\hat{\xi}'_{t|t-1}\lambda_t\right)^{-1}\left(\hat{\xi}'_{t|t-1} \circ \lambda_t\right),$$

$$\hat{\xi}_{t+1|t} = P'\hat{\xi}_{t|t},$$

$$\lambda_t = \begin{bmatrix} f_1(\eta_{1,t};\delta_1^1)\, f_2(\eta_{2,t};\delta_2^1) c^1(\hat{u}_{1,t}^1, \hat{u}_{2,t}^1; \theta_c^1) \\ \\ f_1(\eta_{1,t};\delta_1^0)\, f_2(\eta_{2,t};\delta_2^0) c^0(\hat{u}_{1,t}^0, \hat{u}_{2,t}^0; \theta_c^0) \end{bmatrix},$$

where "$\circ$" is the Hadamard product and c^{S_t} is the density function of C^{S_t} for $S_t = 0,1$. The vector of parameters $\Theta = (\theta_c^1,\ \theta_c^0,\ \delta_1^1,\ \delta_1^0,\ \delta_2^1,\ \delta_2^0,\ p_{11},\ p_{00})$ can then be estimated by maximizing $L(\Theta)$[16]

$$\Theta = \arg\max_{\Theta} \sum_{t=1}^{T} L(\Theta). \tag{8}$$

After estimating the model's parameters, we construct the time-varying dependence of returns and volumes. Since $E\left(C_1(u_1, u_2)\right) = \int_0^1\int_0^1 C_1(u_1, u_2)\, dC_1(u_1, u_2)$, the Kendall's τ of the mixed copula under the positive dependence regime is

$$\tau^1 = w_1[\alpha_1 / (2+\alpha_1)] + (1-w_1)[\alpha_2 / (2+\alpha_2)].$$

[16] To avoid an arbitrary initial value, we first use the simplex search method of Lagarias et al. (1998) to obtain the estimate of Θ ($\hat{\Theta}_0$), which is then used as the initial value to obtain the MLE estimates of Θ ($\hat{\Theta}$).

Similarly, Kendall's τ of the mixed copula under the negative dependence regime is $\tau^0 = w_2[\alpha_3/(2+\alpha_3)] + (1-w_2)[\alpha_4/(2+\alpha_4)]$.[17]

Having Kendall's τ^1 and τ^0, the correlation coefficient of the mixed copula under different dependence regimes can be calculated as $\rho^j = \sin(\pi * \tau^j / 2)$ for j=0, 1. Therefore, the smoothing correlation (ρ_{sm}) is

$$\rho_{sm} = p_{1,sm}\rho^1 - p_{0,sm}\rho^0 = p_{1,sm} \times \sin(A) - p_{0,sm} \times \sin(B)$$

where $A = 0.5\pi \times [w_1\tau_1 + (1-w_1)\tau_2]$, $B = 0.5\pi \times [w_2\tau_3 + (1-w_2)\tau_4]$, and $p_{j,sm}$ is the smoothing probability in regime j for j=0,1 (Kim and Nelson, 1999).[18]

3. Empirical investigation

3.1 Data description

Daily volume and spot price index data for Canada (CAN), France (FRA), Germany (GER), Japan (JAP), the United Kingdom (UK) and the United States (USA) are downloaded from Datastream. The spot price indices are Standard and Poor's / Toronto Stock Exchange Composite Index of Canada (S&P/TSX), Cotation Assistée en Continu of France (CAC 40), Deutscher Aktienindex of Germany (DAX 30 Performance), Tokyo Stock Exchange Index of Japan (TOPIX), Financial Times Stock Exchange 100 Index of UK (FTSE 100), and Standard and Poor's 500 Composite of USA (S&P 500 Composite). Restrictions on cross-border capital flows began to be removed in the early 1990s, and capital was free to move across major industrial countries by 2000. We therefore focus on data from 2000 and later. The sample period starts from 2000/01/03 and ends on 2016/12/31 for all countries except CAN and GER. Due to the data availability of volumes, Germany's sample period

[17] The detailed derivations of the Kendall's correlation and smooth correlation of the mixed copula are given in the appendix.
[18] See the appendix for derivation details.

starts from 2003/08/01 and Canada's ends at 2016/09/15.

The stock return is the log-difference of the corresponding stock price index multiplied by 100. We employ the algorithm proposed by Hodrick and Prescott (1997, HP) to detrend volumes (Statman et al, 2006; Ning and Wirjanto, 2009).[19] Figure 2 plots detrended volumes for all countries and they appear to be stationary.

Table 1 presents summary statistics of the data and points out that both series are stationary as indicated by the ADF and PP unit-root tests. The means of stock returns and volumes are smaller than their respective standard deviations, indicating relatively high risks in stock markets. Moreover, both series exhibit excessive kurtosis and the normality of an individual series is strongly rejected as indicated by the Jarque-Bera test. Lastly, the Pearson return-volume correlation coefficient is significantly negative for most countries.

3.2 Empirical copula table

In Table 2, we calculate an empirical copula table to realize the dependence structure of data. We first rank the pair of return and volume in ascending order and then divide each series evenly into 10 bins. Bin 10 includes the observations with the highest values and bin 1 includes the observations with the lowest values. The ranks for returns (i) are on the horizontal axis while the ranks for volume (j) are on the vertical axis. The number of observations in cell (i, j) reveals information about the relationship between returns and volumes. If there is a positive right (left) tail dependence between the two series, we would expect more observations in cell (10,10) (cell (1,1)). However, if negative right (left) tail dependence between the two series appears, we would then expect more observations in cell (1,10) (cell (10,1)).

[19] The plots of the volumes reveal nonlinear secular trends over time. We therefore apply the HP filter to detrend volumes, and the smoothing parameter in the HP filter is set to $6*10^6$ (Ning and Wirjanto, 2009). The empirical results in Section 3 are not qualitatively affected if the first difference of volume ($\Delta X_{2t} = X_{2t} - X_{2t-1}$) is applied.

Taking France as an example, the number of observations in cell (1, 10) is 103, indicating that there are 103 observations, out of 4,347 observations, where returns lie below the 10th percentile (the 1/10th quantile) and the volumes are above the 90th percentile (the 9/10th quantile). The number of observations in cell (10, 10) is 89, indicating that there are 89 observations where both returns and volumes lie above their respective 90th percentiles (the 9/10th quantiles). The numbers in other cells are all smaller than those in the above two cells, reflecting the U-shaped tail dependence for both variables.

The results from Table 2 also reveal evidence of negative left and positive right dependences for the remaining five countries. The numbers of observations in cell (1,1) and cell (10,1) are 12 and 19 for FRN, 20 and 29 for CAN, 4 and 15 for GER, 21 and 17 for JAP, 16 and 26 for UK, and 20 and 17 for USA. These numbers are small relative to the numbers in cell (10,10) and cell (1,10), indicating the importance of taking into account the dependence between returns and volumes under different market conditions.

3.3 Estimation results

The top panel of Table 3 reports parameter estimates of marginal models and indicates that most of them are significant at the 5% level. The middle and bottom panels of Table 3 report estimated dependences and tail dependences, which are constructed based on the estimated shape parameters, the $\hat{\alpha}_i$s. Standard errors of dependence and tail dependence are constructed using the Delta method.

Several results are observed from Table 3. First, the estimated transition probability is much larger for the positive return-volume dependence regime ($\hat{p}_{11}$) than for the negative dependence regime ($\hat{p}_{00}$) for all countries. This implies that duration is much longer for the positive regime than for the negative regime. As indicated by Figure 3, smoothing probabilities for the positive dependence regime are similar for most countries and are high for most of the sample period. Hong and Stein (2003) point out that, under normal market conditions, volumes and returns appear to have a positive dependence since pessimistic investors fail to dominate stock markets due to short-sale constraints. Figure 4 plots the smoothing dependence of returns and volumes for all countries, indicating that the return-volume dependence switches frequently between positive and negative regimes. The periods in Figure 4 with a positive return-volume dependence generally match the periods in Figure 3 with a high smoothing probability for the positive dependence regime.

Next, the volatilities of return ($\hat{\sigma}_1^i$, i=0,1) and volume ($\hat{\sigma}_2^i$, i=0,1) are significant at the 5% level under both the positive (i=1) and negative (i=0) dependence regimes for all countries, and they are more volatile under the negative regime than under the positive regime. Tauchen and Pitts (1983) showed that both volume and return volatilities increase if traders react diffusely to new information. Our results agree with their findings since both optimistic and pessimistic traders are involved under the negative dependence regime and react differently to new information.

Third, under the positive dependence regime, the results from Table 3 indicate that $\hat{\rho}_2$ and $\hat{\varphi}_2$ are significant at conventional levels for all countries except UK. However, $\hat{\rho}_1$ and $\hat{\varphi}_1$ are small and insignificant for all countries. These results indicate that (extremely) high volumes are more likely to synchronize with (extremely) high returns, but (extremely) low volumes are unlikely to coexist with (extremely) low returns. Hence dependence and tail dependence are both asymmetric under the positive dependence regime for 5 of the 6 countries, which agrees with results found in Ning and Wirjanto (2009).[20]

Under the negative dependence regime, $\hat{\rho}_4$ is significant but $\hat{\rho}_3$ is insignificant at conventional levels for all countries. High volumes are significantly dependent with low returns, but low volumes do not have a significant relationship with high returns. As for the tail dependence, $\hat{\varphi}_4$ is significant but $\hat{\varphi}_3$ is insignificant for all countries. Extremely high volumes are significantly dependent with extremely low returns, but extremely low volumes do not have a significant relationship with extremely high returns. These results indicate that both dependence and tail dependence are asymmetric under the negative dependence regime.

Although volumes reflect the arrival of information, our results point out that the return-volume dependence for downward price ticks is significant only when volumes are high relative to trend. It is, therefore, not appropriate for investors to predict price changes based on volumes when they are low relative to trend. Besides, the significance of $\hat{\rho}_4$ and $\hat{\rho}_2$ and the insignificance of $\hat{\rho}_1$ and $\hat{\rho}_3$ support an old Wall Street adage that "It takes volume to make price moves".

Fourth, the results from Table 4 indicate that the dependence of extremely low returns with extremely high volumes ($\hat{\varphi}_4$) is significantly greater than that of extremely high returns with extremely high volumes ($\hat{\varphi}_2$) for FRA, GER, JAP and UK. Hong and Stein (2003) predict that negative skewness in returns will be most pronounced around the periods of heavy trading volumes. Our finding of $\hat{\varphi}_4 > \hat{\varphi}_2$ supports negative skewness in returns found by Hong and Stein (2003) and Chen et al. (2001).

Table 4 also points out a significantly larger return-volume dependence for

[20] Volume has been detrended by the HP filter, and hence it measures the deviation from its trend level.

downward price ticks than for upward price ticks when volumes are high relative to trend ($\hat{\rho}_4 > \hat{\rho}_2$) except for CAN. Empirically, Wood et al. (1985) and Chen (2012) indicate a larger return-volume dependence for downward price ticks than for upward price ticks, but Ying (1966), Epps (1975) and Jain and Joh (1988) find the opposite. Our finding that $\hat{\rho}_4 > \hat{\rho}_2$ for most countries points out that the asymmetric return-volume dependence obtained by Wood et al. (1985) and Chen (2012) are supported only when volumes are high relative to trend.

Both dependence and tail dependence are weaker when returns and volumes are high than when returns are low but volumes are high, supporting Hong and Stein (2003)'s view of heterogeneous investors with short-sale constraints. The reason is that focusing on heterogeneous investors, bearish investors did not initially participate in the market under normal market conditions because of short-sale constraints. When markets decline, bullish investors bail out of the market and bearish investors become the marginal supporting buyers. More signals and hidden information regarding bearish investors are revealed and learned. After digesting the newly released hidden information, fully rational, risk-neutral arbitrageurs re-enter the market to short the position, which results in an increase in market participants and trading volumes and hence an increase in ρ_4 and φ_4. This is because returns are negatively skewed conditional on high trading volumes when heterogeneous opinions among investors vary greatly (Hong and Stein, 2003) and because the return-volume dependence increases with market participants (Tauchen and Pitts, 1983).

To justify the appropriateness of adopting the dependence-switching copula model, we evaluate its goodness-of-fit relative to single-copula models and mixture copula models using the Akaike and Bayes information criteria (AIC and BIC). [21] Eight different copula models are considered: Gaussian copula, Student-t copula, (rotated) Clayton, (rotated) survival Clayton copula, mixture Clayton copula, and mixture rotated Clayton copula. We also report the log likelihood value (LV) of different models. The results from Table 5 indicate that the estimated AIC (BIC) from the dependence-switching copula model is smaller than those from the single-copula and mixture copula models for all countries. Besides, the dependence-switching copula model also has the highest LV for different countries. These results support the appropriateness of adopting the dependence-switching copula model to examine the dependence structure between returns and volumes.

If our model is correctly specified and estimated, we should find that the relationship between returns and volumes is positive (negative) when the smoothing correlation $\hat{\rho}_{sm,t}$ is positive (negative). We therefore estimate the following threshold model:

$$X_{2t} = \alpha_1 + \beta_1 \times X_{1t} + \varepsilon_{1t}, \quad \text{if } \hat{\rho}_{sm,t} > 0,$$
$$X_{2t} = \alpha_2 + \beta_2 \times X_{1t} + \varepsilon_{2t}, \quad \text{if } \hat{\rho}_{sm,t} < 0.$$

The results from Table 6 indicate that $\hat{\beta}_1$ is positive and $\hat{\beta}_2$ is negative with the absolute value of $\hat{\beta}_2$ greater than $\hat{\beta}_1$ for all countries. We also report dependence estimates under positive and negative dependence regimes ($\hat{\rho}^1$ and $\hat{\rho}^0$) based on our dependence switching model and find that $\hat{\rho}^0 > \hat{\rho}^1$ for all countries.[22]

[21] Consider a sample with size T and assume that the number of estimated parameters is K. The AIC and BIC are defined as follows: $\mathrm{AIC(K)} = -2\ln \widehat{\mathrm{LV}}(\Theta) + 2 * \mathrm{K}$, $\mathrm{BIC(K)} = -2\ln \widehat{\mathrm{LV}}(\Theta) + \mathrm{K} * \ln(\mathrm{T})$, where $\ln \widehat{\mathrm{LV}}(\Theta)$ is the estimated log likelihood value. The model with the minimum AIC (BIC) is selected as the best model based on the AIC (BIC).

[22] Dependence estimates under the negative and positive dependence regimes ($\hat{\rho}^0$ and $\hat{\rho}^1$) are 0.145 and 0.108 for CAN, 0.240 and 0.136 for FRA, 0.228 and 0.122 for GER, 0.331 and 0.132 for JAP, 0.144 and 0.042 for UK, and 0.255 and 0.191 for USA.

The results from the $\hat{\beta}_i$s agree with those from the $\hat{\rho}^i$s; this supports that our model is correctly specified and estimated.

4. Driving forces of return-volume dependence

Examining driving forces accounting for the time-varying, asymmetric, return-volume dependence is important in literature (Karpoff, 1987). According to the microstructure framework approach, returns and volumes are both related to the arrival of unanticipated information (Andersen, 1996). Hence, the time-varying, return-volume dependence, $\rho_{sm,t}$, could be affected by the intensity of information flow, which is measured by return volatility (Andersen, 1996). Several authors point out that the price range between the highest and lowest log security prices over a fixed sampling interval is a fine proxy variable for the stochastic volatility of returns (Garman and Klass, 1980; Yang and Zhang, 2000; Alizadth et al., 2002; Brandt and Jones, 2006). We, therefore, measure the intensity of information flow by the stock price differential between the daily highest and lowest and then apply it to explain the time-varying dependence between returns and volumes. The regression equation is given as follows:

$$\hat{\rho}_{sm,t} = \alpha_1 + \beta_1 \times p_{HL,t} + \varepsilon_t \,,$$

where $p_{HL,t} = \log(P_{Ht}) - \log(P_{Lt})$ is the log price differential between the daily highest (P_{Ht}) and lowest (P_{Lt}). Since $\hat{\rho}_{sm,t}$ is a truncated variable with its value lying between -1 and 1, we estimate the above censored model with the maximum likelihood estimation method. The results from the first panel of Table 7 reveal that $\hat{\beta}_1$ is significantly negative at conventional levels for all countries in the sample. The increase in the intensity of information flow tends to drive the return-volume dependence regime from the positive regime to the negative regime, resulting in the increase of the volatility of returns and volumes. This is because return and volume volatilities are larger under the negative dependence regime than under the positive regime, as indicated in Table 3. Besides, the dependence is stronger under the negative dependence regime than under the positive dependence regime.[23] Therefore, our results echo the findings in Tauchen and Pitts (1983) and Harris (1986) that the return-volume dependence increases with the intensity of information flows.

Next, Li and Wu (2006) point out that liquidity is another factor affecting return-volume dependence. They point out that the process of volume includes liquidity trading and information flow components, but the liquidity trading is treated as a constant in Andersen (1996), and hence it has no effect on return volatility.[24] Li and Wu (2006) relax this assumption by postulating that liquidity trading can lower return volatility. Furthermore, Li and Wu (2006) empirically find that the effect of liquidity trading on return volatility is significant, and hence it should be an important driving force for the time-varying, return-volume dependence.

The liquidity index (Lq_t) is widely measured by the ratio of the daily total local currency value of shares traded (DVT_t) to the absolute value of returns ($|X_{1t}|$): $Lq_t = DVT_t \ /|X_{1t}|$, with the restriction of $X_{1t} \neq 0$ (Amihud et. al., 1997; Berkman and Eleswarapu, 1998). However, the restriction of $X_{1t} \neq 0$ is violated for some dates in our data. We therefore follow Amihud (2002) to construct the illiquidity index: $ILq_t = |X_{1t}|/DVT_t$.[25] The time-varying, return-volume correlation is then regressed on the illiquidity index as follows:

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[23] See footnote 23 for estimates.

[24] Andersen (1996) points out that the focus of the market microstructure literature is on intraday patterns rather than interday dynamics, so there are typically no explicit predictions regarding the relation among several variables such as bid-ask spread and market liquidity on return volatility at the daily frequency.

[25] Data for the daily total dollar value of shares traded are available from Datastream for all countries except the United States. We, therefore, measure this variable for the U.S. by multiplying the daily number of shares traded with the closing price at time t .

$$\hat{\rho}_{sm,t} = \alpha_1 + \beta_1 \times ILq_t + \varepsilon_t \,.$$

The results from the second panel of Table 7 indicate that $\hat{\beta}_1$ is significantly negative for all countries at the 1% level, indicating that the increase in liquidity (illiquidity decreases) tends to move the return-volume dependence toward the positive dependence regime, which has small return and volume volatilities as indicated by Table 3. Besides, under the positive dependence regime, the stock market mainly reflects the private information from optimistic investors, and there are few short-sale transactions since pessimistic investors bail out of the market. Hence, transaction costs are lower under the positive dependence regime. In other words, our results indirectly support the finding that an increase in liquidity decreases transaction costs and return volatilities (Chordia et al., 2000, 2001, 2002).

Although information flow and liquidity are both helpful in driving the time-varying, return-volume dependence, one may be interested in knowing the dominant factor of the two. We therefore include both variables in the regression equation simultaneously. The results from the bottom panel of Table 7 indicate that the estimated coefficients of information flow and illiquidity are significant for all countries except CAN, in which the estimated slope coefficient is significant for illiquidity but not for information flow. Hence, both the intensity of information flow and liquidity trading are important driving forces of time-varying, return-volume dependence. An increase in liquidity tends to move the return-volume dependence toward the positive dependence regime. However, an increase in the intensity of information flow tends to drive the return-volume dependence regime to the negative regime.

5. Conclusions

This paper applied the dependence switching copula model, proposed by Wang et al. (2013), to explore the time-varying dependence structure between stock returns and trading volumes. The advantage of our model is that it allows us to consider four different market conditions: rising returns/rising volumes, falling returns/falling volumes, rising returns/falling volumes, and falling returns/rising volumes. We estimate parameters in marginal models and the copula functions jointly since the unobserved state variable enters into marginal distributions and copula functions. Using daily data over 2000-2016 for six major industrial countries, we find that the volatilities of return and volume are larger for the negative dependence regime than for the positive dependence regime. Next, the (tail) dependence of high returns and high volumes is significantly lower than that of low returns and high volumes for most countries, which supports the view of heterogeneous investors with short-sale constraints and negative skewness in returns. Third, return-volume dependence and tail dependence are both asymmetric under the positive and negative dependence regimes, respectively. Finally, both the intensity of information flow and liquidity trading are important in driving the time-varying, return-volume dependence. Our results shed light on uncovering the time-varying correlation between stock returns and volumes and illuminate the factors that drive the above correlation.

Appendix

The purpose of this appendix is to derive the tail dependence coefficient (TDC), Kendall's τ and the correlation coefficient ρ of the mixed copula that combines the Clayton copula and the Survival Clayton copula.

A.1. Derivation of the tail dependence of the mixed copula.

According to Nelsen (1999), the right and left TDCs in terms of copulas are

$$\varphi_R = \lim_{\nu \to 1} \frac{1-2\nu + C(\nu,\nu)}{1-\nu},$$

$$\varphi_L = \lim_{\nu \to 0} \frac{C(\nu,\nu)}{\nu},$$

where C is a copula function. The analytical expression of the Clayton and the Survival Clayton copulas are

$$C^C(u_1,u_2;\alpha_1) = (u_1^{-\alpha_1} + u_2^{-\alpha_1} - 1)^{-1/\alpha_1},$$

$$C^{SC}(u_1,u_2;\alpha_2) = u_1 + u_2 - 1 + C^C(1-u_1, 1-u_2;\alpha_2).$$

Therefore,

$$C^C(\nu,\nu) = (\nu^{-\alpha_1} + \nu^{-\alpha_1} - 1)^{-1/\alpha_1} = (2\nu^{-\alpha_1} - 1)^{-1/\alpha_1},$$

$$C^{SC}(\nu,\nu) = 2\nu - 1 + C^C(1-\nu, 1-\nu;\alpha_2).$$

The right and left TDCs of the Clayton copula are

$$\varphi_R^C = \lim_{\nu \to 1} \frac{1-2\nu + C^C(\nu,\nu)}{1-\nu} = \lim_{\nu \to 1} \frac{-2 + 2\nu^{-\alpha_1 - 1}(2\nu^{-\alpha_1} - 1)^{-(1/\alpha_1)-1}}{-1} = 0,$$

$$\varphi_L^C = \lim_{\nu \to 0} \frac{C^C(\nu,\nu)}{\nu} = \lim_{\nu \to 0} (2 - \nu^{\alpha_1})^{-1/\alpha_1} = 2^{-1/\alpha_1}.$$

Furthermore, the right and left TDCs of the Survival Clayton copula are

$$\varphi_R^{SC} = \lim_{\nu \to 1} \frac{1-2\nu + C^{SC}(\nu,\nu)}{1-\nu} = \lim_{\nu \to 1} \frac{C^C(1-\nu, 1-\nu)}{1-\nu} = \lim_{t \to 0} \frac{C^C(t,t)}{t} = 2^{-1/\alpha_2},$$

$$\varphi_L^{SC} = \lim_{\nu \to 0} \frac{C^{SC}(\nu,\nu)}{\nu} = \lim_{\nu \to 0} \frac{2\nu - 1 + C^C(1-\nu, 1-\nu)}{\nu} = \lim_{t \to 1} \frac{1-2t + C^C(t,t)}{1-t} = 0.$$

Consider a mixed copula that mixes the Clayton copula with the Survival Clayton copula, which is used to proxy a positive regime:

$$C^1(u_1, u_2; \theta_1^c) = w_1 C^C(u_1, u_2; \alpha_1) + (1-w_1) C^{SC}(u_1, u_2; \alpha_2).$$

The right TDC of the mixed copula is

$$\varphi_R^1 = \lim_{\nu\to 1}\frac{1-2\nu+C^1(\nu,\nu)}{1-\nu} = \lim_{\nu\to 1}\frac{1-2\nu+w_1C^C(\nu,\nu)+(1-w_1)C^{SC}(\nu,\nu)}{1-\nu}$$

$$= w_1\lim_{\nu\to 1}\frac{1-2\nu+C^C(\nu,\nu)}{1-\nu}+(1-w_1)\lim_{\nu\to 1}\frac{1-2\nu+C^{SC}(\nu,\nu)}{1-\nu}$$

$$= w_1\varphi_R^C+(1-w_1)\varphi_R^{SC} \quad =(1-w_1)\varphi_R^{SC}.$$

By analogy, the left TDC of the mixed copula is

$$\varphi_L^1 = \lim_{\nu\to 0}\frac{C^1(\nu,\nu)}{\nu} = \lim_{\nu\to 0}\frac{w_1C^C(\nu,\nu)+(1-w_1)*C^{SC}(\nu,\nu)}{\nu}$$

$$= w_1\varphi_L^C+(1-w_1)\varphi_L^{SC} = w_1\varphi_L^C.$$

A similar result can be derived under a negative regime measured by $C^0(u_1,u_2;\theta_0^c)=w_2C^C(1-u_1,u_2;\alpha_3)+(1-w_2)C^{SC}(1-u_1,u_2;\alpha_4)$, since $C^0(u_1,u_2;\theta_0^c)$ is the rotation of $C^1(u_1,u_2;\theta_1^c)$. Hence, we can derive $\varphi_R^0=(1-w_2)\varphi_R^{RSC}$ and $\varphi_L^0=w_2\varphi_L^{RC}$, where φ_R^{RSC} and φ_L^{RC} are the right TDC of the rotated Survival Clayton copula and the left TDC of the rotated Clayton copula, respectively.

A.2. *Derivation of Kendall's* τ *and the correlation coefficient* ρ *of the mixed copula.*

Let $u_i = F_i\ (R_i)$ and $u_i \in [0,1]$ for i=1, 2, where the u_is are the "probability integral transforms" of R_i. Since $E\left(C^1(u_1,u_2)\right)=\int_0^1\int_0^1 C^1(u_1,u_2)dC^1(u_1,u_2)$, then the Kendall's τ of the mixed copula under a positive regime can be written as

$$\tau^1 = 4E\left(C^1(u_1,u_2;\theta_1^c)\right)-1$$

$$= 4E\left(w_1C^C(u_1,u_2;\alpha_1)+(1-w_1)C^{SC}(u_1,u_2;\alpha_2)\right)-1$$

$$= w_1\left[4E(C^C)-1\right]+(1-w_1)\left[4E(C^{SC})-1\right]$$

$$= w_1[\alpha_1/(2+\alpha_1)]+(1-w_1)[\alpha_2/(2+\alpha_2)].$$

Similarly, Kendall's τ of the mixed copula under a negative regime can be written as $\tau^0 = w_2[\alpha_3/(2+\alpha_3)]+(1-w_2)[\alpha_4/(2+\alpha_4)]$.

After obtaining Kendall's τ (τ^1 and τ^0) of the mixed copula, the correlation coefficient of the mixed copula can be calculated as $\rho^j=\sin(\pi\tau^j/2)$ for j=0, 1. Therefore, the smoothing correlation is

$$\rho_{sm} = p_{1,sm}\rho^1 - p_{0,sm}\rho^0$$

$$= p_{1,s}\sin\{\pi[w_1\tau_1 + (1-w_1)\tau_2]/2\} - p_{0,s}\sin\{\pi[w_2\tau_3 + (1-w_2)\tau_4]/2\}$$

$$= p_{1,s}\sin\{0.5\pi[\frac{w_1\alpha_1}{2+\alpha_1} + \frac{(1-w_1)\alpha_2}{2+\alpha_2}]\} - p_{0,s}\sin\{0.5\pi[\frac{w_2\alpha_3}{2+\alpha_3} + \frac{(1-w_2)\alpha_4}{2+\alpha_4}]\},$$

where $p_{j,s}$ for j=0,1 is the smoothing probability in regime j .

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Table 1. Descriptive statistics and unit root tests

		Median	S.D	Skew	Kurt	J-B	ADF	PP	Corr.
CAN	X_{1t}	0.070	1.142	-0.640	12.017	**14504.7**	**-65.676**	**-66.003**	-0.014
	X_{2t}	0.014	1.486	-1.243	9.842	**9267.0**	**-17.030**	**-45.980**	
FRA	X_{1t}	0.034	1.484	-0.033	7.781	**4141.0**	**-32.736**	**-68.433**	**-0.043**
	X_{2t}	0.010	0.314	-1.190	9.978	**9846.7**	**-14.645**	**-44.287**	
GER	X_{1t}	0.101	1.363	-0.055	8.907	**4963.8**	**-58.260**	**-58.384**	**-0.081**
	X_{2t}	-0.001	0.332	-2.264	31.907	**121744**	**-17.996**	**-44.180**	
JAP	X_{1t}	0.036	1.423	-0.340	8.765	**5857.2**	**-63.696**	**-63.914**	0.019
	X_{2t}	-0.010	0.244	-2.231	26.192	**96935.4**	**-18.075**	**-54.441**	
UK	X_{1t}	0.041	1.223	-0.184	9.157	**6795.8**	**-31.746**	**-69.141**	**-0.049**
	X_{2t}	0.020	0.288	-2.097	16.934	**36832.3**	**-16.057**	**-40.260**	
USA	X_{1t}	0.049	1.244	-0.181	10.985	**11382.3**	**-50.920**	**-71.567**	**-0.032**
	X_{2t}	0.005	0.207	-1.008	9.127	**7413.5**	**-15.477**	**-37.901**	

Note: X_{1t} indicates stock returns and X_{2t} represents the detrended trading volumes using the Hodrick-Prescott filter; S.D. and Kurt. indicate the standard deviation and the kurtosis of a series, respectively; Corr. is the Pearson correlation coefficient of X_{1t} and X_{2t}; J-B is the Jarque-Bera test for the normality of a series; ADF and PP are the augmented Dickey-Fuller test and the Philips-Perron test, respectively, for the unit-root hypothesis; Bold-faced numbers indicate significance at the 5% level.

Table 2. Empirical copula table

CAN										FRA									
72	40	26	38	36	32	39	29	37	71	103	43	38	27	27	23	23	28	34	89
55	39	36	29	30	37	36	41	39	77	68	54	38	33	26	21	35	39	45	75
54	50	49	39	35	30	34	39	49	41	61	46	43	42	33	33	41	34	42	60
40	50	46	34	37	45	33	42	41	52	50	43	48	38	37	49	37	36	62	35
46	40	43	40	47	39	38	46	47	34	32	51	44	45	54	37	47	41	40	44
37	50	40	43	35	38	48	49	45	34	41	44	53	35	50	37	42	51	49	32
37	38	44	44	48	38	47	48	45	31	21	42	42	44	47	41	56	67	48	27
31	40	44	41	50	49	43	46	50	26	23	37	38	53	50	54	64	47	42	27
28	39	50	55	50	60	46	36	30	25	24	39	54	56	49	68	35	36	46	27
20	33	42	57	51	52	56	44	36	29	12	35	37	62	61	72	55	56	26	19
GER										JAP									
94	38	29	20	15	15	26	21	28	55	59	29	29	22	25	38	40	49	51	75
60	41	25	27	23	17	25	28	27	69	54	39	40	31	22	37	46	49	43	56
54	40	36	32	30	24	22	33	29	41	52	42	27	40	28	53	35	42	52	46
34	37	28	29	27	35	35	36	48	32	62	37	39	36	36	33	41	33	40	60
31	45	46	27	27	32	27	37	32	38	38	55	44	38	40	41	27	39	53	43
19	28	31	42	37	37	33	39	47	28	46	48	34	51	39	37	44	34	39	45
19	38	41	29	43	37	56	33	24	21	32	42	48	43	51	45	39	44	40	33
13	21	38	41	42	44	33	41	44	24	26	42	47	52	57	50	52	37	30	24
13	27	38	44	51	48	40	36	27	18	27	44	51	50	52	42	45	51	37	18
4	27	29	50	46	53	44	37	36	15	21	39	58	54	67	42	48	39	32	17
UK										USA									
93	44	37	30	25	22	31	34	30	83	110	43	39	24	17	22	27	24	30	92
69	44	38	40	40	33	32	48	38	46	63	36	45	32	32	28	29	43	46	73
52	52	43	48	42	32	35	39	37	49	40	50	53	37	39	36	35	35	46	57
33	48	40	41	39	38	45	44	52	49	40	54	42	37	34	38	52	41	48	41
44	43	48	39	42	33	54	38	46	42	41	47	42	46	33	45	37	42	56	39
31	49	47	49	31	43	40	48	49	41	28	41	54	45	38	47	43	52	47	33
36	43	48	41	48	49	40	47	38	39	39	34	33	45	64	47	41	57	35	32
29	38	44	43	57	47	49	45	54	23	32	45	35	54	57	48	39	44	49	25
26	40	37	48	48	64	52	47	35	31	15	36	40	51	57	54	69	43	43	19
16	27	47	50	56	68	51	39	49	26	20	41	45	56	57	63	55	47	27	17

Notes: Both returns and volumes are sorted in ascending order, and each series is evenly divided into 10 bins. Bin 10 includes the observations with the highest values and bin 1 includes the observations with the lowest values. The ranks for returns (i) are on the horizontal axis while the ranks for volume (j) are on the vertical axis. The number of observations in cell (i, j) reveals information about the relationship between returns and volumes.

Table 3. Estimated coefficients, dependences and tail dependences

	CAN	FRA	GER	JAP	UK	USA
			Marginal Distribution Model			
$\hat{\mu}_1^1$	**0.0634**	**0.1073**	**0.1327**	**0.0317**	**0.0972**	**0.1434**
	(0.0176)	(0.0197)	(0.0212)	(0.0159)	(0.0212)	(0.0207)
$\hat{\mu}_1^0$	**-0.4388**	**-0.6210**	**-0.6778**	**-1.1190**	**-0.4806**	**-0.7220**
	(0.0921)	(0.0652)	(0.1255)	(0.1903)	(0.1907)	(0.1179)
$\hat{\mu}_2^1$	**0.0425**	0.0016	**-0.0694**	-0.0096	0.0065	**-0.0367**
	(0.0122)	(0.0149)	(0.0155)	(0.0121)	(0.0176)	(0.0144)
$\hat{\mu}_2^0$	**-0.2364**	0.0468	**0.3256**	0.3185	0.0683	**0.4136**
	(0.1173)	(0.0875)	(0.0973)	(0.2213)	(0.0906)	(0.0788)
$\hat{\sigma}_1^1$	**0.9295**	**0.8967**	**0.8632**	**0.9395**	**0.9037**	**0.8698**
	(0.0133)	(0.0127)	(0.0165)	(0.0117)	(0.0215)	(0.0159)
$\hat{\sigma}_1^0$	**1.4129**	**1.2911**	**1.2776**	**1.5020**	**1.1797**	**1.3924**
	(0.0618)	(0.0598)	(0.0529)	(0.0938)	(0.0508)	(0.0836)
$\hat{\sigma}_2^1$	**0.6772**	**0.7630**	**0.6862**	**0.7329**	**0.7315**	**0.7358**
	(0.0105)	(0.0127)	(0.0217)	(0.0105)	(0.0380)	(0.0143)
$\hat{\sigma}_2^0$	**2.2601**	**1.8666**	**1.8453**	**2.5697**	**1.7323**	**1.7506**
	(0.0978)	(0.0845)	(0.0876)	(0.1069)	(0.1414)	(0.0591)
Log(L)	-11213.2	-11917.8	-9193.3	-10921.9	-11820.2	-11603.9
			Positive Dependence Regime			
$\hat{\rho}_1$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0127)	(0.0118)	(0.0098)	(0.0458)	(0.0252)	(0.0101)
$\hat{\varphi}_1$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.1767)	(0.1232)	(0.1670)	(0.8083)	(0.3975)	(0.1144)
$\hat{\rho}_2$	**0.1954**	**0.2043**	**0.2663**	**0.3018**	0.0844	**0.2974**
	(0.0401)	(0.0312)	(0.0655)	(0.0526)	(0.0634)	(0.0479)
$\hat{\varphi}_2$	**0.0489**	**0.0665**	**0.0850**	**0.1032**	0.0011	**0.1482**
	(0.0281)	(0.0272)	(0.0433)	(0.0330)	(0.0054)	(0.0444)
$\hat{w}_1$	**0.4488**	**0.3370**	**0.5472**	**0.5691**	0.5094*	**0.3641**
	(0.1361)	(0.0622)	(0.1458)	(0.0998)	(0.2985)	(0.1201)
$\hat{p}_{11}$	**0.9171**	**0.8581**	**0.8541**	**0.9638**	**0.8166**	**0.8555**
	(0.0086)	(0.0149)	(0.0195)	(0.0061)	(0.0553)	(0.0167)
			Negative Dependence Regime			
$\hat{\rho}_3$	0.0309	0.0065	0.0030	0.1005	0.0275	0.0338
	(0.0417)	(0.0626)	(0.0863)	(0.0967)	(0.1255)	(0.0958)
$\hat{\varphi}_3$	0.0000	0.0000	0.0000	0.0035	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0185)	(0.0000)	(0.0000)
$\hat{\rho}_4$	**0.2832**	**0.3086**	**0.3842**	**0.5947**	**0.2393**	**0.4416**
	(0.0569)	(0.0332)	(0.0510)	(0.0411)	(0.0455)	(0.0472)
$\hat{\varphi}_4$	**0.0949**	**0.1915**	**0.2064**	**0.2654**	**0.0814**	**0.2277**
	(0.0371)	(0.0369)	(0.0399)	(0.0182)	(0.0356)	(0.312)
$\hat{w}_2$	**0.5534**	**0.2321**	**0.4197**	**0.5589**	**0.4522**	**0.4705**
	(0.1112)	(0.0412)	(0.0988)	(0.0258)	(0.1952)	(0.0794)
$\hat{p}_{00}$	**0.2600**	**0.1747**	**0.3655**	**0.0611**	**0.2792**	**0.2984**
	(0.0518)	(0.0481)	(0.0433)	(0.0722)	(0.0427)	(0.0438)

Notes: Numbers in parentheses are standard errors. If an estimated coefficient or standard error is less than 5×10^{-5}, then it is reported as 0.0000. Bold-faced numbers indicate significance at the 5% level. "*" indicates significance at the 10% level.

Table 4. Tests for symmetric dependences and tail dependences between the high returns/high volumes case and the low returns/high volumes case.

	CAN	FRA	GER	JAP	UK	USA
$\hat{\rho}_2 = \hat{\rho}_4$	2.5963	**4.2288**	**2.7426**	**11.5920**	**2.9834**	**3.6867**
	[0.1071]	[0.0397]	[0.0977]	[0.0006]	[0.0841]	[0.0548]
$\hat{\varphi}_2 = \hat{\varphi}_4$	1.6048	**6.0226**	**5.8412**	**11.7510**	**4.5285**	1.7437
	[0.2052]	[0.0141]	[0.0157]	[0.0006]	[0.0333]	[0.1867]

Note: Numbers in the table are Wald statistics. Numbers in brackets are p-values. Bold-faced numbers indicate significance at the 10% level. $\hat{\rho}_2$ ($\hat{\varphi}_2$) measures the (tail) dependence of the high returns/high volumes case. $\hat{\rho}_4$ ($\hat{\varphi}_4$) measures the (tail) dependence of the low returns/high volumes case. Bold-faced numbers indicate significance at the 10% level.

Table 5. The goodness-of-fit test of different copula models

	CAN	FRA	GER	JAP	UK	USA
			The Dependence-Switching Copula			
AIC	22458 #	23867 #	18419 #	21876 #	23672 #	23240 #
BIC	22560 #	23969 #	18517 #	21977 #	23774 #	23342 #
LV	-11213 *	-11918 *	-9193 *	-10922 *	-11820 *	-11604 *
			Gaussian Copula			
AIC	23819	24650	19336	23653	24308	24251
BIC	23825	24656	19342	23659	24315	24257
LV	-11909	-12324	-9667	-11825	-12153	-12124
			Student-t Copula			
AIC	23818	24623	19316	23637	24308	24207
BIC	23831	24636	19328	23649	24321	24219
LV	-11907	-12310	-9656	-11816	-12152	-12101
			Clayton Copula			
AIC	23820	24670	19367	23672	24329	24269
BIC	23826	24676	19373	23679	24335	24275
LV	-11909	-12334	-9683	-11835	-12163	-12134
			Survival Clayton Copula			
AIC	23802	24658	19364	23588	24327	24255
BIC	23809	24664	19370	23594	24333	24261
LV	-11900	-12328	-9681	-11793	-12162	-12126
			Rotated Clayton Copula			
AIC	23820	24670	19367	23672	24329	24269
BIC	23826	24676	19373	23679	24335	24275
LV	-11909	-12334	-9683	-11835	-12163	-12134
			Rotated Survival Clayton Copula			
AIC	23785	24520	19207	23666	24235	24115
BIC	23791	24527	19213	23672	24241	24121
LV	-11892	-12259	-9602	-11832	-12117	-12056
			Mixture Clayton Copula			
AIC	23807	24692	19412	23600	24434	24289
BIC	23826	24711	19430	23619	24453	24308
LV	-11901	-12343	-9703	-11797	-12214	-12141
			Mixture Rotated Clayton Copula			
AIC	23792	24539	19236	23667	24255	24127
BIC	23811	24558	19255	23686	24274	24146
LV	-11893	-12267	-9615	-11830	-12124	-12141

Notes: LV, AIC and BIC indicate log likelihood value, Akaike information criterion and Bayes information criterion, respectively. "*" indicates the largest LV across different copula models. "#" indicates the smallest value of AIC and BIC across different copula models. The numbers under Clayton copula are very close to those under Rotated Clayton copula. The difference appears if we report values up to the first decimal.

Table 6. Threshold regression

$$X_{2t}^{+} = \alpha^{+} + \beta^{+} X_{1t}^{+} + \varepsilon_t \ , \ X_{1t} = X_{1t}^{+} \ \text{and} \ X_{2t} = X_{2t}^{+} \ \text{if} \ \hat{\rho}_{sm.t} > 0$$
$$X_{2t}^{-} = \alpha^{-} + \beta^{-} X_{1t}^{-} + \varepsilon_t \ , \ X_{1t} = X_{1t}^{-} \ \text{and} \ X_{2t} = X_{2t}^{-} \ \text{if} \ \hat{\rho}_{sm.t} < 0$$

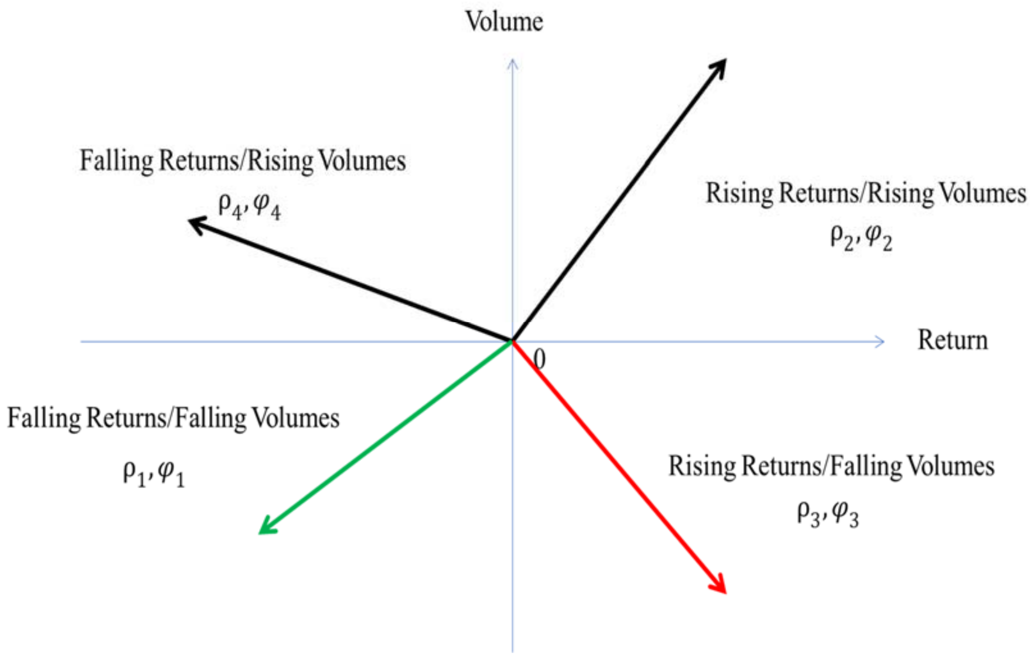
	CAN	FRA	GER	JAP	UK	USA
$\hat{\alpha}^{+}$	**0.0562**	**0.1572**	**0.2607**	**0.0593**	**0.2411**	**0.1755**
	(0.0171)	(0.0211)	(0.0208)	(0.0206)	(0.0174)	(0.0170)
$\hat{\beta}^{+}$	**0.4000**	**0.7372**	**0.6651**	**0.7611**	**0.6565**	**1.0816**
	(0.0877)	(0.0898)	(0.0971)	(0.1055)	(0.0888)	(0.1009)
$\hat{\alpha}^{-}$	**-0.7815**	**-1.3122**	**-1.0961**	**-2.0070**	**-0.8656**	**-1.1742**
	(0.1036)	(0.0860)	(0.0832)	(0.2215)	(0.0471)	(0.0832)
$\hat{\beta}^{-}$	**-0.6843**	**-1.0893**	**-0.5334**	**-1.0351**	**-0.7712**	**-1.3085**
	(0.1312)	(0.1268)	(0.1208)	(0.2569)	(0.0959)	(0.2022)

Notes: X_{1t} indicates stock returns and X_{2t} represents the detrended trading volumes using the Hodrick-Prescott filter. $\rho_{sm,t}$ is the time-varying, smoothing correlation of returns and volumes. X_{1t}^{+} (X_{1t}^{-}) and X_{2t}^{+} (X_{2t}^{-}) are returns and volumes under the positive (negative) dependence regime with $\rho_{sm,t} > 0$ ($\rho_{sm,t} < 0$). The standard error of an estimate is given in parentheses. Bold-faced numbers indicate significance at the 5% level.

Table 7. Driving forces of time-varying, return-volume dependence

	CAN	FRA	GER	JAP	UK	USA
A : $\rho_t = \alpha + \beta_1 \left(\log\left(P_{Ht}\right) - \log\left(P_{Lt}\right)\right) + \varepsilon_t$						
$\hat{\alpha}$	**0.0879**	**0.1037**	**0.0946**	**0.1421**	**0.0183**	**0.1635**
	(0.0013)	(0.0022)	(0.0026)	(0.0017)	(0.0011)	(0.0025)
$\hat{\beta}_1$	**-0.5419**	**-1.4201**	**-2.2706**	**-2.1555**	**-0.8758**	**-3.2439**
	(0.0860)	(0.1114)	(0.1385)	(0.1096)	(0.0589)	(0.1467)
B : $\rho_t = \alpha + \beta_1 \left(\left\|X_{1t}\right\| / DVT_t\right) + \varepsilon_t$						
$\hat{\alpha}$	**0.0921**	**0.1036**	**0.0704**	**0.1230**	**0.0151**	**0.1414**
	(0.0011)	(0.0016)	(0.0020)	(0.0014)	(0.0008)	(0.0020)
$\hat{\beta}_1$	**-0.0502**	**-0.3396**	**-0.3057**	**-13.2010**	**-0.0559**	**-80.3316**
	(0.0034)	(0.0169)	(0.0359)	(1.3893)	(0.0032)	(4.6681)
C : $\rho_t = \alpha + \beta_1 \left(\log\left(P_{Ht}\right) - \log\left(P_{Lt}\right)\right) + \beta_2 \left(\left\|X_{1t}\right\| / DVT_t\right) + \varepsilon_t$						
$\hat{\alpha}$	**0.0912**	**0.1070**	**0.0955**	**0.1425**	**0.0185**	**0.1639**
	(0.0013)	(0.0022)	(0.0026)	(0.0018)	(0.0010)	(0.0025)
$\hat{\beta}_1$	0.1198	**-0.6965**	**-2.1534**	**-2.0316**	**-0.3845**	**-2.6573**
	(0.0973)	(0.1285)	(0.1534)	(0.1240)	(0.0743)	(0.1837)
$\hat{\beta}_2$	**-0.0526**	**-0.0509**	**-0.0749**	**-3.5472**	**-0.0429**	**-30.2181**
	(0.0039)	(0.0047)	(0.0385)	(1.4641)	(0.0040)	(5.7246)

Note: P_{Ht} and P_{Lt} are the daily highest and lowest stock price indices, respectively. DVT_t and $|X_{1t}|$ are the daily total local currency value of shares traded and the absolute value of returns, respectively. Following Amihud (2002), we multiplied the illiquidity measure, $|X_{1t}|/DVT_t$, by 10^6 for all countries except Germany. The standard error of an estimate is given in parentheses. Bold-faced numbers indicate significance at the 5% level.



ρ_i : dependence, φ_i : tail dependence

Figure 1. The dependence structure of returns and de-trended volumes under four different market conditions.

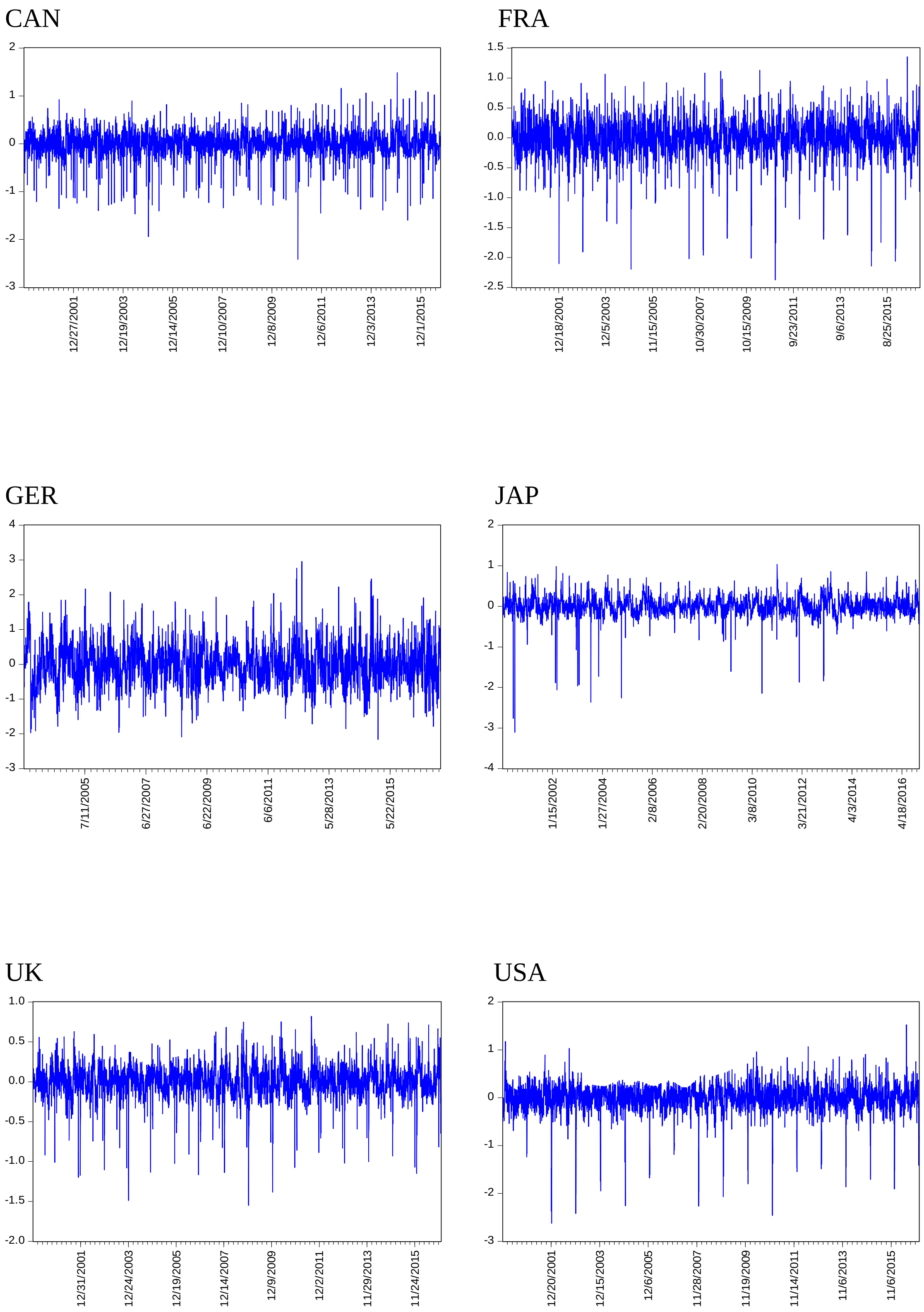


Figure 2. Detrended log volumes using the Hodrick-Prescott filter

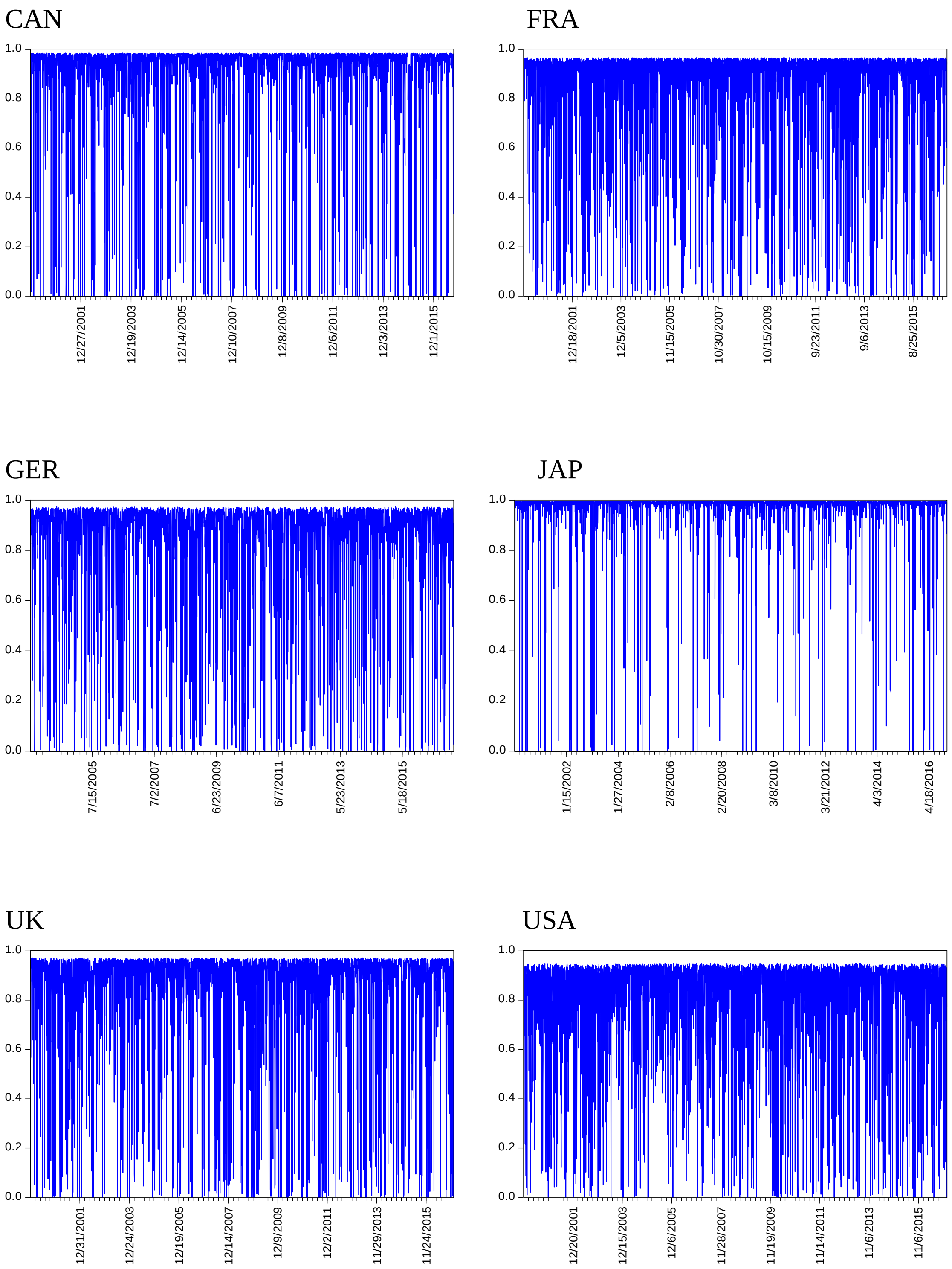


Figure 3. Smoothing probabilities for the positive dependence regime of volumes and returns

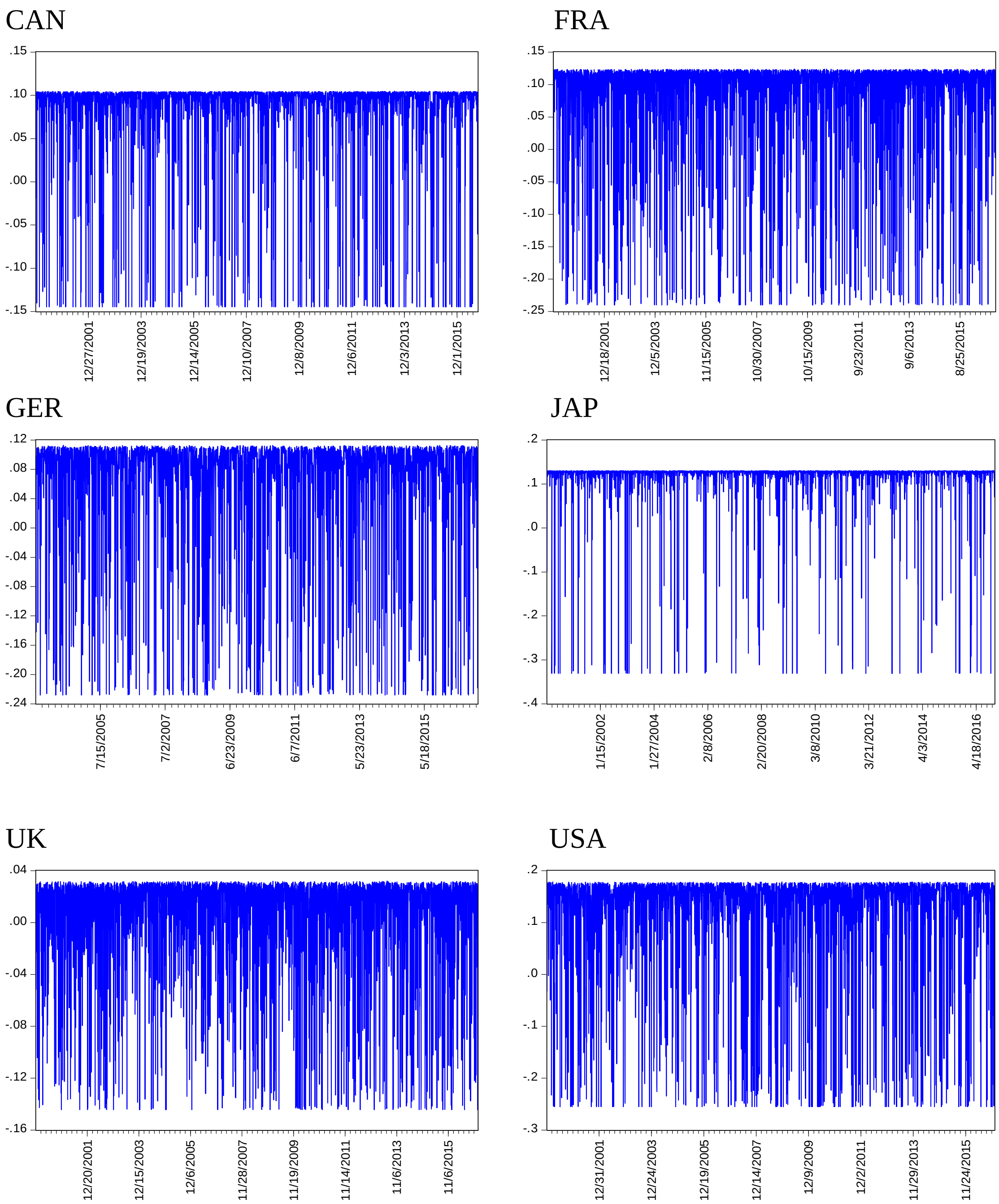


Figure 4. The smoothing correlations of volumes and returns