

Economic Integration and Structure Change in Stock Market Dependence: Empirical Evidences of CEPA

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Abstract

This study investigates dependence structure changes between the Hong Kong and Chinese stock markets as a result of the Closer Economic Partnership Arrangement (CEPA). Four copulas, Gaussian, student t , Gumbel, and Clayton are used to search for unknown dependence structure changes. This study presents two main findings. First, the dependence between the Hong Kong and Chinese stock markets increased significantly following the structure change that occurred on February 2, 2005, about one year after CEPA took effect. Second, the distribution of dependence structure altered from Gumbel copula before the structure change to t copula after the structure change. CEPA's effects not only changed the dependence parameters but also changed the dependence structure's distribution.

JEL classification numbers: G14, G15, F36

Keywords: economic integration, copula, volatility structure change, dependence structure change

1 Introduction

Since end of the Uruguay Round of the General Agreement on Tariffs and Trade (GATT) in 1993, many regions have progressed significantly towards achieving economic integrations. For example, the North American Free Trade Agreement (NAFTA) integrated the United States, Canada, and Mexico into a free trade zone on January 1, 1994. The Euro Zone integrated most European countries into a single monetary union on January 1, 1999. In Asia, many countries or economies have signed free trade agreements

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(FTA) with China. These include the Closer Economic Partnership Arrangement (CEPA) between Hong Kong and China, which took effect on January 1, 2004; the FTA between the Association of Southeast Asian Nations (ASEAN) and China that took effect on January 1, 2010; and the Economic Cooperation Framework Agreement (ECFA) between Taiwan and China that took effect on September 12, 2010. Bilateral or multilateral economic integrations have grown in popularity as they lower tariffs, reduce trade barriers and boost trade and foreign direct investment (FDI) among counterparties. Increased trade and FDI stimulate demand for mutual investment among counterparties, and furthermore, change the dependence structure between their financial markets.

In linear regressions, parameters are usually assumed to be stable, i.e., no structure changes occur in the linear regression parameters. However, in practice, parameter structure changes in linear regressions are often influenced by exogenous variables, such as economic integration. Some studies concerning parameter structure changes in regression divide the samples into two subsamples to test the differences in the subsamples' parameters. Other studies use a dummy variable to distinguish the sample's structure change point and test the significance of dummy variable parameter. Traditionally, the parameter structure change point is assumed to be a known factor in the samples such as the Chow test [1]. However, the structure change point could be unknown or more than one could exist in a set of samples. To determine the true points of structure change, Donald and Andrew [2] use the Wald test and likelihood ratio test (LR) to test for the presence of unknown parameter structure changes. Gombay and Horvath [3] propose a tests' statistic and provide the critical value by Monte Carlo simulation under the LR framework. Bai [4], and Bai and Perron [5] use the least squares method to test for the existence of multiple structure changes in a sample. For the dependence structure change between financial markets due to economic integration, many studies assume that the structure change point is known, for example, Patton [6], Batram, Taylor and Wang [7] and Chung and Lee [8]. These studies assume that the date of economic integration agreements took effect should be considered the structure change point. However, this date might not be the true moment of the dependence structure change. Dias and Embrechts [9] [10] and Manner and Candelon [11] follow Gombay and Horvath's concept [3] and test for unknown dependence structure change point using the copula model.

Economic integration takes time to promote trade and investment among counterparties. Therefore, economic integration might not immediately influence the dependence structure among counterparties' financial markets. If we consider the date that an agreement takes effect to be the structure change point a priori, the research results might display bias. Therefore, this study assumes that the true dependence structure change point is unknown. Following this assumption, this study follows the strategy of Bai [4] to identify the volatility structure change points in a marginal model. To avoid the influence of extreme events, we discard volatility structure change points that can be classified as contagion by extreme events in the Hong Kong and Chinese stock markets. After adopting volatility structure changes excluding extreme event contagion, this study then uses Akaike Information Criteria (AIC) to select the best fit copula, which is used to identify the dependence structure change point. Finally, this study uses the identified dependence structure change point to partition entire sample set into two subsamples to cross-compare their dependence structure distribution.

The major contributions in this paper are first, our discovery of the true point of the dependence structure change between the Hong Kong and Chinese stock markets. The dependence structure change point was identified as being about one year after CEPA

took effect on January 1, 2004. Second, our strategies provide an additional methodology for searching for unknown dependence structure changes due to economic integration. The rest of the paper is organized as follows. Section 2 reviews the existing literature. Data and empirical method are demonstrated in Section 3. Empirical results are displayed in Section 4. Our conclusions are offered in Section 5.

2 Literature Review

Economic integration among regional economies usually triggers changes in stock market dependence among counterparties. Asgharian and Nossman [12] found that stock market interdependence can largely be associated with economic integration. This upholds the work of Phylaktis and Ravazzolo [13], who found that Pacific Rim countries experienced increased financial market integration as a result of economic integration's trade-promoting effect. Johnson and Soenen [14] found that Latin America countries having a high share of trade with the United States also demonstrate a strong positive effect for stock market comovement. In all, economic integration can boost trade and investment among counterparties and, moreover, change the dependence structure among their stock markets.

The stock market dependence structure change has a major impact on financial institutions' assets allocation and risk management. Some researches consider the date that economic integration officially takes effect as the known dependence structure change point and test its significance accordingly, for example, Patton [6], Bartram, Taylor and Wang [7], and Chung and Lee [8]. However, the stock market dependence structure change date might be unknown rather than aligning perfectly with the official economic integration start date. When dealing with an unknown change point, Bai [4] and Bai and Perron [5] provide a test statistic for structure change using the least squares method in a linear regression model. Gombay and Horvath [3] also provide a test statistic under the likelihood ratio framework and provide critical values using the Monte Carlo simulations. Furthermore, Dias and Embrechts [9][10] use Gombay's and Horvath's test statistic in a copula model and propose a strategy to identify a dependence structure's change point. However, different copulas might have different dependence structure change points. Therefore, Caillault and Guegan [15] and Guegan and Zhang [16] suggest using minimum AIC to select the best fit copula before testing for dependence structure change to accommodate potential difference in change point from different copulas' estimation.

3 Data and Empirical Methodology

3.1 Data and Summary Statistics

This study uses the Hang Seng index and the Shanghai Composite index to represent the Hong Kong and Chinese stock markets. Daily closing prices were collected from January 6, 1999 to December 30, 2008 from Datastream. After excluding non-common trading data, a total of 2024 observations were processed. Table 1 reports the summary statistics for the Hong Kong and Chinese stock markets before and after CEPA took effect on January 1, 2004.

Table 1. Summary statistics

Statistics	Before CEPA (1999/1/6~2003/12/30)		After CEPA (2004/1/5~2008/12/30)		Whole period (1999/1/6~2008/12/30)	
	Hong Kong	China	Hong Kong	China	Hong Kong	China
Mean	0.0276	0.0340	0.0092	0.0157	0.0183	0.0248
Standard Deviation	1.7370	1.5741	1.7380	2.0854	1.7371	1.8503
Skewness	-0.1391	0.7320**	-0.2797**	-0.0156	-0.2102**	0.2068**
Excess Kurtosis	2.1783**	5.6527**	6.8551**	2.5006**	4.5356**	3.7188**
$Q^2(6)$	32.3**	86.8**	877.8**	111.3**	945.9**	250.9**
Jarque-Bera	200.7**	1419.3**	2018.3**	266.8**	1748.9**	1180.1**
Linear Correlation	0.1021		0.3531		0.2441	

Note: 1. **(*)denotes the significance at 1%(5%) level. 2. $Q^2(6)$ is the 6-lag Ljung-Box statistic for the squared return.

In all periods, both excess kurtosis and Jarque-Bera show that both Hong Kong and Chinese stock markets possess heavy tail and non-normal distributions. Hong Kong demonstrates negative skew, whereas China's is positive. The null hypothesis of no auto correlation is rejected by the significance of $Q^2(6)$, meaning that the squared return is nonlinear. Therefore, this study uses $GJR-GARCH-t$ to fit both stock markets. In addition, the linear correlation increases from 0.1021 before CEPA to 0.3531 after CEPA meaning that the correlation between Hong Kong and Chinese stock markets soared after CEPA took effect.

3.2 Estimation and Test of the Marginal Model

3.2.1 Marginal Model with Unknown Volatility Structure Change

This study uses univariate $GJR-GARCH(1,1)-t$ to capture volatility in the Hong Kong and Chinese stock markets. The model is defined as

$$r_{i,t} = \mu_{i,t} + \varepsilon_{i,t}, \quad (1)$$

$$\sigma_{i,t}^2 = c_i + a_{i,1}\varepsilon_{i,t-1}^2 + b_i\sigma_{i,t-1}^2 + a_{i,2}I_{i,t-1}\varepsilon_{i,t-1}^2 + \gamma_i D_t, \quad (2)$$

$$\varepsilon_{i,t} | \mathcal{F}_{t-1} = h_{i,t} z_{i,t}, \quad z_{i,t} \sim t_\nu, \quad (3)$$

where $r_{i,t}$ represents the log return for market i at time t . $i=1,2$ stands for the Hong Kong and Chinese stock markets, respectively. Indication function $I_{i,t-1}$ will equal 1 when residuals $\varepsilon_{i,t-1} < 0$; otherwise, $I_{i,t-1}$ will equal 0. The standardize residuals $z_{i,t}$ are assumed to follow the t distribution due to the leptokurtic character, with degree of freedom ν . Dummy variable D_t is designed to capture the volatility structure change. It has an assumed value of 0 before volatility structure change; otherwise, its value is assumed to be 1.

3.2.2 Test for Volatility Structure Change

To test for volatility structure change at q is to test the null hypothesis and alternative hypothesis as follows:

$$H_0 : \sigma_1 = \sigma_2 = \cdots = \sigma_{q-1} = \sigma_q = \cdots = \sigma_T, \quad (4)$$

$$H_1 : \sigma_1 = \cdots = \sigma_{q-1} \neq \sigma_q = \cdots = \sigma_T.$$

The test statistic under the null hypothesis is

$$Z_T = \max_{1 < q < T} (LR_q), \quad (5)$$

$$LR_q = 2 \left[L_q(\hat{\sigma}_q) + L_q^*(\hat{\sigma}_q^*) - L_T(\hat{\sigma}_T) \right], \quad (6)$$

where $L_T(\hat{\sigma}_T)$ is the log likelihood for all samples T . $L_q(\hat{\sigma}_q)$ is the log likelihood for the first q samples before structure change. $L_q^*(\hat{\sigma}_q^*)$ is the log likelihood for the $q+1$ to T samples after structure change. Z_T is the maximum log likelihood ratio test. The larger the value of Z_T , the higher probability that the null hypothesis will be rejected. Gombay and Horvath [3] found under the condition as $x \rightarrow \infty$ and $0 < h(T) \leq l(T) < 1$. When $h(T) = l(T) = (\log T)^{3/2} / T$, the asymptotic distribution probability of $Z_T^{1/2}$ is

$$P(Z_T^{1/2} \geq x) \approx \frac{x^p \exp(-x^2/2)}{2^{p/2} \Gamma(p/2)} \times \left(\log \frac{(1-h)(1-l)}{hl} - \frac{p}{x^2} \log \frac{(1-h)(1-l)}{hl} + \frac{4}{x^2} + O\left(\frac{1}{x^4}\right) \right), \quad (7)$$

where p is the number of parameter changes under the alternative hypothesis.

3.2.3 Multiple Volatility Structure Change Adjustment in the Marginal Model

Manner and Candelon [11] indicated financial markets can suffer from the “contagion effect” in the wake of the extreme events. This contagion effects can create volatility that influences dependence structure changes among stock markets. Their model assumed the existence of only one volatility change point. However, long-term empirical research has indicated the potential existence of multiple volatility structure change points. To avoid influence from extreme events on dependence structure changes, this study follows Bai’s [4] suggestions. First, we test for a single initial structure change point across the entire sample, then partition the samples into two subsamples. Second, we test both subsamples to derive second and third change points. Finally, we partition the two subsamples into more subsamples until no subsamples contain any significant structure change points. After estimating multiple volatility structure change points using the marginal model, we discard the change points close to extreme events and re-estimate

volatility structure changes in the samples showing influenced from CEPA rather than extreme events.

3.3 Conditional Copula

The bivariate copula function combines two different marginal distributions, here $F(z_{1,t}|\psi_{1,t-1})$ and $G(z_{2,t}|\psi_{2,t-1})$, into a joint distribution, here $\Phi(r_{1,t}, r_{2,t}|\psi_{t-1})$. According to Sklar's theorem, the joint conditional cumulative density function (c.d.f.) is defined as

$$\Phi(r_{1,t}, r_{2,t}|\psi_{t-1}) = C(u_t, v_t|\psi_{t-1}) = C\left(F(z_{1,t}|\psi_{1,t-1}), G(z_{2,t}|\psi_{2,t-1})\right),$$

where $u_t = F(z_{1,t}|\psi_{1,t-1})$, and $v_t = G(z_{2,t}|\psi_{2,t-1})$. ψ_{t-1} is the information set at $t-1$.

The probability density function (p.d.f.) of this joint distribution function can be decomposed as a product of a copula p.d.f. and the two marginal p.d.f.s:

$$\varphi(z_{1,t}, z_{2,t}|\psi_{t-1}) = c(u_t, v_t|\psi_{t-1}) \times f(z_{1,t}|\psi_{1,t-1}) \times g(z_{2,t}|\psi_{2,t-1}),$$

where $f(z_{1,t}|\psi_{1,t-1})$ and $g(z_{2,t}|\psi_{2,t-1})$ represent the marginal density functions for the Hong Kong and Chinese stock markets. Distribution of dependence structures exhibit different characters for different copula density functions $c(u_t, v_t|\psi_{t-1})$. This study uses four distinct copula densities function to explore the dependence structure change between the Hong Kong and Chinese stock markets.

The first copula is a Gaussian copula, which possesses symmetry but shows very slim dependence on its tail. Its density function is

$$c^{Gau}(u_t, v_t|\rho_t) = \frac{1}{\sqrt{(1-\rho_t^2)}} \exp\left\{\frac{-\rho_t^2(\phi^{-1}(u_t))^2 + \phi^{-1}(v_t)^2 - 2\rho_t\phi^{-1}(u_t)\phi^{-1}(v_t)}{2(1-\rho_t^2)}\right\},$$

where ρ_t is the dependence parameter. The second copula is a Gumbel copula which exhibits a high probability of right tail dependence. Its density function is

$$c_t^{Gum}(u_t, v_t|\delta_t) = \frac{C_t^{Gau}(u_t, v_t|\delta_t)(\ln u_t \ln v_t)^{\delta_t-1} \left[(-\ln u_t)^{\delta_t} + (-\ln v_t)^{\delta_t}\right]^{\delta_t-1} + \delta_t - 1}{u_t v_t \left[(-\ln u_t)^{\delta_t} + (-\ln v_t)^{\delta_t}\right]^{2-\delta_t-1}},$$

where dependence parameter δ_t has a relationship with kendall τ_t of $\delta_t = 1/(1-\tau_t)$. The third copula is a Clayton copula which has a high probability on left tail dependence. Its

density function is

$$c_t^{Cla}(u_t, v_t | \kappa_t) = \frac{(1 + \kappa_t)(u_t^{-\kappa_t} + v_t^{-\kappa_t} - 1)^{-2-\kappa_t^{-1}}}{(u_t v_t)^{\kappa_t+1}},$$

where dependence parameter κ_t has a relationship with kendall τ_t of $\kappa_t = 2\tau_t / (1 - \tau_t)$. The fourth copula is a t copula, which has both symmetry and heavy tail dependence. Its density function is

$$c(u_t, v_t | \rho_t, \nu) = \frac{1}{\sqrt{1 - \rho_t^2}} \frac{\Gamma\left(\frac{\nu+2}{2}\right)\Gamma\left(\frac{\nu}{2}\right) \left(1 + \frac{1}{\nu}\psi\Omega^{-1}\psi\right)^{-[(\nu+2)/2]}}{\left(\Gamma\left(\frac{\nu+1}{2}\right)\right)^2 \prod_{i=1}^2 \left(1 + \frac{1}{\nu}\psi_i^2\right)^{-[(\nu+1)/2]}}$$

where ρ_t is dependence parameter and ν is the degree of freedom (*d.f.*).

To search for dependence structure change attribute to CEPA, this study assumes ρ_t and τ_t as in the following model

$$\rho_t = \omega + \lambda D_t, \quad (8)$$

$$\tau_t = \omega + \lambda D_t, \quad (9)$$

where ω and λ are parameters to be estimated in the copula function. D_t is the dummy variable whose value is assumed to be 0 before dependence structure change; otherwise, it will be 1. However, the existence of dependence structure change is assumed to be unknown and thus in need of testing.

3.4 Estimation and Test of Bivariate Dependence Structure Change

This study uses both the dependence parameter and dependence distribution to confirm dependence structure change between the Hong Kong and Chinese stock markets can be attributed to CEPA. First, this study uses AIC to choose the best fit copula from the whole samples. Next, the chosen copula is used to identify the dependence parameter structure change point following CEPA's implementation. Next, using this change point, we partition the entire sample into two subsamples. Finally, four copulas are fitted to both subsamples to select the best fit copula for each subsample. If the best fit copula shows alteration before and after dependence parameter structure change, the distribution of the dependence structure is changed.

3.4.1 The AIC

In researches on conditional copula dependence, the copula function is usually assumed to be unchanged. However, the data's distribution structure might be changed for a different time period. Therefore, the best fit copula should be identified before being used to test the dependence structure. Caillaud and Guegan [15] and Guegan and Zhang [16] suggest using AIC to choose the best fit copula. AIC is defined as

$$\text{AIC} = -2L(\hat{\theta}; \varepsilon) + 2r, \quad (10)$$

where $L(\hat{\theta}; \varepsilon)$ is the copula's log likelihood. ε is the residual. $\hat{\theta}$ are the copula's estimated parameters. In the Gaussian copula, the Gumbel copula and the Clayton copula, the estimated parameters are ρ_t , δ_t , and κ_t , respectively. In the t copula, the estimated parameter are ρ_t and ν . r is the number of estimated parameters in the copula. This study will choose as best fit the copula exhibiting the lowest AIC value.

3.4.2 Test of Dependence Structure Change

This study follows the method of Gombay and Horvath [3] and Dias and Embrechts [10] to identify unknown dependence structure change points. Let $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_T$ be the sequence of an independent random vector with uniformly distributed margins and a copula of $C(\mathbf{u}_1; \theta_1, \eta_1), C(\mathbf{u}_2; \theta_2, \eta_2), \dots, C(\mathbf{u}_T; \theta_T, \eta_T)$, respectively, where θ_i and η_i are the copula's parameters and $\theta_i \in \Theta^{(1)}, \eta_i \in \Theta^{(2)}$. Assuming parameter $\eta_i (i = 1, \dots, T)$ is constant, testing if the dependence parameter has a single structure change point conditional upon a single volatility structure change is equal to testing the null hypothesis, which is

$$H_0 : \theta_1 = \theta_2 = \dots = \theta_T = \theta \text{ conditional to} \\ \sigma_1 = \dots = \sigma_q \neq \sigma_{q+1} = \dots = \sigma_T \text{ and } \eta_1 = \eta_2 = \dots = \eta_T = \eta,$$

and testing the alternative hypothesis, which is

$$H_1 : \theta_1 = \dots = \theta_{k^*-1} \neq \theta_{k^*} = \theta_{k^*+1} = \theta_T \text{ conditional to} \\ \sigma_1 = \dots = \sigma_{q-1} \neq \sigma_q = \dots = \sigma_T \text{ and } \eta_1 = \eta_2 = \dots = \eta_T = \eta. \quad (11)$$

If H_0 is rejected, k^* is the structure change point. If $k^* = k$ is known, the likelihood ratio test (LR) is defined as

$$\Lambda_k = \frac{\sup_{(\theta_i, \eta_i) \in \Theta^{(1)} \times \Theta^{(2)}} \prod_{1 \leq i \leq T} c(\mathbf{u}_i; \theta_i, \eta_i)}{\sup_{(\theta_i, \zeta_i, \eta_i) \in \Theta^{(1)} \times \Theta^{(1)} \times \Theta^{(2)}} \prod_{1 \leq i < k} c(\mathbf{u}_i; \theta_i, \eta_i) \prod_{k \leq i \leq T} c(\mathbf{u}_i; \zeta_i, \eta_i)}. \quad (12)$$

When Λ_k is small, the null hypothesis will be rejected easily. Given the copula p.d.f. c , the estimate of Λ_k can be estimated using the following two equations:

$$L_k(\theta, \eta) = \sum_{1 \leq t < k} \log c(\mathbf{u}_t; \theta, \eta), \quad (13)$$

$$L_k^*(\theta, \eta) = \sum_{k \leq t \leq T} \log c(\mathbf{u}_t; \theta, \eta), \quad (14)$$

where $L_k(\theta, \eta)$ is the maximum log likelihood estimate for samples $t = 1, 2, \dots, k-1$, and $L_k^*(\theta, \eta)$ is the maximum log likelihood estimate for samples $t = k, \dots, T$. Therefore, the test for asymptotic distribution of LR is

$$-2 \log(\Lambda_k) = 2 \left[L_k(\hat{\theta}_k, \hat{\eta}_k) + L_k^*(\hat{\theta}_k^*, \hat{\eta}_k^*) - L_T(\hat{\theta}_T, \hat{\eta}_T) \right], \quad (15)$$

where $\hat{\theta}_k$ and $\hat{\theta}_k^*$ represent parameter estimates before and after structure change point k respectively. $\hat{\theta}_T$ and $\hat{\eta}_T$ are the copula parameter estimates for the entire samples. If k is unknown, this study uses a grid search to determine the maximum Z_T and identify the dependence structure change point k . Z_T is defined as

$$Z_T = \max_{1 < k < T} (-2 \log(\Lambda_k)). \quad (16)$$

When the general conditional holds, the smaller the value of Λ_k , the larger the value of Z_T and the easier it will be to reject the null hypothesis. The p -value for asymptotic distribution of $Z_T^{1/2}$ can be calculated by equation (7).

4 Empirical Results

4.1 Marginal Model

This study follows (Bai 1997) to identify the initial volatility structure change point for the entire sample in two marginal models. After partitioning the entire samples into two subsamples by using the initial change point, this study tests the volatility structure change point in both subsamples until no subsample contains a significant volatility structure change point. Table 2 shows the results for the Hong Kong and Chinese stock markets. The Hong Kong stock market has three volatility change points, but the Chinese stock market has only one.

Table 2: Change points for marginal models

	Partition	Period	$Z_T^{1/2}$	p -value	H_0	Date of Change
Hong Kong	I	1999/1/6~2008/12/30	3.37	0.0395	Reject	2007/6/26
	II	1999/1/6~2007/6/26	4.59	0.0004	Reject	2001/12/21
		2007/6/27~2008/12/30	2.43	0.2915	NotReject	
	III	1999/1/6~2001/12/21	2.30	0.4237	Not Reject	
		2001/12/22~2007/6/26	4.30	0.0013	Reject	2004/6/15
	IV	2001/12/21~2004/6/15			Not Reject	
		2004/6/16~2007/6/26	2.80	0.1510	Not Reject	
China	I	1999/1/6~2008/12/30	5.07	0.0000	Reject	2006/11/28
	II	1999/1/6~2006/11/28	2.57	0.3022	Not Reject	
		2006/11/29~2008/12/30	2.03	0.6138	Not Reject	

Note: 1.The significant level is 0.05; 2.The format for date of change is year/month/day in sequence.

The volatility structure change points of June 26, 2007 and December 21, 2001 in the Hong Kong stock market are near the subprime mortgage crisis in 2007 and the 9/11 twin tower bombing in 2001. To avoid influence from such extreme events on the estimation of dependence structure change, the volatility structure change points of June 6, 2004 and November 28, 2006 are chosen for the Hong Kong and Chinese stock markets respectively. The marginal model's estimation results are shown in Table 3. Most estimated parameters are significant and comply with the model's restrictions of $c_i > 0$, $a_{i,1} > 0$, $b_i > 0$ and $a_{i,1} + b_i < 1$. The significance of γ_i indicates that the volatility structure changes of the Hong Kong and Chinese stock markets are significant after June 15, 2004 and November 11, 2006 respectively.

Table 3: Parameter estimates for marginal models

Parameters	Hong Kong	China
$\mu_{i,t}$	0.0362** (0.0122)	-0.0096 (0.0164)
c_i	0.0326 (0.0178)	0.0237** (0.0086)
$a_{i,1}$	0.0001 (0.0297)	0.0551** (0.0211)
b_i	0.8690** (0.0568)	0.8619** (0.0319)
$a_{i,2}$	0.0794 (0.0448)	0.0558 (0.0365)
γ_i	-0.0173** (0.0015)	0.0976* (0.0211)
ν	4.8960** (0.6067)	4.8106** (0.6352)
Date of Volatility change	2004/6/15	2006/11/28
Log-likelihood	-708.7	-1052.3

Note: 1.**(*)denotes the statistical significance at 1%(5%) level; 2.Numbers in parentheses are standard errors except for γ_i .The number in parentheses for γ_i is the p -value from equation (7); 3.The format for date of volatility change is year/month/day in sequence.

4.2 Best Fit Copula

This study uses the entire sample to choose the copula as best fit copula the one having minimum AIC . Table 4 shows the results of estimated parameters and the AIC value for the four static copulas during the time period December 27, 2001 to June 26, 2007. It can be seen that the t copula has the minimum AIC value of -29.44. Therefore, this study chooses the t copula as the best fit copula to identify the unknown dependence structure change point.

Table 4: Copula selected by AIC for the whole period

Copula model	Dependence	$d.f.$	AIC
Gaussian	0.1569** (0.0286)		-26.18
t	0.1587** (0.0302)	15.48** (0.1971)	-29.44
Gumbel	0.0850** (0.0177)		-26.2
Clayton	0.0759** (0.0170)		-18.46

Note: 1. Parameters of dependence and d.f. are derived from a static copula. 2. **(*)denotes the significance at 1%(5%) level. 3. Numbers in parentheses are standard errors. 4. The boldface number in the AIC column indicates the best fit copula function.

4.3 Estimation and Test of Dependence Structure Change

The results of the parameter estimation are shown in Table 5.³ All parameters are significant and reject the null hypothesis that dependence structure did not change. The date of dependence structure change between the Hong Kong and Chinese stock market has been identified as February 2, 2005 which is around one year after CEPA formally took effect. This year-long delay of dependence structure change could be attributable to the fact tariff reductions or mutual investments were eligible only after CEPA took full effect. Therefore, CEPA's full impact was delayed. The most noticeable parameter is λ . It's value is 0.2721 means that dependence increased by 27.21% following the dependence structure change on February 2, 2005.

³We also estimated dependence structure change for the entire sample between January 6, 1999 and December 30, 2008. The date of change is February 2, 2005, the same as in Table 5. The estimate of λ is 0.3468 and $d.f.$ is 16.01. $Z_T^{1/2}$ is 7.94. All parameters are significant at the 0.05 level.

Table 5: Parameter estimates and hypothesis test for change point

	period	ω	λ	$d.f.$	$Z_T^{1/2}$	$p-value$	Date of Change
t	2001/12/22~	0.0798*	0.2721**	24.8**	6.028	0.0000	2005/2/2
copula	2007/6/25	(0.0424)	(0.0652)	(0.2572)			

Note: 1. **(*)denotes the significance at 1%(5%) level. 2.Numbers in parentheses are standard errors.

After identifying the dependence structure change point, the entire sample is partitioned into two subsamples by this change point. AIC is once again employed to choose the best fit copula for each subsample. The results of this test for best fit copula are presented in Table 6. The best fit copula for each subsample is different. Before structure change, the Gumbel copula was the best fit but after the change point, the t copula became the best fit. The change of the best fit copula implies a change in the distribution of dependence structure. Before the structure change, dependence is more correlated on the distribution's right side whereas following the structure change, it is equally correlated on both sides. In other words, before February 2, 2005, the Hong Kong and Chinese stock markets were more correlated when both markets are soared but after February 2, 2005, they showed equal correlation when both markets either soared or dove.

In sum, CEPA's impact not only caused the dependence parameters between the Hong Kong and Chinese stock markets to change but also cause the distribution of their dependence structure to change as well.

Table 6: Test for change-point under different copula function

	Sample Size	Time Interval	Minimum AIC	Date of Change	Best Fit Copula
I	1120	2001/12/27~2007/6/25	-88.29	2005/2/2	t
II	626	2001/12/27~2005/2/1	-13.36		Gumbel
	494	2005/2/2~2007/6/25	-117.72		t

Note: 1.The format for date of change is year/month/day in sequence.

5 Conclusions

This study has two major findings. First, CEPA caused increased dependence between the Hong Kong and Chinese stock markets. Dependence increased about 27.21% after structure change, which this study determined occurred on February 2, 2005, roughly one year after CEPA took effect. Second, the distribution of the dependence structure also changed from the Gumbel copula before structure change to the t copula after structure change. This result implies that the Hong Kong and Chinese stock markets show more correlation before February 2, 2005 when both market soared but exhibited equal correlation for soaring or diving after February 2, 2005. These two findings agree with the results of Phylaktis and Ravazzolo [13] and Johnson and Soenen[14]. In these studies, stock market dependence increase among economic integration counterparties could be attributed to the promotion of trading and mutual investment. As those aims are Hong Kong's and China's original intentions for signing CEPA, this study also can conclude that CEPA appears to have produced its intended effect.

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