行政院國家科學委員會專題研究計畫 成果報告

股票交易量與價格變動高階動差相依關係之探討：copula 方法的應用
研究成果報告(精簡版)

計 畫 類 別 ：個別型
計 畫 編 號 ：NSC 98-2410-H-004-074-
執 行 期 間 ：98 年 08 月 01 日至 100 年 07 月 31 日
執 行 單 位 ：國立政治大學財務管理學系

計畫主持人：杜化宇

處 理 方 式 ：本計畫涉及專利或其他智慧財產權，1 年後可公開查詢

中 華 民 國 100 年 08 月 03 日

1. Introduction

There is extensive literature in finance on the relationship between trading volume and volatility (Karpoff, 1987). The positive correlation between trading volume and return volatility is consistent with most theoretical market microstructure models (O'Hara, 1995). In this study, the volume-volatility relation is examined within the context of a model commonly known as the mixture-of-distributions hypothesis (MDH), which was first introduced by Tauchen and Pitts (1983). The central proposition of MDH is that daily price changes and trading volume are driven by the same underlying latent "news" arrival, or information flow, variable. The arrival of unexpected "good news" results in a price increase, whereas "bad news" results in a price decrease. Both of these events are accompanied by above-average trading activity in the market as it adjusts to a new equilibrium. Accordingly, volatility and trading volume should be positively correlated.

However, the MDH and its empirical studies assume that joint distribution of volume and volatility is bivariate normal conditional upon the arrival of information. It is quite unrealistic to make such assumption. Recently, copula method has been emphasized because of its capability in modeling the dependencies between variables without the constraint of distributional assumption. Further, it can describe the structure of dependence as well as the degree of dependence, which would not only take the non-linear property into account but would also allow a more comprehensive understanding of the volume-volatility relation.[1]

In this paper, we employ single-parameter conditional copulas to represent the dependence between two index returns, conditional upon the historical information provided by previous pairs of index returns. The parameter of the conditional copula, like the marginal densities of the separate index returns, depends upon the conditioning information. The general theory of copulas is covered in the books by Joe (1997) and Nelsen (1999) and finance applications are emphasized by Cherubini et al. (2004). Important conditional theory has been developed and applied to financial market data by Patton (2006a, b).

There is extensive evidence on the relation between price volatility and trading volume, and this relation is robust to various time intervals (hourly, daily, and weekly) and numerous financial markets (equity, currency, and futures)[2]. Despite so many empirical studies on the volatility-volume relation, there is no general consensus about what actually drives their relation. Chan and Fong (2000) examine the role of the number of trades, size of trades, and order imbalance in explaining the

[1] Copulas have recently become increasingly popular in various finance applications, such as modeling default correlations for credit risk management (Li (2000)), modeling portfolio allocation (Hennessy and Lapan (2002)), pricing multivariate contingent claims (Rosenberg (2003)), and modeling time-varying dependence (Patton (2006a,b)).

[2]

volatility-volume relation for a sample of NYSE and Nasdaq stocks. They found that the size of trade is better for explanation and daily order imbalance also plays a role in their relation. Besides market microstructure factors, we conduct an investigation of how volume-volatility relation vary with a measure of stock market uncertainty, as measured by the implied volatility from S&P500 index option (i.e. VIX index) (Connolly (2005,2007)). Our work is motivated by existing theory and empirical studies that suggest price information can be materially influenced by time-varying uncertainty with asset revaluations.

So far, how the market condition affects their relationship has not been examined in the literature. Providing the evidence that market condition plays a role in the relationship between volatility and volume, especially for futures market, is our second contribution. The last contribution is to explain their time-varying dependence by the degree of investor fear gauge, which is measured by market implied volatility.

Our time-varying copula model provides clear evidence that a distinction across market conditions exists. In general, irrespective of futures or spot data, the means of correlations during the turbulent period are higher than those during the normal period. The conditional upper tail dependences are significant during the turbulent period, whereas they are insignificant during the normal period. A significant asymmetric dependence structure during the turbulent period such as the US subprime market crash indicates that the joint probability of volatility and volume will be higher during the turbulent market than it is during the normal period. In this case, the MDH can be supported if the market suffers severely. We also find that the increase in stock market uncertainty leads to the simultaneous increase in volatility and trading volume. The greater the stock market uncertainty is, the higher correlation between volatility and trading volume is.

The paper is organized as follows. The time-varying copula methodology is presented in Section 2. Section 3 describes data and the empirical results. Finally, we conclude in Section 4.

2. Methodology

Our study extends MDH to highlight an asymmetric dependence structure between return volatility and trading volume and conjectures that their dependence tends to be high in highly volatile markets. This copula method is increasing in popularity because it can analyze dependence structures beyond linear correlations. Darrat et al. (2003) examine their contemporaneous correlations by Pearson correlation and show no significant positive contemporaneous correlation between volatility and volume. Their results clearly fail to support the MDH. We argue that model/measurement risk may lead to incorrectly reject the MDH. Thus, this paper aims to provide a more robust method to avoid any misspecification and study how the market condition affects the relation. Moreover, compared with the MDH which relates volume and volatility on a "long-run" contemporaneous basis, our time-varying copula model regards their relationship as time variation. It is intuitive to study how their relationship varies over time and questions why it is time-varying or what drives it to be a dynamic behavior. The specified time-varying structure is particularly important for policy management, arbitrage, forecast, risk control and market efficiency examination.

2.1. The conditional copula model

In a time-varying copula setting, the dependence parameters in the copula function can be modeled as a dynamic process conditional on currently available information. This allows a non-linear, time dependant relationship. The dependence between volume and volatility is therefore estimated conditional on previously estimated time-varying dependencies. The characteristics of dependence process will be discussed in the following section. A typical characteristic of asset returns is volatility clustering and the asymmetric information impact[3]. Like Darrat et al. (2003; 2007) and Girard and Biswas (2007), we assume that the marginal distribution for volatility is characterized by an GJR-GARCH(1,1)-AR(1)-t model. Let R_t and h_t^2 denote return and its conditional variance for period t, respectively. Ω_{t-1} denotes previous information set. The GJR-GARCH(1,1)-AR(1)-t model for return is defined by:

$$R_t = u_i + \emptyset R_{t-1} + \varepsilon_t \qquad \varepsilon_{i,t} \sim iid\ t_{\nu_i}(0, h_t^2) \tag{1a}$$

$$h_t^2 = \omega + \beta h_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 s_{t-1} \varepsilon_{t-1}^2 \tag{1b}$$

with $s_{t-1} = 1$ when ε_{t-1} is negative and otherwise $s_{t-1} = 0$. ν is the degree of freedom. Eq. (1a) represents dynamic changes in the first moment (mean) of returns, while Eq. (1b) describes time variations in the conditional second moment (variance). The return volatility is measured by the conditional variance from Eq. (1b).

[3] The conditional densities of equity index returns are leptokurtic, and their variances are asymmetric functions of previous returns (Nelson, 1991; Engle and Ng, 1993; Glosten et al., 1993)

Let V_t is the natural log of trading volume during time interval t. Assume that the conditional cumulative distribution functions of h_t and V_t are $F_{h,t}(h_t|\Omega_{t-1})$ and $F_{V,t}(V_t|\Omega_{t-1})$, respectively. The conditional copula function, denoted as $C_t(u_t, v_t|\Omega_{t-1})$, is defined by the two time-varying cumulative distribution functions of random variables $u_t = F_{h,t}(h_t|\Omega_{t-1})$ and $v_t = F_{V,t}(V_t|\Omega_{t-1})$. Let Φ_t be the bivariate conditional cumulative distribution functions of h_t and V_t. Using the Sklar theorem, we have

$$\Phi_t(h_t, V_t|\Omega_{t-1}) = C_t(u_t, v_t|\Omega_{t-1})$$
$$= C_t\left(F_{h,t}(h_t|\Omega_{t-1}), F_{V,t}(V_t|\Omega_{t-1})\middle|\Omega_{t-1}\right) \quad (2)$$

The bivariate conditional density function of h_t and V_t can be constructed by the product of their copula density and their two marginal conditional densities, respectively denoted by $f_{h,t}$ and $f_{v,t}$:

$$\varphi_t(h_t, V_t|\Omega_{t-1})$$
$$= c_t\left(F_{h,t}(h_t|\Omega_{t-1}), F_{V,t}(V_t|\Omega_{t-1})\middle|\Omega_{t-1}\right) \times f_{h,t}(h_t|\Omega_{t-1}) \times f_{V,t}(V_t|\Omega_{t-1}) \quad (3)$$

where $c_t(u_t, v_t|\Omega_{t-1}) = \frac{\partial^2 C_t(u_t, v_t|\Omega_{t-1})}{\partial u_t \partial v_t}$, $f_{h,t}(h_t|\Omega_{t-1})$ is the conditional density of h_t and $f_{V,t}(V_t|\Omega_{t-1})$ is the conditional density of V_t[4].

Copula also provides a higher degree of flexibility in estimation by separating marginal and joint distributions. This is convenient in maximum likelihood estimation, because it permits to estimate the parameters of the density in two steps: first the

[4] The appendix describes parameter estimation of the above conditional copula.

parameters of the marginals, and then the parameters of the copula. The two-step approach save computational burden, although it may have a cost in terms of efficiency.

2.2. Bivariate copula density

This study employs the Gaussian, the Gumbel and the Clayton copula for specification and calibration. The Gaussian copula is generally viewed as a benchmark for comparison during the normal period, while the Gumbel and the Clayton copula are used to capture the upper and lower tail dependence, respectively. We particularly focus on the Gumbel copula because we hypothesis that an asymmetric right tail dependence structure between return volatility and trading volume may exist; that is, their dependence tends to be high in highly volatile periods.

The conditional Gaussian copula function is the density of joint standard uniform variables (u_t, v_t) because the random variables are bivariate normal with the time-varying correlation ρ_t. Let $x_t = \Phi^{-1}(u_t)$ and $y_t = \Phi^{-1}(v_t)$, where $\Phi^{-1}(.)$ denotes the inverse of the cumulative density function of the standard normal distribution. The density of the time-varying Gaussian copula can be shown as

$$c_t^{Gau}(u_t, v_t|\rho_t) = \frac{1}{\sqrt{1-\rho_t}} exp\left\{\frac{2\rho_t x_t y_t - x_t^2 - y_t^2}{2(1-\rho_t^2)} + \frac{x_t^2 + y_t^2}{2}\right\} \quad (4)$$

The Gumbel and the Clayton copula can efficiently capture the tail dependence arising from the extreme observations caused by asymmetry. The density of the time-varying Gumbel copula is

$$c_t^{Gum}(u_t, v_t|\delta_t) = \frac{(-\ln u_t)^{\delta_t-1}(-\ln v_t)^{\delta_t-1}}{u_t v_t} \; exp\left\{-\left[(-\ln u_t)^{\delta_t-1} + (-\ln v_t)^{\delta_t-1}\right]^{\frac{1}{\delta_t}}\right\}$$
$$\left\{-\left[(-\ln u_t)^{\delta_t-1} + (-\ln v_t)^{\delta_t-1}\right]^{\left(\frac{1-\delta_t}{\delta_t}\right)^2} + (\delta_t - 1)\left[(-\ln u_t)^{\delta_t-1} + (-\ln v_t)^{\delta_t-1}\right]^{\left(\frac{1-2\delta_t}{\delta_t}\right)}\right\} \quad (5)$$

where $\delta_t \in [1, \infty)$ measures the degree of dependence between u_t and v_t. $\delta_t = 1$ implies an independent relationship and $\delta_t \to \infty$ represents perfect dependence. The density of the time-varying Clayton copula is

$$c_{\theta_t}^{clay}(u_t, v_t|\theta_t) = (\theta_t + 1)\left(u_t^{-\theta_t} + v_t^{-\theta_t} - 1\right)^{-\frac{2\theta_{t+1}}{\theta_t}} u_t^{-\theta_t-1} v_t^{-\theta_t-1} \quad (6)$$

where $\theta_t \in [0, \infty)$ measures the degree of dependence between u_t and v_t. $\theta_t = 0$ implies an independent relationship and $\theta_t \to \infty$ represents perfect dependence.

2.3. Parameterizing time-series variation in the conditional copula

The central proposition of MDH is that daily volatility and trading volume are driven the same underlying latent "news" arrival, or information flow, variable. The degree of contemporaneous relationship indicates that how they simultaneously reflect the news, and it may become dynamic as information arrives randomly or variance of information substantially increases. Modeling their dynamic dependences by applying a time-varying copula allows us to better understand how the market dynamically responds the arrival of information.

Modeling a conditional copula with a time-varying dependence parameter has become prevalent in the literature (Patton, 2006a, b; Bartram et al., 2007; Jondeau and Rochinger, 2006; Rodriguez, 2007). We assume that the dependence parameter is determined by previous information such as its previous dependence and the historical absolute difference between cumulative probabilities of portfolio asset returns[5]. A conditional dependence parameter can be modeled as an AR(1)-like process. The dependence process of a Gaussian copula is therefore:

$$\rho_t = \Lambda(\beta\rho_{t-1} + \omega + \gamma\, \Phi^{-1}(u_{t-1}) \cdot \Phi^{-1}(v_{t-1})) \quad (7)$$

The conditional dependence, ρ_t , depends on its previous dependence, ρ_{t-1} , and the product of the last one observations of the transformed variables $\Phi^{-1}(u_{t-1})$ and $\Phi^{-1}(v_{t-1})$. We include ρ_{t-1} as a regressor to capture any persistence in the dependence parameter, and the product of the last one observation of the transformed variables $\Phi^{-1}(u_{t-1})$ and $\Phi^{-1}(v_{t-1})$, to capture any variation in dependence. This formulation considers both the persistence and the variation in the dependence process. $\Lambda(x)$ is defined as $(1-e^{-x})(1+e^{-x}) = tanh\left(\frac{x}{2}\right)$, which is the modified logistic transformation to keep ρ_t in (-1,1) at all times (Patton, 2006a). Time-varying

[5] There are different ways of capturing possible time variation in a conditional copula. This paper assumes that the functional form of the copula remains fixed over the sample whereas the parameters vary according to some evolution equation, as in Patton (2006a).

dependence processes for the Gumbel copula and the Clayton copula are described as Eq. (9) and (10), respectively.

$$\delta_t = \beta_U \delta_{t-1} + \omega + \gamma|u_{t-1} - v_{t-1}| \quad (8)$$

$$\theta_t = \beta_L \theta_{t-1} + \omega + \gamma|u_{t-1} - v_{t-1}| \quad (9)$$

where $\delta_t \in [1, \infty)$ measures the degree of dependence in the Gumbel copula and has a lower bound equal to 1, indicating an independent relationship, whereas $\theta_t \in [-1,0) \cup (0, +\infty)$ measures the degree of dependence in the Clayton copula.

Both the Gumbel and the Clayton copula are Archimedean copulas which have no linear dependence parameter in their density functions. For comparison with the linear correlations, ρ_t which is between -1 and 1, estimated from the Gaussian copula, δ_t and θ_t are first mapped to Kendall's tau[6]. Kendall's tau is called rank correlation since it can be interpreted as the linear correlation between some" ranks" of the data. A relation between δ_t and Kendall's tau, τ_t, can be represented as $\tau_t = 1 - \delta_t^{-1}$, and a relation between θ_t and Kendall's tau, τ_t, can be represented as $\tau_t = \theta_t/(\theta_t + 2)$. Further, we specify a relation between the linear dependence and Kendall's tau for the Archimedean copulas, which is $\tau_t = \left(\frac{2}{\pi}\right) \sin^{-1} \rho_t$ as shown in Hult and Lindskog (2002).

[6] For general non-elliptical distributions, Joe (1997) introduced three copula-based measures of dependence- Kendall's tau, Spearman's rho, and tail dependence.

Additionally, the parameters δ_t and θ_t estimated from the Gumbel and Clayton copula functions are linked to tail dependence. Tail dependence captures the behavior of the random variables during extreme events. In this study, it measures the probability that we will observe an extremely large trading volume, given an extremely increased volatility. The linkage between conditional Gumbel dependence parameter δ_t and conditional upper tail dependence λ_t^U is described as $\lambda_t^U = 2 - 2^{\frac{1}{\delta_t}}$, while the linkage between conditional Clayton dependence parameter θ_t and conditional lower tail dependence λ_t^L is described as $\lambda_t^L = 2^{-\frac{1}{\theta_t}}$.

3. Data description and empirical results

3.1. Data

The S&P 500 Index and its futures contracts are both employed in order to examine daily trading volume, volatility and their relationships. The volume-volatility relation in futures is not the same as it is in the equity markets because futures are essentially hedging and speculative vehicles[7]. The different purpose between futures traders and equity traders provides an advantage to examine whether the dynamic volume-volatility relationship varies between financial markets.

As the conditional variance is characterized by a GJR-GARCH(1,1)-AR(1)-*t* model given by Eq. (1), the conditional volatility of S&P 500 Index and its futures contracts are depicted in Figure 1. We choose sample period from Jan 2004 to Aug 2008 for two reasons. First, we find a very strong evidence of a structural changebreak[8] in their conditional volatilities. The period from Jan 2004 to Feb 2007 is relatively less volatile. After Mar 2007, the markets in both spot and futures become very volatile and their conditional volatilities substantially increase. We then divide our sample into two subperiods, a normal period from Jan 2004 to Feb 2007 and a turbulent period from Mar 2007 to Aug 2008. Second, the recent outbreak of U.S.

---

[7]

[8] A Chow test is conducted to test for a structural change.

subprime market crash is covered in the turbulent period. This provides a natural experiment to investigate relationship between volume and volatility when financial markets suffer severely and helps to realize whether their relationship varies with market conditions, especially for market crisis.

[Insert Figure 1 here]

3.2. The Measurement of Daily Volatility

Besides the conventional conditional volatility, we also consider the range-based measure of volatility by Garman and Klass (GK) (1980). Chen et al. (2006) and Shu and Zhang (2006) show that the GK range-based measure of volatility provides essentially equivalent results to high-frequency realized volatility measures of volatility, as well as avoiding the problems caused by microstructure effects. For robust check, the classical GK range-based intraday volatility estimator is employed to construct the daily volatility as follows[9]:

$$h_t^{GK} = 0.511(u - d)^2 - 0.019(c(u + d) - 2ud) - 0.383c^2$$

Where u is the difference in the natural logarithms of the high and low prices of the day, the d is the difference in the natural logarithms of the low and opening prices, the c is the difference in the natural logarithms of the closing and opening prices. The volatility values are multiplied by 100. Similarly, the Chow test shows that a very

[9] See GK for the details.

strong structural changebreak=[10] in 26 July, 2007 is evident in the GK range-based measure of volatility.

We form a detrended log trading volume time series by incorporating the procedure used by Campbell et al. (1993). The lead-lag relation should be controlled before studying their dependence structure. The VAR methodology is conducted firstly to examine the possibility of lead-lag interrelationships associated with the SAIH. If a lead-lag relationship is significant, the unexpected residuals from VAR model are used for further examination. Except for the data from S&P 500 Index during the turbulent period, we do not found any lead-lag relationship. Therefore, most of our data set does not support the SAIH[11].

In the following analysis, we therefore

3.3. Estimation results of the time-varying copula models

Table 1 reports the summary statistics for daily trading volume, conditional volatility, GK volatility from the S&P 500 index and its futures contracts. The statistics, especially for mean and standard deviation, are generally higher during the turbulent period, indicating that the turbulent period exhibits not only higher volatility

---

[10] A Chow test is conducted to test for a structural change.

[11]

but also larger trading volume. However, whether their dependence substantially increases during the turbulent period should be methodologically examined.

[Insert Table 1 here]

To avoid any misspecification for the marginal distributions, the copula method allows us do not impose any prior assumption on the distributional form of the marginals and relies on the concept of the "*empirical marginal transformation*". The sample data can be directly transformed into uniform variables, and then be used to estimate copula parameters, which is a classical semi-parametric method and often called a *Canonical Maximum Likelihood Method* (CML) (see Cherubini et al., 2004)[12].

Given that the empirical marginal distributions are obtained, the parameters of time-varying correlations in the Gaussian copula are calibrated and reported in Table 2. In Eq. (7), the parameter β captures the degree of persistence in the dependence and γ captures the adjustment in the dependence process. For futures data, irrespective of the measurement of volatility, the level of dependence substantially increases and the dynamic of dependence clearly changes. We compute the implied

[12] Kim et al. (2007) consider the semiparametric method proposed by Genest et al. (1995) and find that it performs better than the parametric method, such as maximum likelihood and inference function for margins method, when the marginal distributions are unknown which is almost always the case in practice. Chen and Fan (2006) study the property and estimation of copula-based semiparametric time series models, in which copulas are parameterized but the marginal distributions are left unspecified.

time path of conditional dependence between GARCH volatility and volume and present the results in Panel (A) of Figure 2. This figure shows quite clearly the structural break in dependence across different market conditions. Panel (B) of Figure 2 is similar with Panel (A), except for the volatility is measured by Garman and Klass (1980) range-based volatility. For spot data, the dynamic of dependence clearly changes but the level of dependence substantially drops, when volatility is measured by GARCH model. This drop may be caused by the short sales restrictions, especially for market crash. Figure 3 are their implied time path of conditional dependence.

[Insert Table 2 here]

[Insert Figure 2 here]

[Insert Figure 3 here]

The estimated results of the time-varying Gumbel copula model are presented in Table 3. Figure 2 shows the dramatic changes in their dynamic dependence structure. It is noteworthy that the time-varying Gumbel copula fails to describe either spot market in whole period if the volatility is measured by a GARCH model (Figure 3) or futures market during the normal period (Figure 2), but it particularly performs well for futures market during the turbulent period[13] (Figure 2). It also can be found that

[13] The likelihood value for futures during the turbulent period is significantly higher than others in

conditional upper tail dependences in Figure 4 are prominent during the turbulent period, indicating the dependence structures are asymmetric significantly during the turbulent period. This finding illustrates that the joint probability of volatility and volume will be higher during the turbulent market, which is consistent with the MDH where the correlation between variables increases with the variance of the information flow.

Finally, Table 4 reports the estimated results of the time-varying Clayton copula model. It also can be evident that there exists a change in their dynamic structure in futures market across different market conditions. However, its failure in spot market is similar to that of the Gumbel copula, indicating that the Gaussian copula performs better in spot market, if the volatility is measured by a GARCH model. Their dependence structure in spot market is symmetric (Figure 3), whereas it is asymmetric in futures market (Figure 2). Figure 4 also exhibits the changes in their conditional lower tail dependences. In summary, our study provides the evidence that market condition plays a role in the relationship between volatility and volume, especially for futures market.

[Insert Table 3 here]

[Insert Table 4 here]

Table 3.

[Insert Figure 4 here]

Our time-varying copula model provides clear evidence that a distinction exits across different market conditions exists. Statistics of the correlations between GARCH volatility and volume are summarized in Table 5, while those between GK volatility and volume are summarized in Table 6. In general, irrespective of futures or spot data, the means of correlations during the turbulent period are higher than those during the normal period. Moreover, the difference in means is significant, indicating that the correlations are found to significantly change as the condition of market changes. In particular, during the turbulent period, the means of correlation from the Gumbel copula are the highest which implies that their correlations are prominent and may be underestimated if they are specified by other copula functions. In Table 7 and 8, we can consistently find that the difference in statistics of the tail dependence is significant under different market conditions. The conditional upper tail dependences are significant during the turbulent period, whereas they are insignificant during the normal period. A significant asymmetric dependence structure during the turbulent period such as the US subprime market crash indicates that the joint probability of volatility and volume will be higher during the turbulent market than it is during the normal period. In this case, the MDH can be supported if the market suffers severely.

[Insert Table 5 here]

[Insert Table 6 here]

[Insert Table 7 here]

[Insert Table 8 here]

4. The Impact of Market Uncertainty

4.1. VIX and future volume-volatility comovment

In this study, we analyze how the volume-volatility dependence varies with VIX. Whether the comovements between volume and volatility are reliably related to lagged VIX needs to be evaluated, which helps to realize how the volume-volatility dependence varies. Implied volatility from the Chicago Board Options Exchange's Volatility Index is used to measure stock market uncertainty. We estimate the specification with time-varying Gaussian, Gumbel, Clayton, upper tail and lower tail dependences as dependent variables, respectively, and only VIX_{t-1} as an explanatory variable.

As can be seen in Table 9, the estimated a_1 coefficients are positive and statistically significant, indicating that there is a positive relation between the volume –volatility comovement and lagged VIX. Thus, the variation in the level of stock market uncertainty is informative about the future volume –volatility relation.

[Insert Table 9 here]

4.2. Daily VIX changes and variations in contemporaneous volume-volatility comovment

Furthermore, we ask whether the changes in stock market uncertainty[14] are associated with differences in the volume –volatility relation. So far, the issue of

[14] The change in VIX is measured by absolute value of $(\mathrm{VIX}_t - \mathrm{VIX}_{t-1})/\mathrm{VIX}_{t-1}$

whether the volume –volatility relations are associated with the variations in stock market uncertainty has not been examined. In Table 10, we present this issue by sorting daily observations on the day's change in VIX and then calculating subsample dependences for the different variation in VIX groups. Our results suggest that the dependence between the volume and volatility increases during the period with substantial VIX changes.

[Insert Table 10 here]

4.3. Evaluating the conditional copula models

As the development of the multivariate conditional distribution has a dramatic growth, research regarding evaluating multivariate density models becomes prominent (Christoffersen,1998; Rivers and Vuong, 2002; Granger et al., 2006; Chen and Fan, 2006; Patton, 2006a). In addition, the evaluation of copula model is a special case of the more general problem of evaluating multivariate density models (Patton, 2006a). The "region models" of Patton (2006a) are employed to conduct our goodness-of-fit tests and comparisons, which is discussed in the Appendix.

The joint hit test results for the competing copula models are reported in Table 11. For futures data during the turbulent period, the conditional Gaussian and conditional Clayton copula models are rejected at the 5% significance level, whereas the conditional Gumbel copula model fails to the joint test for samples during the normal period. The results of goodness-of-fit tests indicate that the conditional Gumbel copula model perform well during the turbulent period for samples from futures but not from spots, and imply that the turbulent period can produce an apparent asymmetric dependence for futures markets. In this case, their dependence may be underestimated if they are specified by other conditional copula functions. However, the multivariate normal model is more desirable to describe the normal period than any of the asymmetric copula models considered.

[Insert Table 11 here]

5. Conclusion

This study aims to provide a more robust method to avoid misspecifying volume-volatility relation and examine whether the market condition plays a role. Compared with the MDH which relates volume and volatility on a “long-run” contemporaneous basis, our time-varying copula model regards their relationship as time variation. The specified time-varying structure is particularly important for policy management, arbitrage, forecast, risk control and market efficiency examination. A pronounced distinction across market conditions is evident. A significant asymmetric dependence structure during the turbulent period such as the US subprime market crash implies that the joint probability of volatility and volume may be higher during the turbulent market than it is during the normal period. We also find that the increase in stock market uncertainty leads to the simultaneous increase in volatility and trading volume.

Reference

Bartram, S.M., Taylor, S.J., Wang, Y.H., 2007. The Euro and European financial market dependence. Journal of Banking and Finance 31, 1461-1481.

Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading volume and serial correlation in stock returns. The Quarterly Journal of Economics 108, 905-939.

Chan, K., Fong, W.M., 2000. Trade size, order imbalance, and the volatility-volume relation. Journal of Financial Economics 57, 247-273.

Chen, Z., Daigler, R.T., 2008. An examination of the complementary volume-volatility information theory. Journal of Futures Markets 28, 963-992.

Chen, Z., Daigler, R.T., Parhizgari, A.M., 2006. Persistence of volatility in futures markets. Journal of Futures Markets 26, 571-594.

Chen, X., Fan, Y., 2006. Estimation of copula-based semiparametric time series models. Journal of Econometrics 130, 307-335.

Cherubini, U., Luciano, E, Vecchiato, W., 2004. Copula Methods in Finance (England: John Wiley & Sons)

Christoffersen, P. F., 1998. Evaluating interval forecasts. International Economic Review 39(4), 841-862.

Darrat, A.F., Zhang, M., Cheng, L.T.W., 2003. Intrady volume and return volatility of the DJIA stocks: A note. Journal of Banking and Finance 27, 2035-2043.

Darrat, A.F., Zhang, M., Cheng, L.T.W., 2007. Intrady volume and volatility relations with and without public news. *Journal of Banking and Finance* 31, 2711-2729.

Engle, R.F., Ng, V.K., 1993. Measuring and testing the impact of news on volatility. *Journal of Finance* 48, 1749-1778.

Garman, B.M., Klass, M.J., 1980. On the estimation of security price volatility from historical data. Journal of Business 3, 67-78.

Genest, C., Ghoudi, K., Rivest, L., 1995. A semiparametric estimation procedure of dependence parameters in multivariate families of distributions. Biometrika 82(3), 543-552.

Girard, E., Biswas, R., 2007. Trading volume and market volatility: Developed versus emerging stock markets. The Financial Review 42, 429-459.

Glosten, L. R., R. Jagannathan, and D. Runkle, 1993. Relationship between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 48, 1779-1801.

Granger, C.W.J., Terasvirta, T., Patton, A., 2006. Common factors in conditional distributions for bivariate time series. Journal of Econometrics 132, 43-57.

Hult, H, Lindskog, F., 2002. Multivariate extremes, aggregation and dependence in elliptical distributions. Advances in Applied Probability 34, 587-608.

Joe, H., 1997. Multivariate models and dependence concepts. London, U.K.: Chapman & Hall.

Jondeau, E., Rockinger, M., 2006. The copula-garch model of conditional dependences: an international stock market application. Journal of International Money and Finance 25 (5), 827-853.

Kim, G., Silvapulle, M.J., Silvapulle, P., 2007. Comparison of semiparametric and parametric methods for estimating copulas. Computational Statistics & Data Analysis 51, 2836-2850.

Luu, J.C., Martens, M., 2003. Testing the Mixture-of-Distributions hypothesis using “realized” volatility. Journal of Futures Markets 23(7), 661-679.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59, 347-370.

Patton, A.J., 2006a. Modelling asymmetric exchange rate dependence. *International Economic Review* 47(2), 527-556.

Patton, A.J., 2006b. Estimation of multivariate models for time series of possibly different lengths. *Journal of Applied Econometrics* 21, 147-173.

Rivers, D., Vuong, Q., 2002. Model selection tests for nonlinear dynamic models. The Econometrics Journal 5(1), 1-39.

Rodriguez, J.C., 2007. Measuring financial contagion: a coupla approach. Journal of Empirical Finance 14, 401-423.

Shu, J., Zhang, J.E., 2006. Testing range estimators of historical volatility. Journal of Futures Markets 26, 297-313.

Appendix: Evaluation of Conditional Copula Models

Patton(2006a) decomposes the density model into a set of "region" models[15], and each of which should be correctly specified under the null hypothesis that the entire density is correctly specified. The intuition is to compare the number of observations in each region with what would be expected under the null hypothesis. Let $\mathrm{W_t}$ be the multivariate random variables and $\{\mathrm{R_j}\}_{\mathrm{j}}^{\mathrm{K}}$ be regions, and define $Hit_{\mathrm{t}}^{\mathrm{j}} \equiv \mathbf{1}\{\mathrm{W_t} \in \mathrm{R_j}\}$ as a Bernoulli distribution and $\mathrm{M_t} \equiv \sum_{\mathrm{j=0}}^{\mathrm{K}} \mathrm{j} \cdot \mathbf{1}\{\mathrm{W_t} \in \mathrm{R_j}\}$ as a Multinomial distribution. Whether the proposed density model is correctly specified in all K+1 regions simultaneously is tested under the hypothesis

$$H_0: M_t \sim inid\ Multinormial(\boldsymbol{P_t}) \text{ versus } H_1: M_t \sim inid\ Multinormial(\boldsymbol{\Pi_t}).$$

Under the null hypothesis, we have that $\boldsymbol{P_t} = \boldsymbol{\Pi_t}$ where $\boldsymbol{\Pi_t}$ be the vector of true probabilities and $\boldsymbol{P_t}$ be the vector of the probabilities suggested by the model. His logit model for the hits can be specified as $\boldsymbol{\Pi_t}$ to be function of both $\boldsymbol{P_t}$ and variables in the time $\mathrm{t}-1$ information set.

$$\pi_{1t}(\mathbf{Z_t}, \boldsymbol{\beta}, \boldsymbol{P_t}) = \Lambda\left(\lambda_1(\mathrm{Z_{1t}}, \mathrm{B_1}) - \ln\left(\frac{1-\mathrm{p_{1t}}}{\mathrm{p_{1t}}}\right)\right)$$

[15] Regions 1 and 2 correspond to the lower and upper joint 10% tail for each variable. Regions 3 and 4 indicate that bivariate variables belong to the 10th and 25th or 75th and 90th quantiles, respectively. Region 5 is the median region. Regions 6 and 7 are extremely asymmetric if one variable is in the 75th quantile, whereas the other is in the 25th quantile.

$$\pi_{jt}(\mathbf{Z_t}, \boldsymbol{\beta}, \boldsymbol{P_t}) = \left(1 - \sum_{i=1}^{j-1} \pi_{it}\right) \Lambda\left(\lambda_j(Z_{jt}, \beta_j) - \ln\left(\frac{1 - \sum_{i=1}^{j} p_{it}}{p_{jt}}\right)\right) \text{ for } j = 2 \ldots K$$

$$\pi_{0t} = 1 - \sum_{j=1}^{K} \pi_{jt}(\mathbf{Z_t}, \boldsymbol{\beta}, \boldsymbol{P_t})$$

Where $\Lambda(x) = \frac{1}{1+e^{-x}}$ is the logistic transformation, $\mathbf{Z_t} \equiv [Z_1, \ldots, Z_K]'$ is a matrix containing elements from the information set at time $t - 1$ and $\boldsymbol{\beta} \equiv [\beta_1, \ldots, \beta_K]'$ is a vector of parameters to be estimated. Due to the logit model with a restriction $\Pi_t(\mathbf{Z_t}, \mathbf{0}, \boldsymbol{P_t}) = \boldsymbol{P_t}$ for all $\mathbf{Z_t}$, the competing hypotheses can be expressed as $\boldsymbol{\beta} = \mathbf{0}$ versus $\boldsymbol{\beta} \neq \mathbf{0}$. The likelihood function, therefore, to be maximized to obtain the parameter $\boldsymbol{\beta}$ is $\mathcal{L}(\boldsymbol{\Pi}(\mathbf{Z}, \boldsymbol{\beta}, \mathbf{P})|Hit) = \sum_{t=1}^{T} \sum_{j=0}^{K} \ln \pi_{jt} \cdot \mathbf{1}\{M_t = j\}$, and the joint test can be conducted as likelihood ratio test:

$$LR_{All} \equiv -2 \cdot \left(\mathcal{L}(\boldsymbol{P}|Hit) - \mathcal{L}\left(\Pi\left(\boldsymbol{Z}, \hat{\boldsymbol{\beta}}, \boldsymbol{P}\right)|Hit\right)\right) \sim \chi_K^2.$$

Table 1 Summary statistics

This table shows summary statistics for daily trading volume, conditional volatility, GK volatility from the S&P 500 index and its futures contracts. The full sample covers the period from Jan 2004 to Aug 2008 and is divided into two subperiods: normal period (Jan 2004-Feb 2007) and turbulent period (Mar 2007-Aug 2008).

	Mean	Standard Deviation	Skewness	Kurtosis
Panel A: Futures during Turbulent Period				
GARCH volatility	1.16556	0.56083	0.12201	-1.05081
GK volatility	0.34684	0.38755	2.42161	7.74233
Volume	10.82068	0.63370	0.64701	1.60149
Panel B: Futures during Normal Period				
GARCH volatility	0.40004	0.18837	0.88072	0.00375
GK volatility	0.10067	0.11643	2.48549	7.50052
Volume	10.76542	0.61602	1.08606	1.07046
Panel C: Spots during Turbulent Period				
GARCH volatility	1.26208	0.61289	0.24638	-0.85229
GK volatility	0.36217	0.44879	2.67583	9.90287
Volume	0.01180	0.16102	-0.15804	2.35204
Panel D: Spots during Normal Period				
GARCH volatility	0.41266	0.17599	0.92736	0.25963
GK volatility	0.09554	0.11600	2.54414	7.85821
Volume	0.01030	0.12165	0.11536	5.69823

Table 2 Estimated parameters of time-varying Gaussian copula functions

This table shows the estimated parameters of time-varying dependencies in the Gaussian copulas. The time-varying dependence models in Eq. (4) is estimated and calibrated. The parameter β captures the degree of persistence in the dependence and γ captures the adjustment in the dependence process. *LLF*(c) is the maximum copula component of the log-likelihood function.

	GARCH Volatility v.s. Volume	GK Volatility v.s. Volume
Panel A: Futures during Turbulent Period		
β	0.57051	0.81508
ω	0.12518	0.06646
γ	0.16081	0.06794
LLF(c)	46.87900	26.04429
Panel B: Futures during Normal Period		
β	0.48835	0.91151
ω	0.02944	0.02913
γ	0.17652	0.05315
LLF(c)	70.94995	61.99650
Panel C: Spots during Turbulent Period		
β	0.84603	0.43289
ω	0.00293	0.22979
γ	0.03480	-0.06961
LLF(c)	1.62405	15.50691
Panel D: Spots during Normal Period		
β	0.41293	0.51446
ω	0.02634	0.11655
γ	0.16429	0.01318
LLF(c)	32.70562	25.12459

Table 3 Estimated parameters of time-varying Gumbel copula functions

This table shows the estimated parameters of time-varying dependencies in the Gumbel copulas. The time-varying dependence models in Eq. (5) is estimated and calibrated. The parameter β captures the degree of persistence in the dependence and γ captures the adjustment in the dependence process. *LLF*(c) is the maximum copula component of the log-likelihood function.

	GARCH Volatility v.s. Volume	GK Volatility v.s. Volume
Panel A: Futures during Turbulent Period		
β	0.65994	0.50972
ω	0.69435	0.83763
γ	-1.00000	-0.71853
LLF(c)	43.91555	19.92044
Panel B: Futures during Normal Period		
β	0.02320	0.00010
ω	0.14729	-0.19520
γ	-0.76209	-0.16093
LLF(c)	4.31540	2.20792
Panel C: Spots during Turbulent Period		
β	0.00010	0.32684
ω	0.06468	0.75052
γ	-0.08361	0.36844
LLF(c)	4.31728	8.90433
Panel D: Spots during Normal Period		
β	0.04028	0.00010
ω	-0.33350	-0.34965
γ	-0.27176	-0.30292
LLF(c)	0.95828	6.10989

Table 4 Estimated parameters of time-varying Clayton copula functions

This table shows the estimated parameters of time-varying dependencies in the Clayton copulas. The time-varying dependence models in Eq. (6) is estimated and calibrated. The parameter β captures the degree of persistence in the dependence and γ captures the adjustment in the dependence process. *LLF*(c) is the maximum copula component of the log-likelihood function.

	GARCH Volatility v.s. Volume	GK Volatility v.s. Volume
Panel A: Futures during Turbulent Period		
β	0.78059	0.66337
ω	0.36721	0.45572
γ	-1.00000	-1.00000
LLF(c)	39.90310	30.17076
Panel B: Futures during Normal Period		
β	0.37914	0.82614
ω	0.51732	0.22316
γ	-1.00000	-0.47656
LLF(c)	45.24892	68.53910
Panel C: Spots during Turbulent Period		
β	0.10667	0.88533
ω	-0.54885	0.10515
γ	-0.19525	-0.26462
LLF(c)	0.54188	8.46003
Panel D: Spots during Normal Period		
β	0.10620	0.75889
ω	-0.50539	0.15717
γ	-0.28708	-0.30124
LLF(c)	0.77408	24.59224

Table 5 Summary statistics of the dependence between GARCH volatility and volume

This table summarizes the minimum, maximum, mean, standard deviation of the estimates of conditional dependence between GARCH volatility and volume across sample period.

	Min volume-		Max volume-		Mean volume-		Standard Deviation volume-	
	GARCH	GK	GARCH	GK	GARCH	GK	GARCH	GK
Panel A: Futures during turbulent period								
Gaussian	0.28775	0.30000	0.50870	0.44989	0.34723	0.35999	0.04015	0.02392
Gumbel	-	-	0.70710	0.70710	0.38062	0.37369	0.21494	0.15637
Clayton	-	0.00331	0.58180	0.54979	0.34192	0.34872	0.17305	0.13764
Panel B: Futures during normal period								
Gaussian	0.06261	0.19000	0.30665	0.42240	0.15708	0.33473	0.05185	0.02393
Gumbel	-	-	-	-	-	-	-	-
Clayton	0.00145	0.00441	0.50000	0.51036	0.23314	0.32495	0.12788	0.11025
Panel C: Spots during turbulent period								
Gaussian	0.04887	0.30000	0.15867	0.36857	0.09010	0.34522	0.02044	0.01341
Gumbel	-	0.18357	-	0.70710	-	0.31963	-	0.07405
Clayton	-	0.00399	-	0.50000	-	0.20737	-	0.08341
Panel D: Spots during normal period								
Gaussian	0.04917	0.20000	0.27382	0.25043	0.13288	0.23822	0.05109	0.00348
Gumbel	-	-	-	-	-	-	-	-
Clayton	-	0.00558	-	0.50000	-	0.19738	-	0.06445

Table 6 Summary statistics of the tail dependences between GARCH volatility and volume

This table summarizes the minimum, maximum, mean, standard deviation of the estimates of conditional upper and lower tail dependence between GARCH volatility and volume across sample period.

	Min	Max	Mean	Standard Deviation
Panel A: Futures during turbulent period				
Upper Tail	0	0.58578	0.31506	0.17658
Lower Tail	0	0.58851	0.31152	0.19543
Panel B: Futures during normal period				
Upper Tail	0	0	0	0
Lower Tail	0	0.50000	0.17373	0.13374

Table 7 Summary statistics of the tail dependences between GK volatility and volume

This table summarizes the minimum, maximum, mean, standard deviation of the estimates of conditional upper and lower tail dependence between GK volatility and volume across sample period.

	Min	Max	Mean	Standard Deviation
Panel A: Futures during turbulent period				
Upper Tail	0.01	0.59578	0.32005	0.12801
Lower Tail	0	0.55508	0.31371	0.15971
Panel B: Futures during normal period				
Upper Tail	0	0	0	0
Lower Tail	0	0.51178	0.27796	0.13539
Panel C: Spots during turbulent period				
Upper Tail	0.15647	0.58578	0.26728	0.05994
Lower Tail	0	0.50000	0.12039	0.09454
Panel D: Spots during normal period				
Upper Tail	0	0	0	0
Lower Tail	0	0.50000	0.10418	0.06726

Table 8 Lagged VIX and the dependence between volume and volatility

A regression model is applied to study how the volume-volatility dependence varies with lagged level of VIX. The dependent variable can be conditional correlations or conditional tail dependences measured by copula functions. The lagged level of VIX is an explanatory variable, and a_1 is its coefficient a_0 is an intercept term. The symbol * denotes significance at the 5% levels.

	Gaussian Correlation	Gumbel Correlation	Clayton Correlation	Upper Tail Dependence	Lower Tail Dependence
Panel A: Futures data & GARCH volatility					
$\mathbf{a_0}$	-0.4039*	-1.0601*	-0.0058	-0.1126*	-0.8784*
$\mathbf{a_1}$	0.2285*	0.4343*	0.1005*	0.1213*	0.3598*
$\mathbf{R^2}$	0.3775	0.3000	0.0322	0.0383	0.3020
F-statistic	706.9588	499.6618	38.7355	46.3763	504.4157
Panel B: Futures data & GK volatility					
$\mathbf{a_0}$	-0.1392*	-1.1942*	0.1202*	-1.0233*	0.0089
$\mathbf{a_1}$	0.1482	0.4707*	0.0772*	0.4033*	0.1018*
$\mathbf{R^2}$	0.4820	0.5312	0.0319	0.5404	0.0380
F-statistic	1084.8410	1321.3450	38.4378	1370.9880	46.0509
Panel C: Spot data & GK volatility					
$\mathbf{a_0}$	-0.1087*	-1.0219*	0.1470*	-0.8548*	0.0306
$\mathbf{a_1}$	0.1366*	0.4028*	0.0193*	0.3369*	0.0283*
$\mathbf{R^2}$	0.6541	0.6096	0.0058	0.6124	0.0108
F-statistic	2207.2870	1822.2390	6.8027	1844.0880	12.7826

Table 9 Summary Statistics for the volume-volatility dependence sorted by VIX variation

This table reports the association between daily VIX changes and the volume –volatility relation. The VIX change criteria refer to the percentile range for the daily change in VIX, from the smallest changes (0 to 5th percentile) to the largest changes (95th to 100th percentile). Subsample dependences for the different variation in VIX groups are therefore calculated.

VIX variation Criteria	Gaussian Correlation	Gumbel Correlation	Clayton Correlation	Upper Tail Dependence	Lower Tail Dependence
Panel A: Futures data & GARCH volatility					
0 to 5th pctl.	0.19847	0.11528	0.29709	0.25112	0.09537
5th to 25th pctl.	0.20579	0.08755	0.25911	0.20283	0.07256
25th to 50th pctl.	0.21306	0.10799	0.25329	0.20226	0.08932
50th to 75th pctl.	0.21745	0.11511	0.26024	0.20996	0.09537
75th to 95th pctl.	0.23376	0.16242	0.28209	0.23518	0.13437
95th to 100th pctl.	0.26032	0.22538	0.32999	0.29320	0.18645
Panel B: Futures data & GK volatility					
0 to 5th pctl.	0.25652	0.06175	0.32906	0.05308	0.27714
5th to 25th pctl.	0.25775	0.06234	0.32940	0.05356	0.28755
25th to 50th pctl.	0.26233	0.07504	0.32028	0.06426	0.27361
50th to 75th pctl.	0.26224	0.08436	0.33378	0.07231	0.28793
75th to 95th pctl.	0.27604	0.12532	0.33171	0.10726	0.28991
95th to 100th pctl.	0.27245	0.14997	0.36385	0.12763	0.32873
Panel C: Spot data & GK volatility					
0 to 5th pctl.	0.25714	0.04900	0.20586	0.04113	0.10986
5th to 25th pctl.	0.25868	0.05548	0.19650	0.04648	0.10240
25th to 50th pctl.	0.25946	0.06751	0.19243	0.05637	0.09917
50th to 75th pctl.	0.26239	0.07453	0.19446	0.06229	0.10451
75th to 95th pctl.	0.27364	0.10181	0.20484	0.08520	0.11418
95th to 100th pctl.	0.27470	0.12104	0.24350	0.10105	0.15830

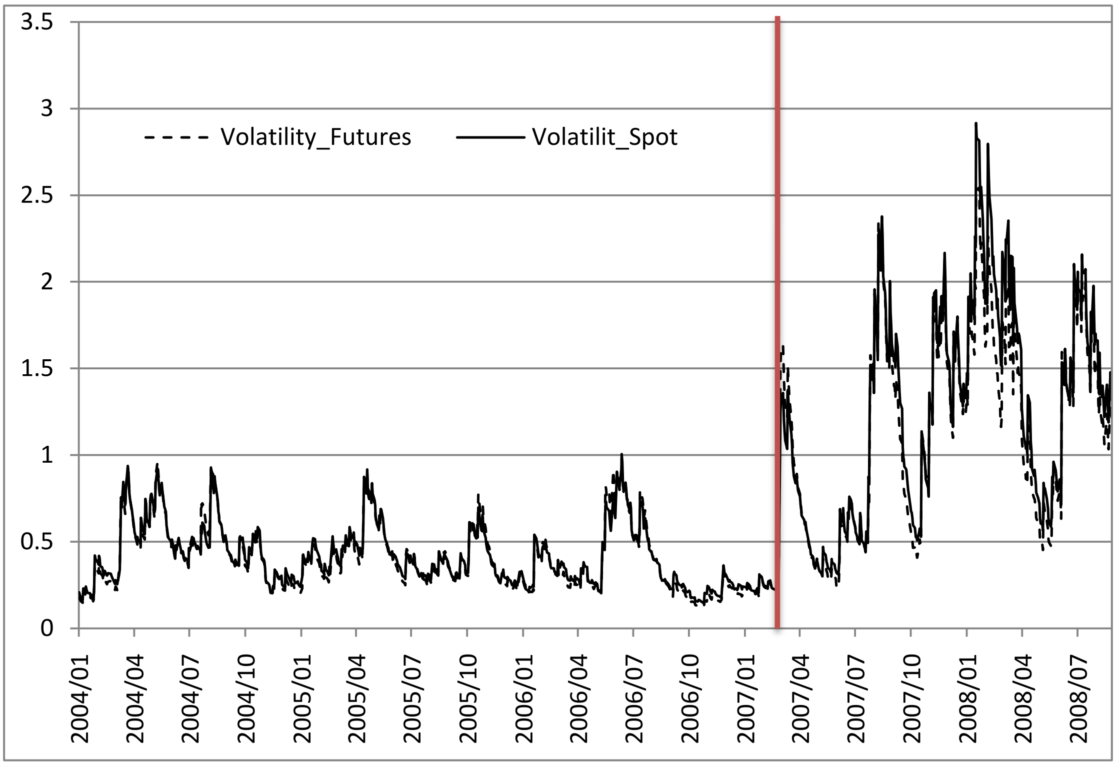
Table 10 Joint hit test results for the copula models

The *p*-values of joint hit tests if the models are correctly specified in all regions are reported. A *p*-value less than 0.05 indicates a rejection of the null hypothesis that the model is well specified. * denotes the significance at 5% level.

	Time-Varying Gaussian copula	Time-Varying Gumbel copula	Time-Varying Clayton copula
Panel A: Time-varying dependence structure between GARCH volatility and volume			
Futures during turbulent period	**0.04178***	0.11322	**0.03673***
Futures during normal period	0.33715	**0.00010***	0.30784
Spots during turbulent period	0.14409	**0.00010***	**0.00010***
Spots during normal period	0.22398	**0.00010***	**0.00010***
Panel B: Time-varying dependence structure between GK volatility and volume			
Futures during turbulent period	**0.04253***	0.12172	**0.04167***
Futures during normal period	0.77308	**0.00010***	0.82799
Spots during turbulent period	0.21870	0.23301	0.19799
Spots during normal period	0.31795	**0.00010***	0.12525

Figure 1 The conditional volatility of S&P 500 Index and its futures contracts

As the conditional variance is characterized by a GJR-GARCH(1,1)-AR(1)-*t* model given by Eq. (1), the conditional volatility of S&P 500 Index and its futures contracts are depicted in this Figure. A very strong evidence of a structural break[16] in their conditional volatilities can be found. The period from 2004 to Feb 2007 is relatively less volatile. After Mar 2007, the markets in both spot and futures become very volatile and their conditional volatilities substantially increase.



[16] A Chow test is conducted to test for a structural change.

Figure 2 Implied time path of conditional dependence between volatility and volume for futures data

This figure depicts implied time path of conditional dependence between volatility and volume for futures data. Panel (A) employs the GARCH volatility, while Panel (B) applies Garman and Klass (1980) range-based volatility. This figure shows quite clearly the structural break in the dependence across different market conditions.

(A) Conditional Volatility **(B) GK Volatility**

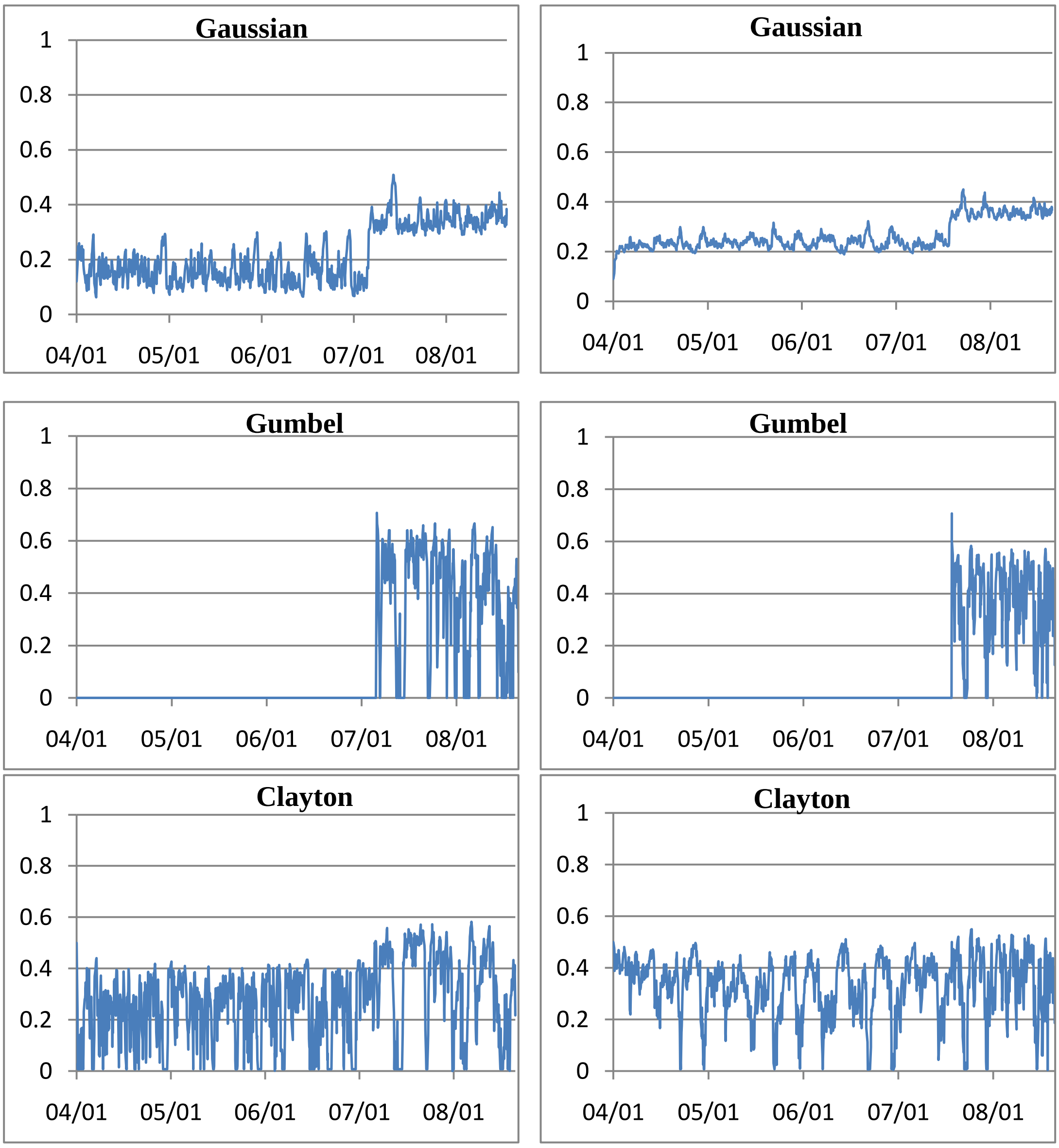


Figure 3 Implied time path of conditional dependence between volatility and volume for spot data

This figure depicts implied time path of conditional dependence between volatility and volume for spot data. Panel (A) employs the GARCH volatility, while Panel (B) applies Garman and Klass (1980) range-based volatility.

(A) Conditional Volatility **(B) GK Volatility**

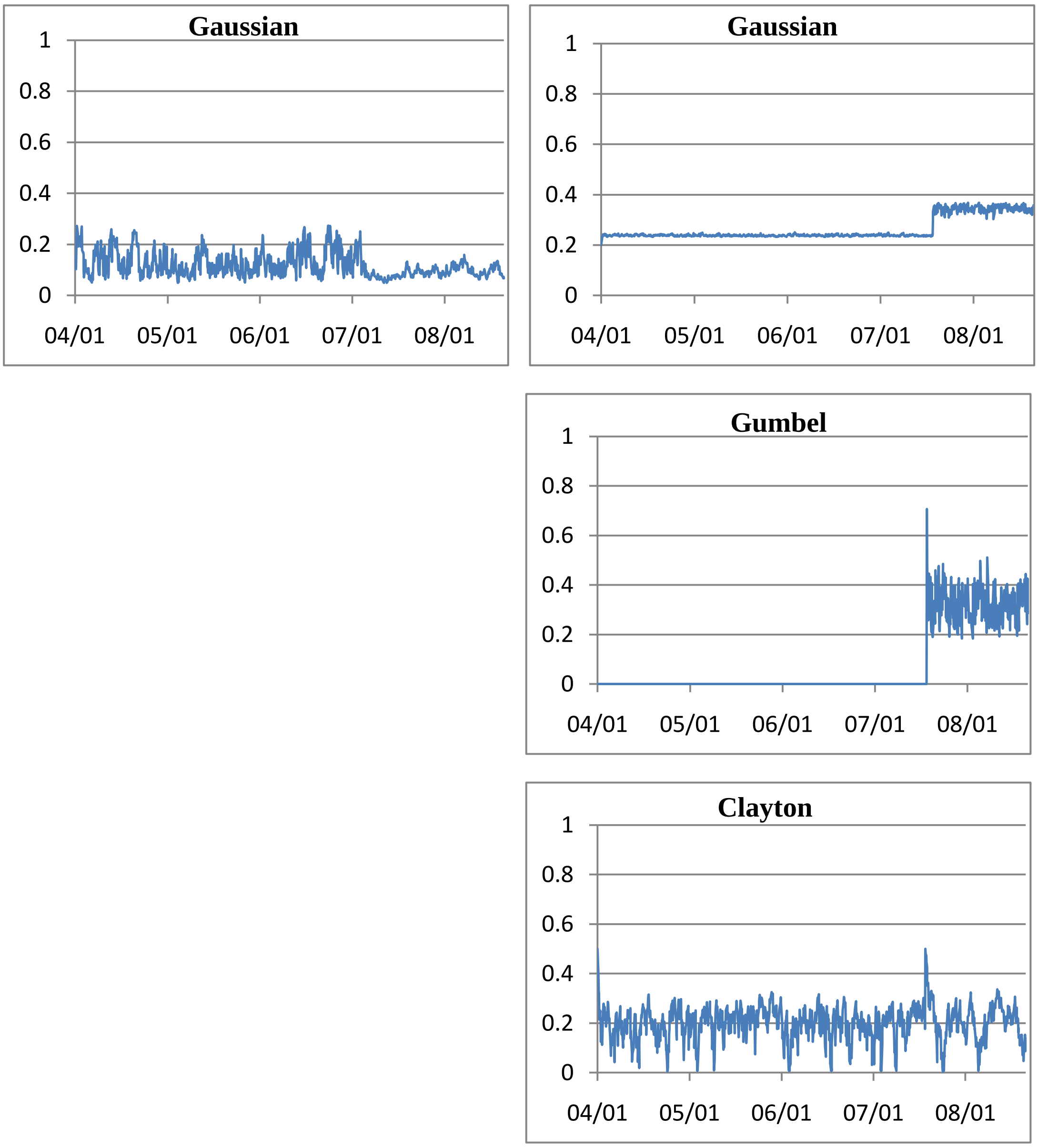
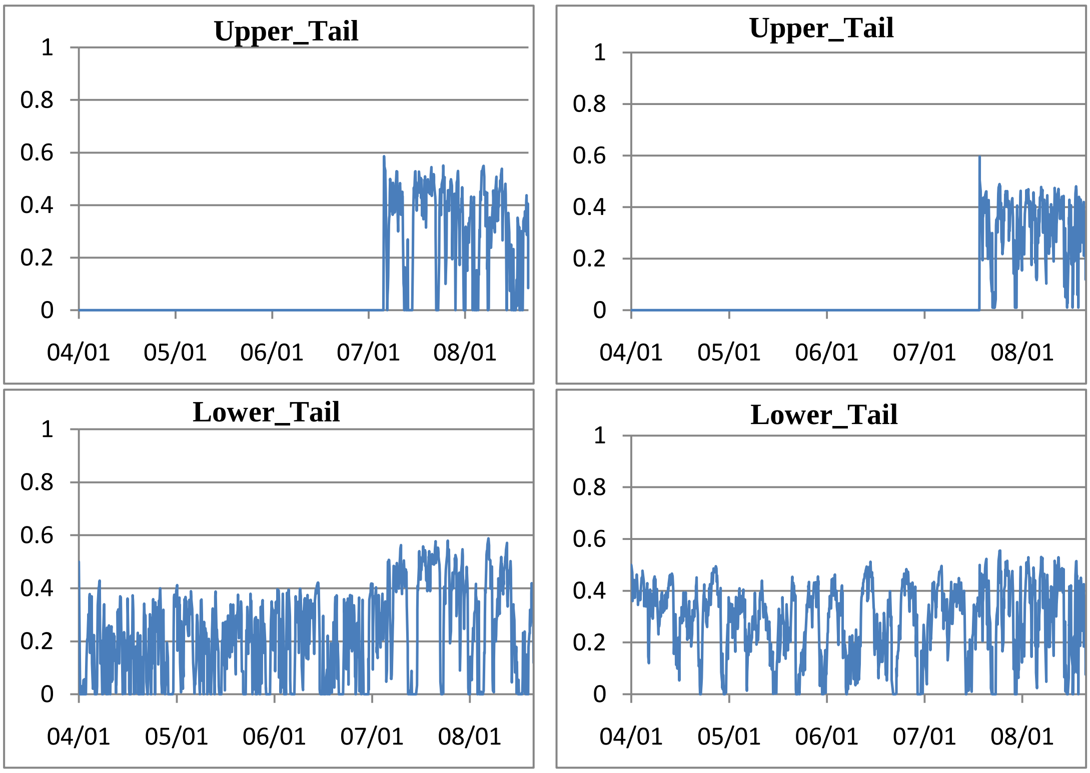


Figure 4 Implied time path of conditional tail dependence between volatility and volume for futures data

This figure depicts implied time path of conditional tail dependence between volatility and volume for futures data. Panel (A) employs the GARCH volatility, while Panel (B) applies Garman and Klass (1980) range-based volatility. This figure shows quite clearly the structural break in the upper tail dependence across different market conditions.

(A)Conditional Volatility **(B) GK Volatility**



國科會補助計畫衍生研發成果推廣資料表

日期:2011/08/03

<table>
<tr><td rowspan="3">國科會補助計畫</td><td>計畫名稱: 股票交易量與價格變動高階動差相依關係之探討：copula方法的應用</td></tr>
<tr><td>計畫主持人: 杜化宇</td></tr>
<tr><td>計畫編號: 98-2410-H-004-074-　　　　學門領域: 財務</td></tr>
<tr><td colspan="2">無研發成果推廣資料</td></tr>
</table>

98 年度專題研究計畫研究成果彙整表

計畫主持人：杜化宇	計畫編號：98-2410-H-004-074-
計畫名稱：股票交易量與價格變動高階動差相依關係之探討：copula 方法的應用	

成果項目			量化：實際已達成數（被接受或已發表）	量化：預期總達成數(含實際已達成數)	量化：本計畫實際貢獻百分比	單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	無

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估 ■達成目標 □未達成目標（請說明，以 100 字為限） 　　□實驗失敗 　　□因故實驗中斷 　　□其他原因 說明：
2. 研究成果在學術期刊發表或申請專利等情形： 論文：□已發表 □未發表之文稿 ■撰寫中 □無 專利：□已獲得 □申請中 ■無 技轉：□已技轉 □洽談中 ■無 其他：（以 100 字為限）
3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限） 有關選擇權市場效率性及微觀結構設計的研究為目前財務金融的趨勢之一，許多的實證以被提出。本計畫可在此領域有幾個明顯的貢獻：(1)本研究對於衍生性商品盤前期間交易必要性的理論提供了實證的證據。(2)價格學習的行為雖然已在許多領域上作了探討，本研究則首先將此探討應用至衍生性金融商品盤前期間的交易。(3)衍生性金融商品價格的效率性雖已存在相當多的研究，本研究則從不同的角度來探討此議題，間接地也支持了此盤前期間交易存在的必要性。(4)本研究的觀點及結果也提供了日內價格行為未來研究的一個新的方向。(5)本研究已提供資訊理論研究的一個新視野。過去的資訊實證研究大都使用以收盤價為主的日資料，本研究則將此領域的研究帶進了日內的資料及微觀結構的因素。