行政院國家科學委員會專題研究計畫 成果報告

動態 copula 模型下投資組合風險值估計之研究
研究成果報告(精簡版)

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計畫主持人：陳怡璇

計畫參與人員：博士班研究生-兼任助理人員：施冠宇

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Hedged Portfolio Value-at-Risk Estimation using a Time-varying Copula: An Illustration of Model Risk

1. Introduction

Value-at-risk (VaR) has become one of the most popular tools for risk measurement. However, it is subject to model risk, which involves the choice of models, parameters, and their implementation. Previous studies have generally discussed potential estimation biases and model risk in the VaR model (Jorion, 1996; Kupiec, 1999; Rich, 2003; Miller & Liu, 2006; Brooks & Persand, 2002). This paper assesses the potential loss of accuracy in hedged portfolio value–at-risk (HPVaR) due to estimation risk and shows that model risk in HPVaR can be attributed to inappropriate use of the correlation coefficient and normal joint distribution[1]. Jorion (1996) first indicated that VaR estimates was themselves affected by their sampling variation or "estimation risk". Brooks and Persand (BP) (2002) investigated a number of statistical modeling issues in determining market-based capital risk requirements. They highlighted several potential pitfalls in commonly applied methodologies and concluded that model risk could be serious in VaR calculation[2]. The above analysis considered univariate distribution only. This study, however, addresses this issue for bivariate distributions. Similar to that of Christoffersen and Goncalves (CG) (2005), this study employs the bootstrap resampling technique to quantify ex ante the magnitude of estimation risk by constructing confidence intervals around point HPVaR estimates.

This paper also reexamines whether a more accurate HPVaR estimate under the alternative copula-based joint distributions could be derived using the fifth percentile (5%) instead of the first percentile (1%), as currently adopted by the Basle Committee[3]. BP (2002) found that standard errors could be more severe for the first

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[1] The correlation coefficient only measures the "degree" or "level" of dependence, which reflects the overall strength of the relation. However, it fails to model the "structure" of dependence, which describes the manner in which two assets are correlated. In addition, it is neither robust enough for heavily tailed distributions nor adequate for non-linear relationships.

[2] They found that when the actual data is fat-tailed, using critical values from a normal distribution in conjunction with a parametric approach can lead to a substantially less accurate VaR estimate than using a nonparametric approach.

[3] An important issue in risk management practice is the coverage rate that should be required by the minimum capital risk requirements (MCRRs). To ensure adequate coverage, the Basle Committee chose to focus on the first percentile (1%) of return distributions. In other words, risk managers are

percentile of normal return distribution. They suggested that the closer the quantile was to the mean of the distribution, the more accurately VaR could be estimated. Thus, to ensure covering virtually all probability losses, the use of a smaller coverage rate (say, 95% instead of 99%) combined with a larger multiple was preferred. If the estimation error under the 99 % coverage rate is larger than that of the 95% coverage rate, the BP argument is supported in our study. From the univariate VaR to the bivariate HPVaR, we inquire whether the superiority of 95% coverage rate is consistent and persistent.

Copulas enable the modeler to construct flexible multivariate distributions exhibiting rich patterns of tail behavior, ranging from tail independence to tail dependence, and different kinds of asymmetry. For modeling financial risks, they are an alternative measure of correlation (Embrechts et al., 1999). This paper employs single-parameter conditional copula to represent the dependence between index futures and spot returns, conditional on historical information provided by a previous pair of index futures and spot returns. The parameter of the conditional copula, which is time-varying, depends on conditional information. This study also models the dependence structure as a mixture of different copulas with parameters changing over time. Using the hybrid copula, parametric or nonparametric marginals with quite different tail shapes[4] can then be combined in a joint risk distribution to preserve the original characteristics of the marginals (Rosenberg & Schuermann, 2006)[5]. By applying a time-varying copula approach, our conditional HPVaR model easily passes associated criticisms and avoids a biased estimation in HPVaR.

Based on the results of three backtests (unconditional and conditional coverage test, the dynamic quantile test, the distribution and tail forecast test), this study demonstrates that, under all significance levels (95% and 99%), the copula-based HPVaR model exhibits performance superior to the conventional constant conditional correlation (CCC) GARCH model (Bollerslve (1990)) and dynamic conditional correlation (DCC) GARCH model (Tse and Tsui (2002)). From the bootstrapped evidence, this study also finds that the closer the quantiles are to the mean of the distribution, the smaller the estimation error will be for both copula-based and conventional models. Our findings support and extend that of BP (2002), that is, the superiority under 95% coverage rate is confirmed for both univariate and multivariate VaR estimations.

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required to hold sufficient capital to absorb all but 1 percent of expected losses, rather than the 5 percent level used by Risk Metrics in the J.P. Morgan approach (1996).

[4] In general, marginal distributions are estimated separately.

[5] Mixtures of copulas are also copulas. See Nelsen (1999) for details.

2. Methodology

2.1. Conditional copula model

We assume that the marginal distribution for each portfolio asset return (index and its corresponding futures) is characterized by a GJR-GARCH(1,1)-AR(1)-*t* model since the asymmetric information impact is a well-known effect with financial assets[6]. Similar to the appendix in Patton (2006a), we perform a marginal distribution specification test. The test results suggest that the models for the conditional means of the spot and futures returns are AR(1). Let $R_{i,t}$ and $h_{i,t}^2$ denote asset *i*'s return (spot (s) or futures (f)) and its conditional variance for period t, respectively. Ω_{t-1} denotes a previous information set. The GJR-GARCH(1,1)-AR(1)-*t* model for asset return *i* is defined by[7]:

$$R_{i,t} = u_i + \emptyset_i R_{i,t-1} + \varepsilon_{i,t} \tag{1a}$$

$$h_{i,t}^2 = \omega_i + \beta_i h_{i,t-1}^2 + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \alpha_{i,2} s_{i,t-1}\varepsilon_{i,t-1}^2 \tag{1b}$$

$$\mathrm{z}_{i,t}|\Omega_{t-1} = \sqrt{\frac{\nu_i}{h_{i,t}^2(\nu_i-2)}}\varepsilon_{i,t} \qquad z_{i,t} \sim iid\ t_{\nu_i} \tag{1c}$$

$$i \in \{s, f\}$$

with $s_{i,t-1} = 1$ when $\varepsilon_{i,t-1}$ is negative and otherwise $s_{i,t-1} = 0$. ν_i is the degree of freedom.

Cherubini et al. (2004) claimed that copula functions with upper (or lower) tail dependence are suggested in VaR applications, and a time-varying copula is quite capable of calculating portfolio VaR. We thus employ the Gaussian, the Gumbel and the Clayton copula for specification and calibration. The Gaussian copula is generally viewed as a benchmark for comparison, while the Gumbel and the Clayton copula are used to capture upper and lower tail dependence, respectively. The Clayton copula is especially pertinent because the evidence indicates that equity returns exhibit more joint negative extremes than joint positive extremes, leading to the observation that stocks tend to crash together but not boom together (Poon et al., 2004; Longin &

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[6] 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)

[7] In Enders (2004), the Eq. (1c) can be alternatively expressed as $\varepsilon_{i,t}|\Omega_{t-1} \sim t_{\nu_i}(0, h_{i,t}^2)$.

Solnik, 2001; Bae et al., 2003)[8]. Appendix A illustrates the bivariate copula densities used in this study.

Since a portfolio with time-invariant dependences among its components seems unreasonable in reality, a conditional copula with a time-varying dependence parameter has become prevalent in the literature (Patton, 2006a,b; Bartram et al., 2007; Jondeau & Rochinger, 2006; Rodriguez, 2007). Following the studies of Patton (2006a) and Bartram et al.(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[9]. A conditional dependence parameter can be modeled as an AR(1)-like process because autoregressive parameters over lag one are rarely different from zero (Bartram et al.[10], 2007; Samitas et al., 2007). The dependence process of a Gaussian copula is therefore:

$$\rho_t = \Lambda(\beta\rho_{t-1} + \omega + \gamma|u_{t-1} - v_{t-1}|) \tag{2}$$

where $u_t = F_{s,t}(z_{s,t}|\Omega_{t-1})$ and $v_t = F_{f,t}(z_{f,t}|\Omega_{t-1})$ in Appendix A. The conditional dependence, ρ_t, depends on its previous dependence, ρ_{t-1}, and historical absolute difference, $|u_{t-1} - v_{t-1}|$. u_t and v_t are two time-varying cumulative distribution functions of random variables, as defined in appendix A. This formulation captures 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 dependence processes for the Gumbel copula and the Clayton copula are described as Eq. (3) and (4), respectively.

$$\delta_t = \beta_U\delta_{t-1} + \omega + \gamma|u_{t-1} - v_{t-1}| \tag{3}$$

$$\theta_t = \beta_L\theta_{t-1} + \omega + \gamma|u_{t-1} - v_{t-1}| \tag{4}$$

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 $\theta_t \in$

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[8] The general theory of copulas is described 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).

[9] 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).

[10] Bartram et al. (2007) assumed that the time-varying dependence process follows an AR(2) model.

$[-1, \infty)$ measures the degree of dependence in the Clayton copula. Boundaries of parameters are set up in the estimation software.

2.2. Hybrid method: A mixture of copulas

To find the copula that best estimates the HPVaR, we also consider some possible mixtures of different copulas. As indicated by Rosenberg and Schuermann (2006), integrated risk management requires a method, such as a mixture of copulas, to incorporate realistic marginal distributions. Combining realistic marginal distributions enables us to capture essential empirical features of various risks (market, credit, and operational)11. Hu (2006) pointed out that empirical applications so far have been limited to using individual copulas; however, there is no single copula that applies to all situations. A mixed model is better able to generate dependence structures that do not belong to one particular existing copula family. By carefully choosing the component copulas in the mixture, a model that is simple yet flexible enough to generate most dependence patterns in financial data can be constructed12. Beyond Hu's study, we propose a "time-varying mixture copula" (or conditional mixture copula) to generate more flexible dependence structures than existing copula families.

To capture all possible dependence structures, our time-varying mixture copula is comprised of a conditional Gaussian copula, a conditional Gumbel copula, and a conditional Clayton copula. The mixture copula can be defined as

$$C_t^{Mixture}(u_t, v_t | \rho_t, \delta_t, \theta_t)$$

$$= w_t^{Clay} C_t^{Clay}(u_t, v_t | \theta_t) + w_t^{Gum} C_t^{Gum}(u_t, v_t | \delta_t) + (1 - w_t^{Clay} - w_t^{Gum}) C_t^{Gau}(u_t, v_t | \rho_t) \quad (5)$$

where $\mathrm{w}_\mathrm{t}^{\mathrm{Clay}}$ is the time-varying weight of the conditional Clayton copula, and $\mathrm{w}_\mathrm{t}^{\mathrm{Gum}}$ is the time-varying weight of the conditional Gumbel copula. Let $\mathrm{w}_\mathrm{t}^{\mathrm{Clay}}, \mathrm{w}_\mathrm{t}^{\mathrm{Gum}} \in [0,1]$ and $\mathrm{w}_\mathrm{t}^{\mathrm{Clay}} + \mathrm{w}_\mathrm{t}^{\mathrm{Gum}} \leq 1$. These weights reflect the structures of

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[11] Regardless of the initial risk source in financial collapses (such as the outbreaks of subprime markets), all portfolios composed of an index and its corresponding futures are subject to at least two types of risk: market, credit and operational risk. The distributional shape of each risk type varies considerably. Market risk typically generates portfolio value distributions that are nearly symmetric and often approximated as normal. Credit (and especially operational) risk generates more skewed distributions because of occasional extreme losses.

[12] Hu (2006) suggests some implications for risk management. First, the use of multivariate normality and correlation coefficients to measure dependence may significantly underestimate the downside risk, while that computed using a mixed copula is much more realistic. Second, in risk measurement, the valuation model should include both the structure and the degree of dependence.

dependence and capture changes in tail dependence13. For instance, after an increase in w_t^{Clay}, the copula assigns more probability mass to the left tail. Compared to the models of Hu (2006), Li (2000), and Lai et al. (2007), our mixture copula model is not restricted to static weights as theirs, but extends to a time-varying version to flexibly capture the dynamics of dependence structures.

2.3. Data and HPVaR estimation with the time-varying copula

The Monte Carlo simulation is widely used to generate draws from stochastic models. In particular, the copula framework makes it easy to simulate portfolio returns from a general multivariate distribution (Meneguzzo & Vecchiato, 2004). Given a chosen copula function and its estimated time-varying parameter in the previous section, the multivariate random variables $\{u_t, v_t\}$can be generated. For each copula function, we generate 200 pairs of $\{u_t, v_t|\rho_t, \delta_t, \theta_t\}$ conditional on dynamic dependence coefficients $\rho_t, \delta_t, \ or\ \theta_t$. Therefore, at time *t*, conditional joint distributions such as $c(u_t, v_t|\rho_t)$, $c(u_t, v_t|\ \delta_t)$ and $c(u_t, v_t|\ \theta_t)$ can be obtained.

The next step is to convert conditional uniform random variables $\{u_t, v_t|\rho_t, \delta_t, \theta_t\}$, generated from conditional joint distributions, to portfolio component returns by constructing empirical distributions for each sample day. We use historical data from the previous sixty and ninety trading days and roll them over. Thus, given the estimated conditional joint distribution of asset returns, replicated samples can be drawn for the portfolio components.

To demonstrate the application of this time-varying copula in HPVaR estimation, we constructed a hedged portfolio comprised of the S&P 500 index and its index futures. The sample period covers January1, 2004 to October 29, 2007, including the outbreak period of the U.S. subprime market collapse from August to October 2007. A total of 998 daily observations for the index and index futures are obtained. Hsu et al. (2008) proposed copula-based GARCH models for estimating optimal hedge ratio, and found that they perform more effectively than other dynamic hedging models. We intuitively employ copula-based GARCH models to form hedged portfolios since conditional joint distributions of portfolio components in this study are specified as the Gaussian, Gumbel and Clayton copulas. On the other hand, assuming the optimal weight of the hedged portfolio as its conditional minimum-variance hedge ratio keeps

[13] Hu (2006) defined these weights as *shape parameters* to reflect dependence structures.

all variables under a time-varying version[14]. In this way, the conditional variance-covariance matrix of residual series from $(\varepsilon_{s,t}, \varepsilon_{f,t})$ in (1a), is denoted by

$$Var\left(\varepsilon_{s,t}, \varepsilon_{f,t} \middle| \Omega_{t-1}\right) = \begin{bmatrix} h_{s,t}^2 & h_{sf,t} \\ h_{sf,t} & h_{f,t}^2 \end{bmatrix},$$

The optimal conditional minimum-variance hedge ratio, $\{H_t^* | \Omega_{t-1}\}$, can then be defined as

$$H_t^* = \frac{\hat{h}_{sf,t}}{\hat{h}_{f,t}^2} \qquad (6)$$

and

$$\hat{h}_{sf,t} = h_{s,t} h_{f,t} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z_{s,t} z_{f,t} \varphi_t\left(z_{s,t} z_{f,t} \middle| \Omega_{t-1}\right) dz_{s,t} dz_{f,t}$$

where $\varphi_t\left(z_{s,t} z_{f,t} \middle| \Omega_{t-1}\right)$is a bivariate conditional joint density function of $z_{s,t}$ and $z_{f,t}$.[15] We therefore obtain the distributions of portfolio returns, $\{p_t | H_t^*\}$, conditional on dynamic hedge ratios. Using α quantile of the conditional portfolio distributions as the conditional HPVaR estimates, HPVaRs conditional on time-varying dependences between portfolio components are estimated for each sample day.

3. Empirical results of HPVaR estimation

3.1. Estimation results of the time-varying copula models

Table 1 reports summary statistics for the S&P 500 index returns and its futures returns. Table 2 shows estimated parameters of the marginal distributions characterized by a GJR-GARCH(1,1)-AR(1)-t model given by Eq. (1). As Table 2 indicates, most of the parameters are at least significant at the 5 percent level.

The Inference Function for Margins (IFM) method is implemented by estimating the marginal distribution parameters prior to the copula function parameters to enhance estimation efficiency. Joe and Xu (1996) pointed out that the IFM method makes inference for many multivariate models computationally feasible. It allows one to compare models for the dependence structure and make a sensitivity analysis of the models. In addition, it is more robust against outliers or perturbations of the data than the maximum likelihood method. Given that the marginal distributions are estimated, the parameters of time-varying correlations in the Gaussian copula are calibrated and reported in Panel A of Table 3. Appendix B describes the parameter estimation of the conditional copula. In Eq. (2), the parameter β captures the degree of persistence in

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[14] The minimum variance hedge ratio (MVHR), which is the ratio of futures contracts to a specific spot position that minimizes variance of hedged portfolio returns, has been broadly used as a futures hedging strategy.

[15] According to the Sklar theorem, the joint distribution can be represented as a copula function.

the dependence and γ captures the adjustment in the dependence process. Panels B and C in Table 3 report the estimated parameters of time-varying asymmetric dependences specified by the Gumbel and the Clayton copula, respectively. Equations (3) and (4) are their time-varying dependence processes. As suggested by Joe and Xu (1996), we apply the jackknife method to estimate the standard errors of the parameters. Appendix B describes the detail for implementing the IFM method with the jackknife for estimating standard errors.

Table 4 reports summary statistics of the weight estimates of conditional mixture copulas. These weights are estimated by MLE according to Eq. (5). Panel A reports the weight estimates across the entire sample period, while Panel B focuses on the period of the U.S. subprime market crash from August to October 2007. The statistics of weight estimates in the conditional Clayton copula generally are only marginally higher than those in the conditional Gumbel and around four to five times higher than those in the conditional Gaussian copula, indicating the conditional mixture copulas allocate more weights on left tail dependence to reflect the fact that markets are more likely to crash together than to boom together, especially during the U.S. subprime market crash. Figure 1 depicts a time series plot of the time-varying weight estimates of conditional mixture copulas.

3.2. Statistical results of conditional HPVAR estimates

Implementing the Monte Carlo simulation generates replicated samples for the index and futures returns given the estimated parameters of the time-varying dependence models in each sample day. As the optimal weight of a hedge portfolio is assumed to be its conditional minimum-variance hedge ratio in Eq. (6), conditional distributions for portfolio returns are generated for each sample day. Furthermore, 1% and 5 % quantiles of the conditional portfolio distributions are used to estimate the conditional HPVaR. Table 5 summarizes the statistics of the conditional HPVaR across the sample period. D60 and D90 are the rolling horizons, and indicate that the empirical distributions are constructed using historical data from the previous sixty and ninety trading days, respectively16. Accordingly, 998 empirical distributions across sample period are obtained. As Table 5 shows, regardless of the significance level or the rolling horizon, the conditional HPVaR estimates specified by the Clayton copula are the most strict for each statistic, whereas the Gaussian copula produces the most tolerant estimates.

A violation occurs if the actual portfolio return is worse than the HPVaR estimate. Violation numbers measure the frequency of violation, and mean violation refers to

[16] The empirical distributions are constructed by previous sixty and ninety trading days to convert uniform variables from marginal distributions to simulated index and futures returns.

the average loss in excess of the HPVaR estimates. The violation frequency is the largest in the Gaussian copula. Since the portfolio assets exhibit asymmetric dependence, especially for lower tail dependence, the stricter HPVaR estimate of the Clayton copula should be used. Table 5 shows that conditional HPVaR estimates from the Clayton copula have fewer violations and exceed by less than other copulas. The number of violations in the mixture copula is lowest, and its statistics are more modest than others.

For comparison, Figure 2 shows the time series plots of conditional HPVaR estimates with different significance levels (99% and 95%) and different rolling horizons (60 and 90 trading days). In general, the conditional HPVaR estimates from the Clayton copula are more strict than others, as was quite evident during the U.S. subprime market crash period. Note that the time series for the HPVaR estimates of the mixture copula are also less volatile.

4. Conclusion

The conventional HPVaR estimation method commonly used in current practice exhibits considerable biases due to model specification errors. This study uses HPVaR estimation to illustrate that model risk is attributable to inappropriate use of the correlation coefficient and normal joint distribution. We improve the HPVaR estimation and reduce its model risk by relaxing the conventional assumption of normal joint distribution and developing an empirical model of time-varying HPVaR conditional on time-varying dependencies between portfolio components. To demonstrate the dynamic hedging version of time-varying HPVaR comparisons, both single-parameter conditional copulas and copula mixture models are applied to form flexible joint distributions.

HPVaR estimates for optimal hedged portfolios are computed from various copula models, and backtesting diagnostics indicate that the copula-based HPVaR outperforms the conventional HPVaR estimator at the 99% and 95% significance level. Our results also demonstrate that estimation risk is more severe under nominal coverage probability of 99 percent than with 95 percent. In other words, due to estimation risk, the HPVaR point estimate with 99 percent coverage rate is quite uncertain. The copula-based model is acceptable even with estimation risk, whereas the GARCH models are absolutely invalid.

Our findings have significant implications for regulators. First, the benefit of applying the copula model to HPVaR estimation is identified after considering model risk. Second, to reduce estimation risk, HPVaR estimation using a smaller nominal coverage rate (say, 95% instead of 99%) is preferred.

行政院國家科學委員會補助國內專家學者出席國際學術會議報告

99 年 10 月 18 日

附件

報告人姓名	陳怡璇	服務機構及職稱	中華大學財務管理學系 助理教授
會議 時間 地點	99 年 7 月 14 日至 99 年 7 月 16 日 新加坡	本會核定補助文號	NSC 98-2410-H-216-007
會議名稱	(中文)2010 財務學會亞洲研討會 (英文) 2010 FMA Asian Conference		
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報告內容應包括下列各項：

一、參加會議經過

此篇論文報告於 Session 19 “Investment 1”，報告順序為第三，並且本人亦評論同一場次的論文

二、與會心得

與國際知名學者交流，獲得頗多正面的意見

三、考察參觀活動(無是項活動者省略)

四、建議

國際學術研討會對於研究績效有非常實質的助益，希望有更多的經費可補助及鼓勵國內學者多參加，將有助於國際學術交流

五、攜回資料名稱及內容

註冊費收據及會議議程紙本資料

六、其他

無研發成果推廣資料

98 年度專題研究計畫研究成果彙整表

計畫主持人：陳怡璇　　計畫編號：98-2410-H-216-007-

計畫名稱：動態 copula 模型下投資組合風險值估計之研究

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	1	1	100%		博士級研究生一人
		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	1	100%	篇	已投稿 Journal of Futures Markets
		研究報告/技術報告	0	0	100%		
		研討會論文	1	1	100%		出席 2009 FMA European Conference, Turin, Italy.
		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）

   The conventional hedged portfolio value-at-risk (HPVaR) estimation method commonly used in current practice exhibits considerable biases due to model specification errors. This study improves HPVaR estimation by relaxing the conventional assumption of normal joint distribution and developing an empirical model of time-varying HPVaR that is conditional on time-varying dependences among portfolio components.