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Estimation and Testing of Portfolio Value-at-Risk Based on L-Comoment Matrices

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This study employs L-comoments introduced by Serfling and Xiao (2007) into portfolio Value-at-Risk estimation through two models: the Cornish–Fisher expansion (Draper, N. R. & Tierney, D. E., 1973) and modified VaR (Zangari, P., 1996). Backtesting outcomes indicate that modified VaR outperforms and L-comoments give better estimates of portfolio skewness and excess kurtosis than do classical central moments in modeling heavy-tailed distributions.© 2009 Wiley Periodicals, Inc. Jrl Fut Mark 30:897–908, 2010

INTRODUCTION

Value-at-Risk has emerged as one of the standard risk measures. As an extension from the univariate case, portfolio Value-at-Risk (PVaR) helps determine the downside risk level of the whole portfolio and ideally allows for the measurement of the contribution of each risk factor within. Though challenging, one of the directions for PVaR estimation is solely based on the Cornish–Fisher expansion (Cornish & Fisher, 1937), which relies solely on an adjustment factor to estimate percentiles for non-normal distributions. The Cornish–Fisher

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expansion is known for its decomposable and analytical expression, because of a normality assumption on the return distribution. However, the adjustment factor is reliable only if the distribution is close enough to being normal (Dowd, 2005). This reliability issue calls for refinements, including the major ones such as: (1) Draper and Tierney (1973) utilize more terms in the expansion to enhance estimation accuracy and (2) Zangari (1996) corrects the skewness and excess kurtosis of the Gaussian quantile function, producing the modified VaR (mVaR). Accordingly, the performance of those two refinements are contingent upon an estimation of the moments. However, current practices mostly rely on the traditional moment estimation.

Moment estimation has played a crucial role in financial analysis, e.g. portfolio optimization and capital asset pricing model (Elton, Gruber, Brown, & Goetzmann, 2002), yet it is criticized for its heavy reliance on assumptions about second order or higher moment in the multivariate portfolio analysis. The assumptions for moment estimation are hardly supported by financial return series. For example, the traditional central moments are confined to sufficiently light-tailed distributions, while financial return series exhibit heavy-tailed properties. Hosking (1990) proposes L-moments as a better alternative for higher moment estimators, as he claims that L-moments, based solely on a finite first moment assumption, are analogous to central moments and give a coherent estimation with traditional central moments. L-Moments also give a better description of heavy-tailed distributions that financial return series usually demonstrate. Their application can be exercised not only parametrically, but also in a semiparametric and nonparametric modeling setting. Serfling and Xiao (2007) extend the model to a multivariate scenario and define multivariate L-moments or L-comoments, i.e. Gini-covariance, L-coskewness, and L-cokurtosis for orders of 2, 3, and 4, respectively. While analogous to traditional central moments, L-comoments are effective new descriptive tools and outperform in a nonparametric moment-based description of a possibly heavy-tailed distribution. So far, L-comoments have not been applied to PVaR estimation and the estimation performance has not yet been evaluated via backtesting.

This study employs six foreign exchange rate series to compose three portfolios with bivariate series. I implement two kinds of PVaR estimation and the estimates are tested through three kinds of backtesting. The outcomes indicate that the Cornish–Fisher expansion is not suitable for heavy-tailed distributions. Furthermore, mVaRs outperform in PVaR estimation and L-comoments improve the estimation for moments.

The organization of the paper is as follows. Following section discusses the PVaR models, central moments, L-comoments, and backtesting. Penultimate section describes the data sources and discusses the estimation and testing results. The last section concludes.

PVAR, CENTRAL MOMENT, L-COMOMENTS, AND BACKTESTING

PVaR

For a portfolio with n assets, PVAR at confidence level α is specified as follows:

$$VaR(\alpha) = -F^{-1}(\alpha). \tag{1}$$

Here, the return series and their respective weights are denoted as $r = (r_1, \ldots, r_n)'$ and $\omega = (\omega_1, \ldots, \omega_n'$, while $F^{-1}(\cdot)$ is the quantile function associated to the cumulative density function $F(\cdot)$ of the portfolio return distribution (r_p).

Under a location-scale representation, the portfolio return can be expressed as:

$$r_p = \omega'\mu + \sqrt{m_2}u \tag{2}$$

where μ and m_2 represent the portfolio mean and the second central moment. Here, u denotes a random variable with distribution function $G(\cdot)$ of zero mean and unit variance.

Gaussian VaR (GVaR), the PVaR under multivariate normality assumption, can be expressed as:

$$GVaR(\alpha) = -\omega'\mu - \sqrt{m_2}\Phi^{-1}(\alpha) \tag{3}$$

where $\Phi^{-1}(\alpha)$ denotes the quantile function of the standard normal distribution at α significance level.

Zangari (1996) corrects the skewness and excess kurtosis of GVaR and proposes the modified VaR (mVaR) defined as follows:

$$\omega = (\omega_1, \ldots, \omega_n)'$$

$$GVaR(\alpha) + \sqrt{m_2}\left[-\frac{1}{6}(z_\alpha^2 - 1)s_p - \frac{1}{24}(z_\alpha^3 - 3z_\alpha)k_p + \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)s_p^2\right] \tag{4}$$

where s_p and k_p are the portfolio skewness and excess kurtosis, respectively, and z_α equals $\Phi^{-1}(\alpha)$. In effect, the mVaR calculation relies on the first four moments. Favre and Galeano (2002) conclude that the skewness and the kurtosis effect are high if the VaR is computed at 99%. In essence, the moment estimation plays an important role in approximating the downside risk at extremal significance levels.

To extend GVaR to a non-normal return distribution, the Cornish–Fisher expression can be applied to the quantile function in GVaR, and the corresponding PVaR is denoted as CFVaR and defined as:

$$CFVaR = -\omega'\mu - \sqrt{m_2}G^{-1}(\alpha)$$
$$G^{-1}(\alpha) = z_\alpha + \frac{1}{6}(z_\alpha^2 - 1)s_p + \frac{1}{24}(z_\alpha^3 - 3z_\alpha)k_p - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)s_p^2 \quad (5)$$

It is proved by several literatures that the Cornish–Fisher approximations hardly improve performance even when we increase the order of approximation (see, for example, Hardle, Kleinow, & Ulfig, 2002; Jasche, 2002). Accordingly, this study only extends the mVaR and CFVaR expressions to the second order.

Central Moments

Both Equations (4) and (5) highlight that the portfolio moments are key components in PVaR estimation. Traditionally, the qth orders of portfolio central moments are defined as $m_q = E[(r_p - \omega'\mu)^q]$, and we have:

$$m_2 = \omega'\Sigma\omega$$
$$m_3 = \omega' M_3 \otimes (\omega \otimes \omega)$$
$$m_4 = \omega' M_4 \otimes (\omega \otimes \omega \otimes \omega)$$

where $\otimes$ stands for the Kronecker product. Moreover, M_3 and M_4, the third and fourth orders of portfolio moments, are the co-skewness matrix and co-kurtosis matrix and are defined as:

$$M_3 = E[(r - \mu)(r - \mu)' \otimes (r - \mu)]$$
$$M_4 = E[(r - \mu)(r - \mu)' \otimes (r - \mu)'(r - \mu)']$$

The portfolio skewness (s_p) and excess kurtosis (k_p) are given by:

$$s_p = m_3/(m_2)^{3/2} \quad (6)$$
$$k_p = m_4/(m_2)^2 - 3 \quad (7)$$

(Boudt, Peterson, & Croux, 2008)

L-Comoments

Serfling and Xiao (2007) extend the univariate L-moments of Hosking (1990) to a multivariate framework and introduce multivariate L-moment matrices to characterize descriptive features, which are typically dispersion, skewness, and kurtosis. They claim this innovative methodology offers interpretations similar to classical central moments, but only requires a first-order moment assumption. Their empirical analysis indicates that L-comoments provide more stable and efficient estimates than the classical central version. Consequently, L-comoments outperform in modeling heavy-tailed data in both parametric and nonparametric settings, and their outperformance increases with increasing order of moments and with increasing heavy tailedness.

For the n-ordered observations from a univariate distribution $x_{1:n} \leq x_{2:n} \leq \cdots \leq x_{n:n}$, the nth L-moment is defined as:

$$\lambda_n = n^{-1} \sum_{j=0}^{n-1} (-1)^j \binom{n-1}{j} E(x_{n-j:n}). \tag{8}$$

L-moments possess attractive properties in comparison to classical central moment analogues, including better asymptotic approximation to sampling distribution.

The L-moments sequence (λ_n) can also be expressed as the expected value of an order statistics, i.e.:

$$\lambda_n = \int_0^1 F^{-1}(u) P^*_{n-1}(v) dv \tag{9}$$

where $P^*_n(v) = \sum_{j=0}^{n} p^*_{n,j} v^j$ with $p^*_{n,j} = (-1)^{n-j} \binom{n}{j} \binom{n+j}{j}$. By the orthogonality of orthogonal polynomials $p^*_{n,j}$, λ_n captures the information about F. Expressed as a covariance,

$$\lambda_n = Cov[x, P^*_{n-1}(F(x))]. \tag{10}$$

Recall that the qth order central comoment matrices are defined as:

$$Cov[x^i - \mu_i, (x^j - \mu_j)^{q-1}]. \tag{11}$$

Thus, the qth order L-comoment can be defined as:

$$\lambda_{q[ij]} = Cov[x^1, P^*_{q-1}(F_j(x^j))], q \geq 2 \tag{12}$$

if Equations (10) and (11) are combined together. In essence, L-comoments are based on a comprehensive pairwise approach for descriptive measures with dimensions higher than 2. L-Comoments can provide estimates of dispersion, correlation, skewness, kurtosis, etc. in a multivariate setting.

Backtesting

Backtesting helps avoid model misspecification and differentiate the model performance under special conditions from a faulty model. In effect, backtesting

TABLE I
Construction of Conditional Exceptions

	Conditional		
	Day Before		
Current Day	*No Exception*	*Exception*	*Unconditional*
No exception	$T_{00} = T_0(1 - \pi_0)$	$T_{10} = T_1(1 - \pi_1)$	$T(1 - \pi)$
Exception	$T_{01} = T_0(\pi_0)$	$T_{11} = T_1(\pi_1)$	$T(\pi)$
Total	T_0	T_1	$T = T_0 + T_1$

Note. T_{ij} denotes the number of days in which state *j* occurred in one day while it was state *i* the previous day. π_i represents the probability of observing exceedances conditional on state *i* the previous day.

can balance Type I against Type II statistical errors in PVAR estimation. There are two major criteria for backtesting: unconditional rate of exceedances (UC) and independence of the exceedances (IND). It is expected that the significance level represents the maximum probability of observations exceeding VaR estimates if the model is correctly calibrated.

Under the null hypothesis that the significance level is the true probability of exceedances occurring, the test statistics are a log-likelihood ratio specified as:

$$LR_{UC} = -2\ln[(1-p)^{T-N}p^N] + 2\ln\{[1-N/T]^{T-N}(N/T)^N\} \sim \chi^2(1) \qquad (13)$$

where T is total days and N is the number of exceedances. This asymptotically follows a χ^2 distribution with one degree of freedom (Kupiec, 1995).

For the independence test of the exceedances, the first job is to set up a series, which indicates if the daily VaR estimate is exceeded or not. If the VaR estimate is not exceeded by the actual loss, the exceedance indicator is set at 0, or 1 otherwise. The next job is to observe the switches of exceedances. Table I shows how to construct a table of conditional exceptions. The log-likelihood test statistics are specified as:

$$\begin{aligned} LR_{IND} = &-2\ln[(1-\pi)^{(T_{00}+T_{10})}\pi^{(T_{01}+T_{11})} \\ &+ 2\ln[(1-\pi_0)^{T_{00}}\pi_0^{T_{01}}(1-\pi_1)^{T_{10}}\pi_1^{T_{11}}] \sim \chi^2(1) \end{aligned} \qquad (14)$$

where T_{ij} denotes the number of days in which state j occurred in one day while it was state i the previous day. Moreover, π_i represents the probability of observing an exceedance conditional on state i the previous day. It asymptotically follows a χ^2 distribution with one degree of freedom. The first term is specified under the hypothesis that the exceedances are independent across the sample, or $T_1 = T_0 = T_{11} = (T_{01} + T_{11})/T$. The second term is the maximized likelihood for the observed data. This test helps confirm if the exceedances are serially correlated, i.e. to examine whether the model makes systematic errors in the VaR estimates.

The conditional coverage (CC) test is designed to simultaneously test if the VaR violations are independent and the average number of exceedances is correct. The test statistics for conditional coverage are actually the sum of the test statistics of unconditional coverage and independence, i.e. $LR_{CC} = LR_{UC} + LR_{IND}$ (Christoffersen, 1998).

EMPIRICAL ANALYSIS

The foreign exchange rate series is known for its volatility process and this vibrant property makes it a challenging candidate for PVaR estimation. Six series are selected to compose three portfolios with equal weights. All the six foreign exchange series against the US dollar are retrieved from the Central Bank of the Republic of China (Taiwan) (http://www.cbc.gov.tw) for this study: Canadian Dollar, Australian Dollar, Korean Won, UK Pound, Indonesia Rupiah, and Thai Baht, and they are labeled as CAD, AUD, KRW, BGP, IDR, GBP, IDR, and THB, respectively. The data cover the period between January 5, 1993 and March 13, 2009. Natural log-returns on a daily basis are calculated and the time series plot is exhibited in Figure 1. Table II presents the summary statistics. Significant leptokurtic or fat-tailed phenomenon exists, because of excessive kurtosis. Jarque-Bera test statistics overwhelming confirm the departure of normality of the six series. The QQ plots in Figure 2 show a significant departure from normality for the six return series.

The six return series are grouped, in order of increasing non-normality, into three bivariate portfolios: Portfolio I: CAD + AUD; Portfolio II: IDR + THB;

TABLE II
Summary Statistics

	CAD	*AUD*	*IDR*	*THB*	*KRW*	*GBP*
Min	−3.74E − 02	−6.80E − 02	−3.32E − 01	−6.32E − 02	−2.03E − 01	−4.69E − 02
Mean	6.61E − 07	6.93E − 06	4.39E − 04	8.50E − 05	1.57E − 04	2.70E − 05
Median	0.00E + 00	−7.70E − 05	0.00E + 00	0.00E + 00	0.00E + 00	0.00E + 00
Max	3.31E − 02	7.61E − 02	3.03E − 01	7.40E − 02	1.35E − 01	3.96E − 02
Total N	4.03E + 03	4.03E + 03	4.03E + 03	4.03E + 03	4.03E + 03	4.03E + 03
Std Dev.	4.75E − 03	7.76E − 03	1.75E − 02	5.83E − 03	9.56E − 03	5.81E − 03
Skewness	7.06E − 02	6.15E − 01	5.74E − 01	6.05E − 01	−1.16E + 00	2.85E − 01
Kurtosis	5.99E + 00	1.06E + 01	9.96E + 01	3.72E + 01	1.08E + 02	5.17E + 00
Jarque-Bera normality test statistics	6010.64 (0.00)	19210.48 (0.00)	1661269 (0)	231205.3 (0.0)	1943319 (0.00)	4518.802 (0.000)

Null Hypothesis: data are normally distributed. *P*-value in parenthesis.k_p

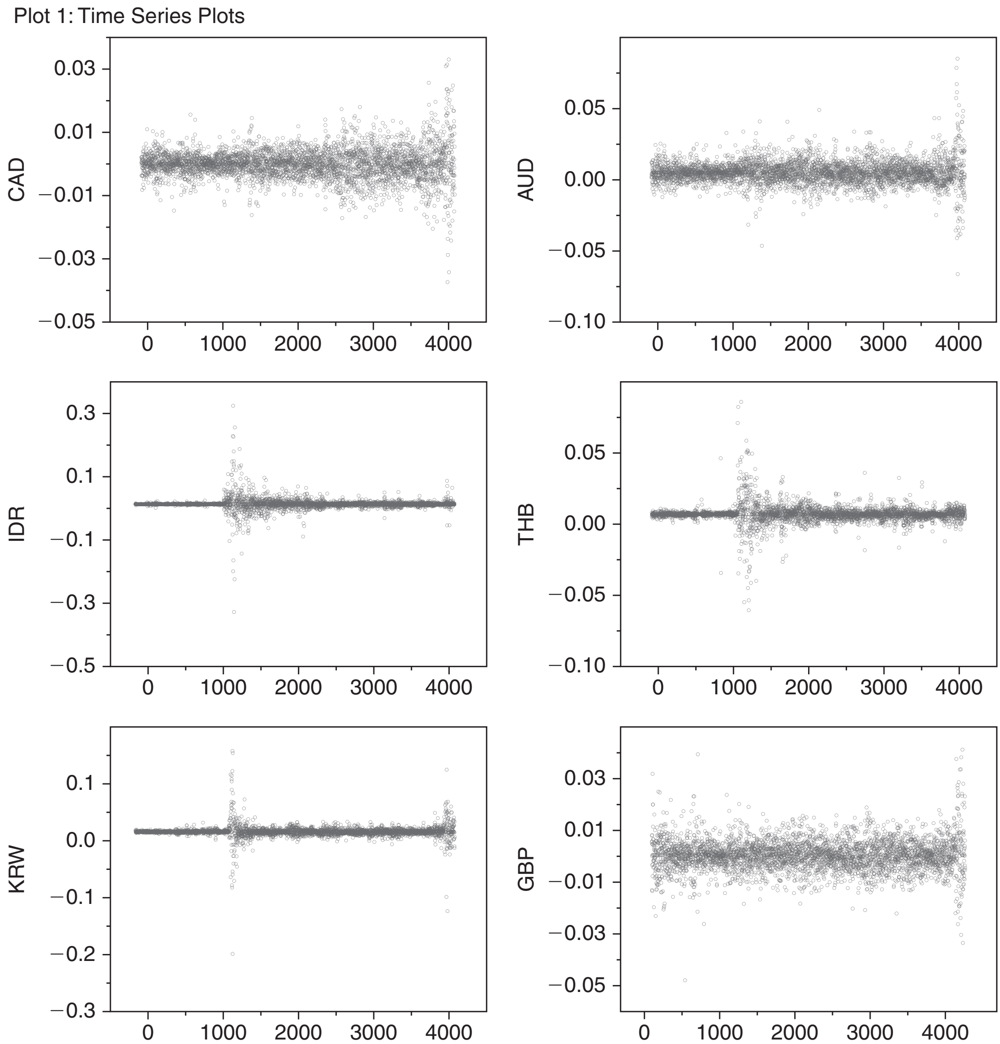

FIGURE 1
Time series plots.

and Portfolio III: KRW + GBP. Table III shows there is significant disparity in the estimates of portfolio skewness and excess kurtosis by the classical central moments and L-comoments. Figure 3 summarizes the PVaR estimates vs. their respective portfolio returns. The left and right panels show the respective contrasts at 5 and 1% significance levels. In general, CFVaR give more modest downside risk estimates than mVaR. This disparity becomes more significant as the tail areas move toward more extremal significance levels. Backtesting outcomes have significant implications in moment estimation

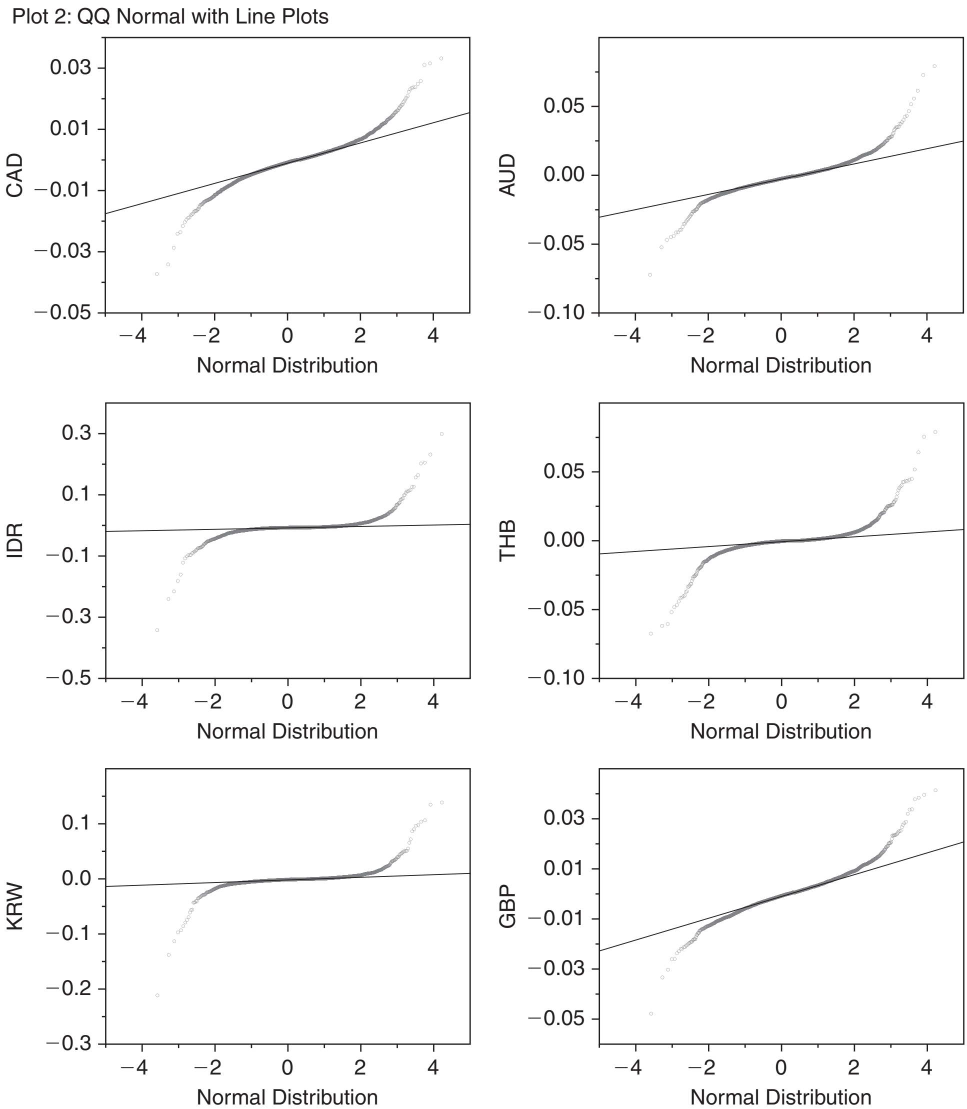

FIGURE 2
QQ normal with line plots.

and PVaR expressions by contrasting the estimates by the aforementioned methods (Table IV). In general, CFVaR underperforms mVaR in the PVaR estimation.

In the univariate setting, Cornish–Fisher expansion is a quick analytical approximation, but its performance significantly deteriorates with a departure from normality. Consequentially, CFVaR fails to give adequate performance in tail modeling, especially at higher dimensions. This disadvantage does not

TABLE III
Estimates of Portfolio Skewness and Excess Kurtosis

Method		*Classical Central Moments*	*L-Comoments*
Portfolio I: CAD + AUD	s_p	0.39341181	0.26537
	k_p	4.881089818	26.0841
Portfolio III: IDR + THB	s_p	0.574206378	0.58633
	k_p	80.48015391	47.9926
Portfolio II: KRW + GBP	s_p	−0.65107669	0.64693
	k_p	56.47661884	48.5317

Note. s_p: portfolio skewness, k_p: portfolio excess kurtosis

TABLE IV
Outcomes of Backtesting of PVAR Estimates

Model Significance Level		*mVaR(M)*		*mVaR(L)*		*CFVaR(M)*		*CFVaR(L)*	
		1%	*5%*	*1%*	*5%*	*1%*	*5%*	*1%*	*5%*
Portfolio I: CAD + AUD	UC	×	×	×	×	×	×	×	×
	IND	◦	◦	◦	◦	◦	◦	◦	◦
	CC	×	×	◦	◦	×	×	×	◦
Portfolio II: IDR + THB	UC	×	×	×	×	◦	×	×	×
	IND	×	×	◦	◦	×	×	×	×
	CC	×	×	◦	×	×	×	×	×
Portfolio III: KRW + GBP	UC	×	×	×	×	×	×	×	×
	IND	×	×	◦	◦	×	×	×	×
	CC	×	×	◦	×	×	×	×	×

× and ◦ represent rejection and nonrejection of the null hypothesis, respectively. The significance level for each null hypothesis is set at 10%. UC, unconditional coverage test; IND, independence test of the exceedances; CC, conditional coverage test.

change much with the traditional central moments or with the innovative L-comoments.

In the results, mVaRs do not pass the test of rate of exceedances, and neither do CFVaR, due to the number of major crises in the data period. However, mVaRs do not make any systematic mistake and pass the independence test and conditional coverage test. On the other hand, L-comoments exhibit significant improvement in the mVaR estimation. The mVaRs estimated by L-comoments, denoted as mVaR(L), outperform those done through traditional central moments, denoted as mVaR(M), at significance levels of both 5 and 1%. Noticeably, mVaR(L) gives sufficiently satisfactory performance in estimating the portfolio's downside risk in this study.

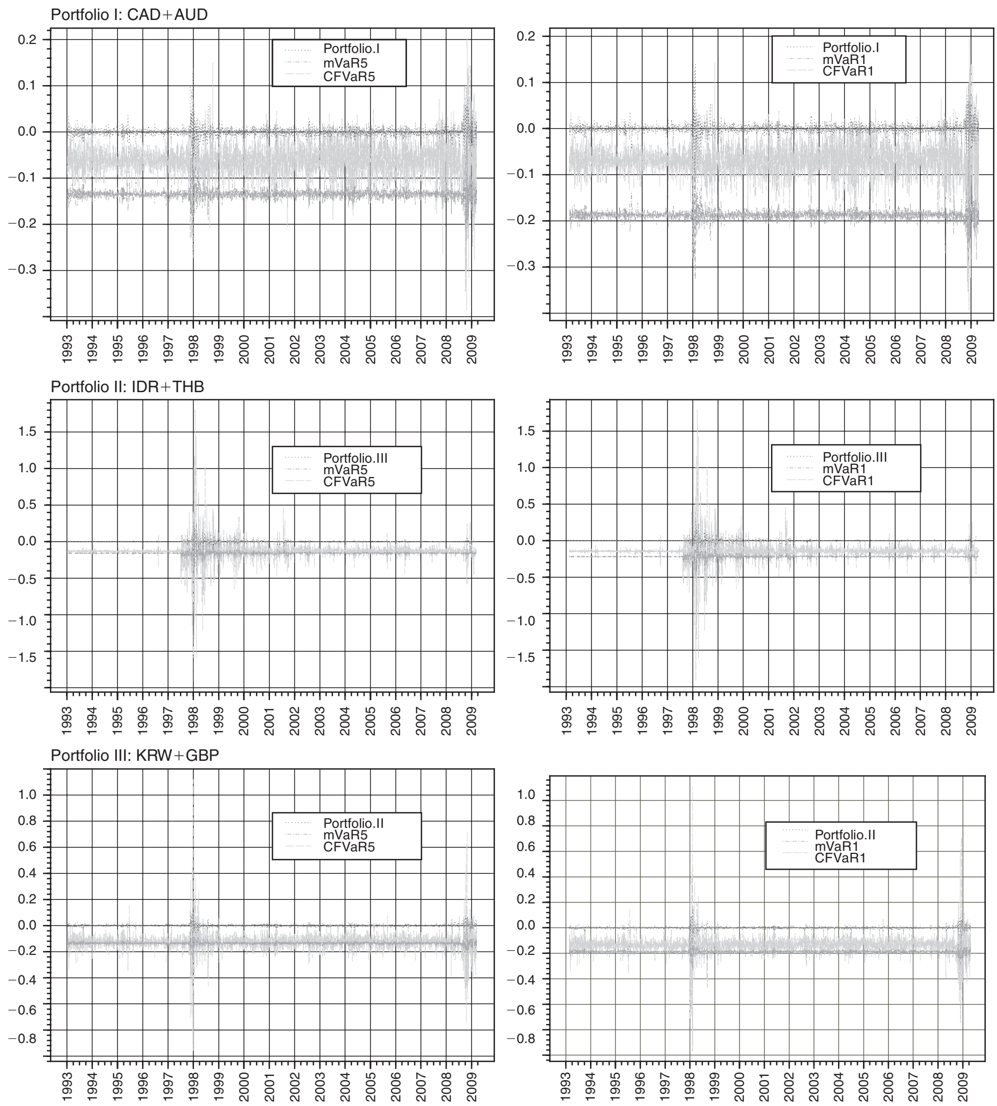

FIGURE 3

Portfolio returns vs. their PVaR estimates. Portfolio I: CAD + AUD; Portfolio II: IDR + THB; Portfolio III: KRW + GBP. The left and right panels show the respective contrasts at 5 and 1% significance levels.

CONCLUSION

The estimation of PVaR has been a challenging task, especially for non-normal returns. Previous research focuses on the derivatives of the location-scale representation, and the Cornish–Fisher expansion and mVaR are the current favorites. It is based on the assumptions that an adjustment in the higher moments or correction of portfolio skewness and excess kurtosis can help improve the estimation. This study highlights the estimation issues of the key components: the central moments. In addition to the classical central moments, this study employs the L-comoments introduced by Serfling and Xiao (2007), and their respective performance on the Cornish–Fisher expansion and mVaR are examined via backtesting.

The outcomes herein indicate that the Cornish–Fisher expansion is not suitable for the downside risk estimation of multivariate non-normal returns. Furthermore, mVaRs give better performances at the 5 and 1% significance levels. L-comoments enhance the outperformance, and backtesting shows favorable outcomes. This study not only helps identify mVaR as an acceptable candidate for PVaR estimation but also alerts that the classical central moments may not be suitable for estimating portfolio skewness and excess kurtosis in heavy-tailed distribution.

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國科會補助專題研究計畫項下國際合作研究計畫國外研究報告

日期：99 年 6 月 28 日

計畫編號	NSC 96 - 2416 - H - 343 - 005 - MY3		
計畫名稱	探討風險 - 報酬關係之三篇論文專案		
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出國時間	99 年 6 月 14 日至 99 年 6 月 26 日	出國地點	Toronto, Canada

一、 國際合作研究過程

此次利用學期末短期訪問加拿大多倫多大學 Field Institute，除了聆聽幾場演講，並得就近請教多位大師以外，期間並參加了該單位陸續所舉辦之兩次國際性重大會議：2010 Insurance: Mathematics and Economics 年會與 2010 Bachelier Congress 年會，收穫可謂豐富。

二、研究成果

已初步獲得可行研究方案重要者包括：

(一) Portfolio Value-at-Risk 以往利用分量估計之結果，仍易受到參數穩定性

(parameter stability)、估測方法本身缺陷等所限，致使估測結果往往被質疑強烈性(robustness)不足，故而可以提議利用超過某界限值之中位數，以取代一般所較廣為接受之尾端期望值(conditional tail expectation)，亦即超過某界限值之平均值。如此一來，加以結合 multivariate order statistics 之新近研究，預計可已有所突破。

(二) 所發表論文中將 Gram-Charlier expansion 推廣至多維情況應用於用於 Portfolio Value-at-Risk 估測以外，還可以運用於 multivariate contingent claims 以及 rainbow option pricing 等。

(三) 隨著諸多問卷與市場訪調資料的公布，microeconometrics 的應用也將逐步擴大，財金議題的相關研究也應逐步投入。

(四) 在精算界所廣泛應用討論之 Wang's transform 已應用於 catastrophe bond 等保險評價與風險管理等議題，目前尚未延伸至非常態分佈與多維情況，尚待嘗試開發。

(五) 回顧測試(backtesting)以往著重在於異常現象之發生頻率(frequency)、次數(count)與相互獨立性(independence)，較少討論其持續性(duration)與異常現象之強度(intensity)，應可從 compound Poisson process 來探討其綜合現象。

(六) 另外以往討論風險測量值尚未加入風險偏好程度(risk preference)之因素，也應可納入討論分析。

二、 建議

無

三、其他

結識加拿大精算學界數位學者，分別任教於 Toronto University, Simon Fraser

University, Waterloo University 等，將持續洽商長期訪問事宜。

國科會補助專題研究計畫項下出席國際學術會議心得報告

日期：99 年 04 月 21 日

計畫編號	NSC 96－2416－H－343－005－MY3		
計畫名稱	探討風險－報酬關係之三篇論文專案(3/3)		
出國人員姓名	劉威漢	服務機構及職稱	淡江大學財務金融學系 助理教授
會議時間	2010 年 4 月 16 日 至 2010 年 4 月 17 日	會議地點	University of Illinois at Chicago
會議名稱	(中文) R 在財務領域之應用 (英文) R/Finance 2010: Applied Finance with R		
發表論文題目	(中文)根基於多維度偏態分佈之改良式一般化 Gram-Charlier 展開式 (英文) Improved Generalized Gram-Charlier Expansions based on Multivariate Skew Distributions		

一、 參加會議經過

基於國際 R 社群部分成員之互動(例如會議召集人 Peter Carl, Dirk Eddelbuettel, Brian Peterson, Jeff Ryan) ，以及去年同一會議之成功經驗，今年受邀與會發表個人近來研究焦點。

二、 與會心得

(一) 高頻分析仍是深具研究潛力，與會者中數位來自於避險基金業界，亦從技術專業中獲利豐厚，甚幸 R 也有幾種套件已經開發完成，完成深值得熟悉後投入實證研究。

(二) Marc Wildi 所著專書"Signal Extraction"中: 宣稱所開發之預測能力優於其

他傳統方法，並有 R 套件配合，頗受到與會者矚目，令人引發學習興趣。

(三) 另有一些 R 套件可供雲端運算以及電腦多核心演算，個人正逐步熟悉應用中。

三、考察參觀活動(無是項活動者略)

四、建議

國內學術機構也應儘早召開類似會議，結合產學專業人士以建立地區性連絡社群網絡，進一步發展 R 在財務領域之應用。

五、攜回資料名稱及內容

無研發成果推廣資料

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）

全球金融風暴方興未艾，除了整頓市場紀律，產官學界無不努力尋求改進量化管理之技術，風險測量值之測度在多維情況下之深入探討更是深具意義。技術本身除了尤其在於投資組合管理方面至為關鍵風險管理，其他領域例如營運風險，也是深具實用價值，深值持續精進研發。

Liu, W.-h. (2010). "Estimation and testing of portfolio value-at-risk based on L-comoment matrices." Journal of Futures Markets.

Liu, W.-h. and Z. Zhou (2009). "Inflation-hedging behavior of a securitized real estate market: Empirical evidence from Hong Kong." International Real Estate Review 12(3): 221-251.