Measurements of the Effects of Socio-Economic Reforms

by

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June, 2003

Abstract

Korea has experienced tremendous changes in economic structure and regulatory statutes in the past half century. In particular, at the behest of the IMF after the financial crisis in 1997, numerous economic reform measures have been proposed and implemented. Past studies on the effectiveness of these reform measures have focused on the change in mean and volatility of the rate of equity returns. Many reform measures, however, seem to be designed to reduce low-end risk to avoid another financial crisis. In this paper we propose to use the ratios of low quantiles (Value-at-Risk) or mean excess losses (Conditional Value-at-Risk) of the distributions of equity returns as a summary statistics for the effectiveness of risk-reducing reform measures. Their usefulness is demonstrated by using Korean equity return data.

Measurements of the Effects of Socio-Economic Reforms

1. Introduction

There exists a voluminous literature on the East Asian financial crisis, which addresses the causes of the crisis, institutional and legal reforms and restructuring efforts taken by each country, and the assessment of the various reforms. One of the recurring theme in this literature is the institutional weakness of the financial sector before the crisis in credit and risk assessment capabilities, prudential supervision and governance, inadequate capital ratios, and preparation in capital market opening.

The restructuring and reform programs after the crisis focused on the improvement of such institutional weakness and improving the quality of bank loan portfolios that has been deteriorated since the onset of the financial crisis. In Korea, the National Assembly passed financial reform bills in December, 1997 which granted independence to the central bank with price stability as its main objective, established a unified financial regulatory agency (the Financial Supervisory Commission and the Financial Supervisory Board), and enhanced prudential regulations over financial institutions for safe and sound operations.

Financial reform bills are followed by massive restructuring of the financial sector, forced closures and mergers, and massive infusion of public funds for recapitalization and disposal of non-performing loans. In particular, enhanced prudential regulations involved the improvement of the BIS capital adequacy ratio, strengthening prudential rules in risk assessment and management, and the improvement of transparency and accountability to the level of the international standard.

Implementation of these reforms is expected to help the competitiveness of the financial industry, and to ensure its safety, soundness and stability. Though the financial reforms will help the profitability of the financial industry and promote the efficiency of resource allocation, their main function seems to be a reduction in the downside risk and prevention of another big surprise. In this paper, we are interested in constructing a statistical index that measures the relative success of the downside-risk reducing function of the financial reforms[1].

Our choice of the statistical index is based on the premise that, in a country with well developed financial markets, asset prices incorporate all information about the current and expected future effects of various reforms which are deemed important to domestic as well as international investors. Financial reforms are expected to affect not only the location and scale of the distribution, but also the shape of the distribution. Furthermore, they will also affect the joint distribution of asset prices across different industries or countries.

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[1] The downside risk of financial industry must be affected not only by the reforms specifically targeted to the industry, but also by other social, political and educational reforms. However, since our index is based on the relative performance of the financial industry against the performance of a benchmark industry or economy, the effects of other changes will be removed as long as they affect both sectors equally.

Statistics that are widely used to represent the location, scale and shape properties of the distribution are the mean, variance, correlation, skewness and kurtosis coefficients. These statistics play important roles in the analysis of financial data for the optimum portfolio or for the test of contagion hypothesis of financial crisis. However, individually, they are not sufficient to describe the changes in the distributions. The statistical index we wish to construct is to capture the changes in the distribution, in particular, changes in the low tails of the distribution of asset prices or asset returns.

There are several statistics that can serve our purpose. The first candidate is the Value-at-Risk (VaR), which is a low-end percentile of a distribution and is expected to capture the changes in location, scale, skewness and kurtosis of the asset return distributions. Since the introduction of JP Morgan's RiskMetrics system in 1995, the VaR has become a standard tool for risk management partly because it is an easily interpretable summary measure of risk and also has an appealing rationale. We offer another interpretation of the VaR as a measure of aggregate effects of reforms that are designed to reduce the downside risk[1]. This interpretation is also in line with the event studies which are used frequently in finance literature. A typical event study examines the presence of abnormal returns around the time of certain events. Thus, it is interested in finding the changes in the tail probability for a given critical value and association of such changes with certain regulatory changes, while the VaR analysis is interested in finding the critical value for a given tail probability. In addition to the VaR based index, we may also consider an index based on a related concept, the conditional Value-at-Risk (CVaR) or mean excess loss. While the VaR focuses only on the probability of loss, it does not indicate the extent of the losses that might be suffered beyond the threshold amount indicated by VaR. The CVaR quantifies such losses, which is the conditional expectation when the losses exceed the level of VaR.

Another candidate we may consider is from the view point of investors. Assuming that investors are risk-averse expected utility maximizers, we may use the changes in the stochastic dominance of the distributions in the second or third degree. If the distribution after the financial reform dominates the previous distribution in the second degree, the expected utility of all risk averse investors will be higher, and the reform can be considered as a success. Though it is an attractive alternative, we suspect that the complete stochastic dominance relationship will hold rarely over time. To implement this alternative we need to develop preference ordering on the basis of incomplete or partial stochastic dominance. And thus, we have not tried

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[1] The VaR risk management rules are similar in spirit to the 'safety-first rule' which is affected by the changes in the shape of the distribution. In this sense, our index based on the VaR may be considered as an index from the view point of the investors who follow the safety-first rule or an extreme case of prospect theory. Since the VaR is affected by many common risk factors other than the reform measures we need a benchmark VaR to isolate the effects of the reform measures on the distribution.

this approach in this paper.

In the next section, we present brief descriptions of the VaR based index of the assessment of the changes, and discuss the estimation strategies. Importance of the choice of flexible distribution function in the estimation of VaR and CVaR is also discussed. In section 3, we applied the procedure to the Korean financial market daily return data. The results are encouraging: the index seems to reflect the events in regulatory changes well. The likelihood of excessively large losses of the finance and banking sectors relative to the entire equity market have stabilized since mid 2000. However, the level of excess loss risks are not lower than the pre-financial crisis levels. The paper concludes in section 4 with a summary of the findings and suggestions for future studies.

2. Methodology

The Value-at-Risk is the low-end percentile (usually 1% or 5%) of the distribution of asset returns, and is taken as a measure of the market risk of a portfolio. Though the concept of the VaR is simple and attractive, its estimation is not unique. There is a wide variety of estimation models and methods, and there are substantial evidences that different methodologies lead to significantly different estimates of VaR for the same portfolio. The quality of inference we can derive from the VaR estimates thus depend critically on the quality and accuracy of the model.

Since we wish to interpret the changes in the VaR as an indicator of the effects of various socio-economic reforms and restructuring, we need to identify the data series of an economic sector which is the target of the reforms and hence affected the most by the reforms. An examination of the changes in the VaR of a target data series over time may reveal the effects of reforms, and one may design a formal test of the stability of the VaR. However, the distribution of asset returns are subject to many shocks other than the reform measures, and we need to control the effects of such shocks.

A reasonable approach to accomplish this is through a comparison of the target series VaR and the VaR of a benchmark data series. It will be ideal to have a benchmark data which is subject to the same set of shocks as the target series VaR, while it is not affected or affected the least by the reforms under study. For example, when we are interested in the effects of reform measures in, say, the financial sector, we may take the VaR of the composite return index of the entire market excluding the financial sector as the benchmark VaR. The differences or ratios of the target and benchmark VaR's will show the effects of the reforms aimed at the target series.

Identification of the target and benchmark data series becomes less important when one is interested in the international comparison. A comparison of the VaR's of the same economic (say, financial) sector in two countries is expected to show the relative successes of the sector specific policies. It is conceivable that a comparison of the VaR's of the composite return indices of two countries can reveal the relative effects of all socio-economic changes between the two countries.

Another important issue to consider is the choice of the distribution function for the estimation of the VaR. JP Morgan's RiskMetrics system assumes a joint normal distribution of asset returns. However, it is well known that financial asset returns are in general leptokurtic and skewed, and VaR estimates based on the normality assumption can lead to significantly biased estimates. There exist a large number of skewed leptokurtic parametric distributions functions in the literature that have been employed in the analysis of individual financial data. The first set of parametric distribution functions are introduced to capture the excess kurtosis, and includes the central Student's t distribution, the *generalized error distribution* (GED) and the *generalized t* (GT) distribution. The GED has one shape parameter and the GT distribution has two shape parameters. Both distributions can be leptokurtic as well as platykurtic, while the central t can only be leptokurtic[1].

Though these distributions can capture the leptokurtic nature of the financial data, they cannot accommodate the skewness. This motivated Hansen (1994) to generalize the central t distribution by introducing a skewness parameter. Since Hansen's method can be applied to any symmetric distribution, the GED and GT distributions are subsequently generalized to take asymmetric distributional forms by Theodossiou (1998, 2000). In earlier literature, Tauchen and Pitts (1983) and Hsieh (1989) employed the normal-lognormal mixture distribution and McDonald (1991) introduced the exponential generalized beta of the second kind (EGB2) distribution, which has two shape parameters. More recently, a noncentral t distribution is used in Harvey and Siddique (1999) in their study of the stochastic process of the skewness, and Nagahara (1999) and Bera and Premaratne (2001) introduced the Pearson Type IV distribution, which has two shape parameters[2]. Figure 1 shows the density curves of skewed t (ST), skewed GED (SGED), skewed GT (SGT), Pearson Type IV (P4), and EGB2 distributions, along with a normal density curve for a comparison. All densities shown in Figure 1 have the same mean and same variance.

Our study requires VaR estimates of at least two series of asset returns including the benchmark asset

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[1] The central t-distribution is used in Bollerslev (1987), Hsieh (1989), Baillie and DeGannaro (1990) and De Jong, Kemna and Kloeck (1990) among others, the GT distribution is introduced by McDonald and Newey (1988), and the GED is used in Baillie and Bollerslev (1989) and Nelson (1991). The GED is also called Power Exponential distribution, or Subbotin distribution, or Box-Tiao distribution, and it nests several distribution functions such as normal, and Laplace distributions. The GT distribution nests the GED, central t and normal distributions.

[2] In addition to these distributions, the Gram-Charlier, Edgeworth and Edgeworth-Sargan asymptotic expansions have been used in finance literature, particularly in option pricing. See for example Jarrow and Rudd (1982), Lee and Tse (1991), Mauleón and Perote (1999, 2000), Clews, Panigirtzoglou and Proudman (2000), Dinenis, Flamouris and Hatgioannides (2000), Giamouridis and Tamvakis (2002), among others. See also Mittnik and Paolella (2003) for the use of a family of α-stable distributions.

returns. An efficient estimation thus requires a multivariate distribution function which is flexible enough to be able to generate the empirical values of skewness and kurtosis of financial data. Unlike in the case of univariate models, however, there have been little efforts to introduce more flexible distribution functions beyond the multivariate Student's t distribution. The common form of multivariate t distribution is characterized by a symmetric positive definite covariance matrix and a degree of freedom parameter. Since the marginal distributions of the multivariate t are scalar multiples of univariate t, this distribution can account for the thick tails of individual distribution. However, it requires all variables to share the same parameter for the degree of freedom, and hence all variables are restricted to have equally thick tails. Furthermore, it is a symmetric distribution and hence, cannot accommodate the skewness in the data[1]. This can be a serious drawback particularly when the major interest is in the comparison of the estimates of tail probabilities of different data series. In this paper, we will estimate the unconditional distribution functions of the target series and benchmark series individually by using one of the flexible distribution functions discussed above.

The choice of the distribution function depends on the degree of their flexibility. It was shown in Choi and Hwang (2003) that the SGED is one of the most flexible distribution functions among the distribution functions mentioned above in the sense that it can cover the widest range of skewness and kurtosis. In particular, it can be platykurtic as well as leptokurtic. In the empirical application to the rates of returns of Korean stocks, we found that many subsamples exhibit platykurtic sample moments. Consequently, we use the SGED in the empirical application.

The density function of a Hansen-type skewed GED with a zero location parameter and unit scale parameter is given by[2]

$$f(y; k, \lambda) = \begin{cases} C e^{-|y|^k / b_1}, & b_1 = 2(1-\lambda)^k \quad \mathit{if} \;\; y < 0 \\ C e^{-|y|^k / b_2}, & b_2 = 2(1+\lambda)^k \quad \mathit{if} \;\; y \geq 0 \end{cases} \tag{1}$$

where k is a positive shape parameter, λ is a skewness parameter in an interval (-1, 1), and

$$C = \frac{k}{2^{(1+1/k)}\Gamma(1/k)}$$

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[1] See Mauleón and Perote (1999) for a bivariate t distribution model, and Fiorentini, Sentana and Calzolari (2000) for the analytical score functions and the test of normality under multivariate t distribution. Mauleón and Perote (1999) also introduced a Edgeworth-Sargan distribution model, which is a multivariate version of Gram-Charlier expansion. Recently, skewed multivariate Student's t (Azzalini and Capitanio (2003)) and skewed multivariate Laplace (Kotz, Kozubowski and Orski (2003)) distributions have been introduced in the statistics literature, but, to our best knowledge, they have not been used in the analysis of financial data. Wang (2001) used multivariate normal mixture distribution in the analysis of financial data.

[2] See Choi and Hwang (2003) for more details of the distribution function.

where Γ is a gamma function. The density function of a SGED with a location parameter α and scale parameter θ can be derived from a linear transformation $X = \alpha + \theta Y$. The VaR and the CVaR of X are derived in Appendix.

3. Empirical Application

Parameters of a distribution function are typically estimated by maximizing the likelihood function of unconditional distribution or the conditional distribution in the form of a GARCH model. Since we are interested in finding the change in a distribution relative to another distribution over time, the simplest method for our purpose is to use the rolling window. This approach requires a choice of window width and the size of increments, which can be critical in detecting any changes. A wide window width or a large increment may miss detecting relatively short-lived changes. On the other hand, a narrow window width or a small increment can lead to inefficient estimates of parameters and may not smooth out pure random shocks[1]. To avoid over-smoothing, we used a rolling window of size 125 days (6 months) with 10 day (two week) increments in our empirical analysis.

We used the data set of daily percentage rates of return in Korean stock market[2]. This data set has 1771 observations that cover the sample period of 1995/1/4 - 2001/7/2, and includes data on KOSPI index (excluding finance sector), finance sector (excluding banking sector) and banking sector. As mentioned earlier, there are many subsamples of each data series which show platykurtic sample moments, i.e., sample kurtosis coefficients less than 3. Among the distribution functions described above, the only distribution functions that allow such properties are the SGED and SGT distributions. Since the SGT distribution has one more parameter than the SGED and the maximum likelihood estimation of its parameters often does not converge, we use the SGED. Parameters of the unconditional SGED distribution are estimated by the maximum likelihood method and ratios of VaR and CVaR between a pair of data series are computed by using the sample in each window.

The left hand side panels of Figure 2 show the ratios of VaR and CVaR (dashed line) between finance sector and KOSPI, between banking sector and KOSPI, and between banking and finance sectors. The right hand side panels show the ratios which are estimated from the standardized sample in each window. This is

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[1] In the earlier version of this paper, we reported the results of numerical experiments that examined how well the VaR and CVaR ratios between two series of data computed from the rolling window estimates capture the changes in one distribution when parameters are estimated by the maximum likelihood from subsamples of rolling window. The results showed that these ratios detect the changes of distribution shape parameters quite well.

[2] Bong Soo Lee generously provided the data that he used in his paper with Heungsik Choe, “Korean bank governance reform after the Asian financial crisis,” Working paper, April 2003.

to isolate the effects of changes in skewness and kurtosis[1].

Both VaR and CVaR ratios stay close to each other except for a few short periods. The ratios of the finance and banking sectors against KOSPI are greater than one for most periods of the series. This indicates that the two sectors have a greater risk of large losses, which is an expected result as the KOSPI is a broad market index and is diversified more than the finance or the banking sector alone. The ratios of the banking sector to the finance sector are also greater than one for most part of 1997 through 1999, indicating a greater risk in the banking sector than the finance sector around the financial crisis and two years after the crisis[2].

Since late 1995, the risk of excess losses in the finance and banking sectors relative to the overall KOSPI index was improving till June, 1997 for the finance sector and till September, 1996 for the banking sector. As the financial crisis loomed up, the risk of excess losses in both sectors rose sharply, peaking off in August 1997, and then declined sharply perhaps in anticipation of the IMF funding agreement on December 3, 1997. It is interesting to notice that, compared to the financial sector, the banking sector seems to respond more quickly to the factors that cause a decline in excess loss risk and more slowly to the factors that cause an increase in the excess loss risk.

Overall increases in the risk of excess losses in both sectors followed the earlier sharp declines, reaching the peak in June, 1999 for the financial sector and in September, 1999 for the banking sector despite of a flurry of reform activities such as the change in the selection procedure of bank president (03/02/98), establishment of financial Supervisory Commission (04/01/98), Bank Act Revision hearings (10/21/98) and draft of the revision (12/15/98) and management reforms of a major bank (04/13/99)[3]. Perhaps in anticipation of certain passage of the Bank Act Revision in December 1999, the excess loss risks started decline early in the financial sector and two months before the passage of the new law in the banking sector. After further reform activities from mid April to early June, 2000, the completion of work-outs earlier than expected in particular, the excess loss risks of these two sectors relative to the KOSPI index have stabilized.

The excess loss risks after various reform measures during 1998 through mid 2000 seem to have settled at a level a little higher than the low levels of excess loss risks before the effects of financial crisis set in. It appears that various reform measures aggravated the excess loss risks at their introduction and implementation stages.

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[1] Since the results and interpretations of the two panels are similar, we will concentrate our discussion on the left panel.

[2] Choe and Lee (2003) define the pre-crisis period as the period till September 30, 1997. The windows of the samples that include this date are between two vertical lines in Figure 2.

[3] The dates of special events are borrowed from Choe and Lee (2003).

To see the benefit of using a flexible distribution function SGED, we also estimated the ratios of VaR and CVaR by using the maximum likelihood estimates of normal distribution parameters and by using the RiskMetrics method[1]. Figure 3 presents these results. Note that the ratios of VaR and CVaR are almost identical for both cases. The RiskMetrics method produces more volatile ratios, which is expected because of the fast decaying weights. Comparisons of the VaR ratios between the SGED and normal, and between the SGED and RiskMetrics are presented in Figure 4. In general, the ratios based on the normal distribution show less variations than the estimates from the SGED. Consequently, the normal distribution underestimates the risk of excess losses when the risk is relatively high, and overestimates it when the risk is relatively low.

4. Conclusion

We proposed in this paper to use the ratios of VaR and/or CVaR to detect the effects of financial reform measures on the premise that the current and expected effects of such measures are best summarized in the movements of prices and rates of returns of financial assets. They are particularly useful when one wishes to analyze the effects of financial reform measures which are designed to reduce an excessive loss or financial crisis. We proposed to use the ratios of VaR's or CVaR's between the target series and benchmark series to control the effects of the events which affect both data series.

It is important for a proper analysis to use a flexible distribution function that can be leptokurtic/platykurtic and skewed in the estimation of the distribution function of the rates of returns. We proposed to use the skewed generalized error distribution (SGED). This distribution can be leptokurtic as well as platykurtic, and it covers all skewness and kurtosis of the sample that we used in this paper.

The VaR and CVaR of the daily rates of returns of the KOSPI, the financial and banking sectors in Korean stock market are estimated using the SGED distribution. Both estimates show the variation of the ratios which can be matched with several events of regulatory changes. The estimates also show that the likelihood of excessively large losses of the finance and banking sectors relative to the entire equity market have stabilized since mid 2000. However, the level of excess loss risks are not lower than the pre-financial crisis levels. To illustrate the importance of using a sufficiently flexible distribution function we also presented the estimates of VaR and CVaR by using the maximum likelihood estimates and RiskMetrics estimates of a normal distribution. The RiskMetrics estimates generate much more volatile estimates and it is difficult to draw any conclusion about the effects of financial reforms from them. The normal distribution tends to underestimate the risk of excess losses when the risk is relatively high, and overestimates it when

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[1] The RiskMetrics assumes a normal distribution, but computes the variance by a exponentially declining weighted sum of the squared deviation of the return rate from the mean. The decay rate of 0.94 is commonly used.

the risk is relatively low.

Though the concept of the VaR and CVaR is simple and attractive, its focus on the gloomy situation may not fit the objectives of all research. One may be interested in the effects of policy changes on the stability of the distribution, i.e., not only on the low tails, but also on the upper tails. The typical measure of the stability, or lack of stability, is the variance (volatility) of the return. The variance cannot capture the changes in the shape of the distribution in a satisfactory way. As an alternative, one may examine the changes in the inter-quantile ranges.

Figure 1. Probability Densities

(μ_1=0.02, μ_2=0.4, β_2=5)

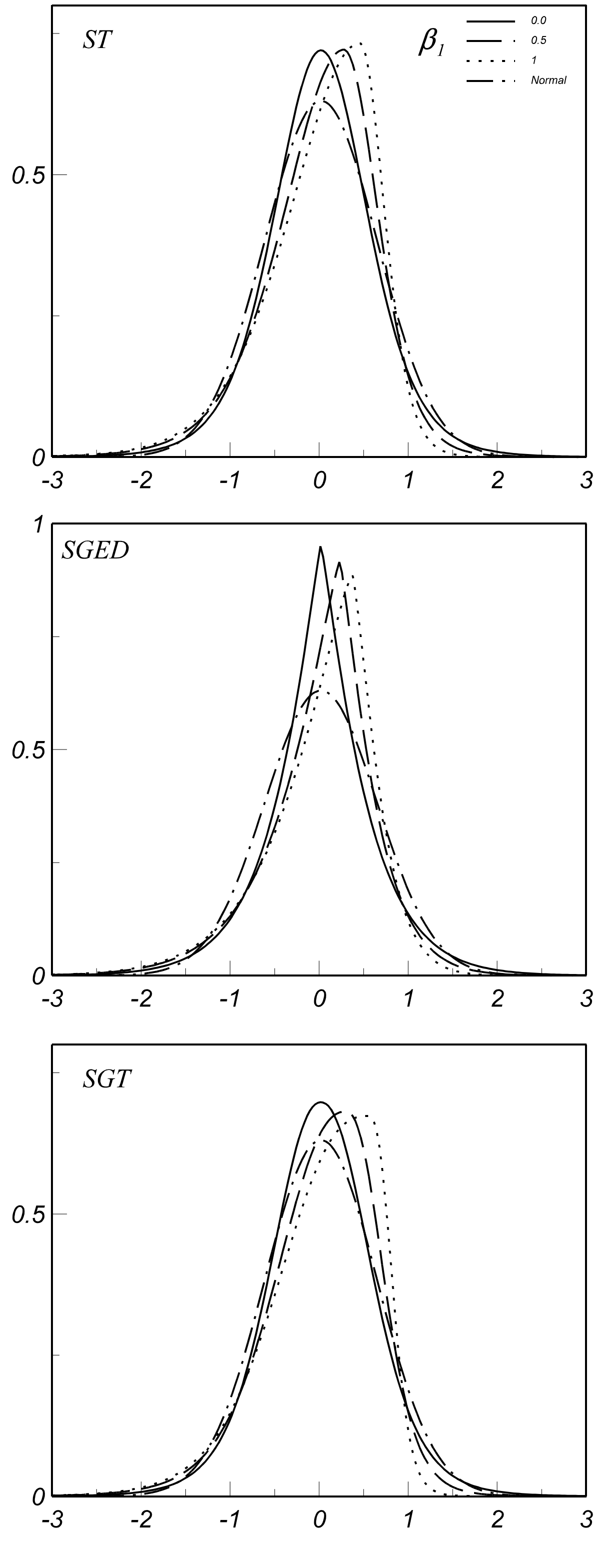


Figure 2. Ratios of VaR and CVaR - SGED Distribution

(wn=125, dn=10)

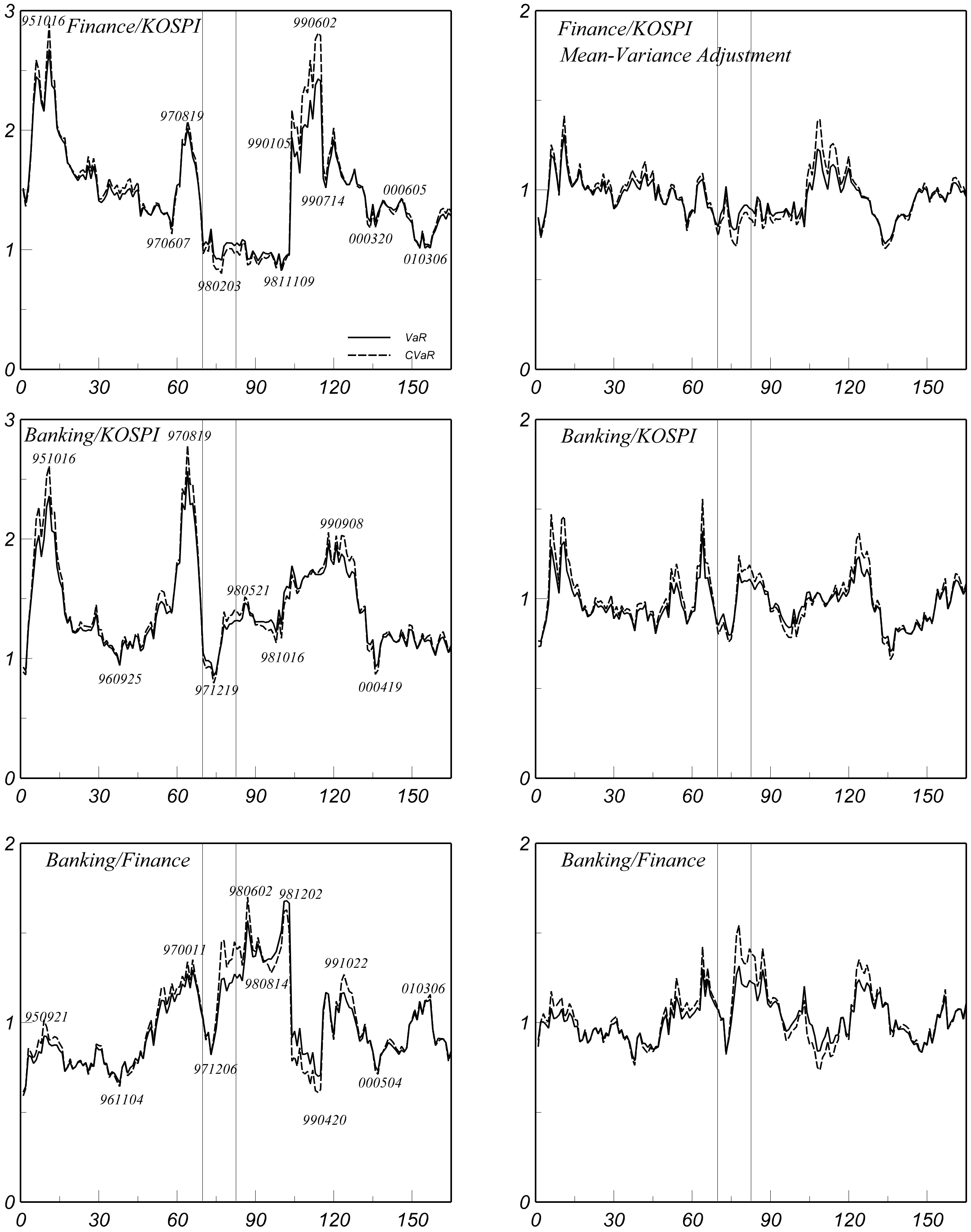


Figure 3. Ratios of VaR and CVaR under Normal and RiskMetrics

(wn=125, dn=10)

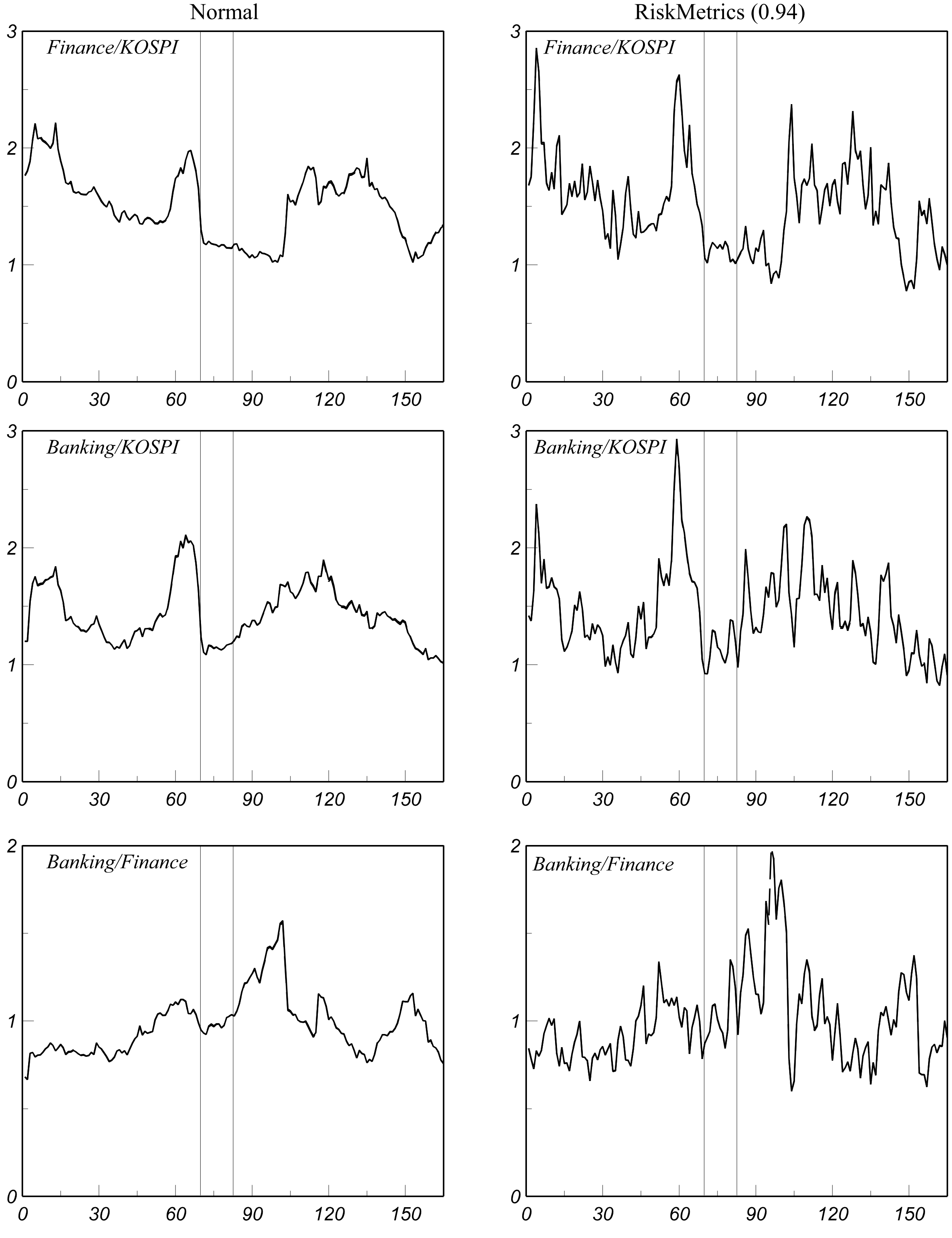
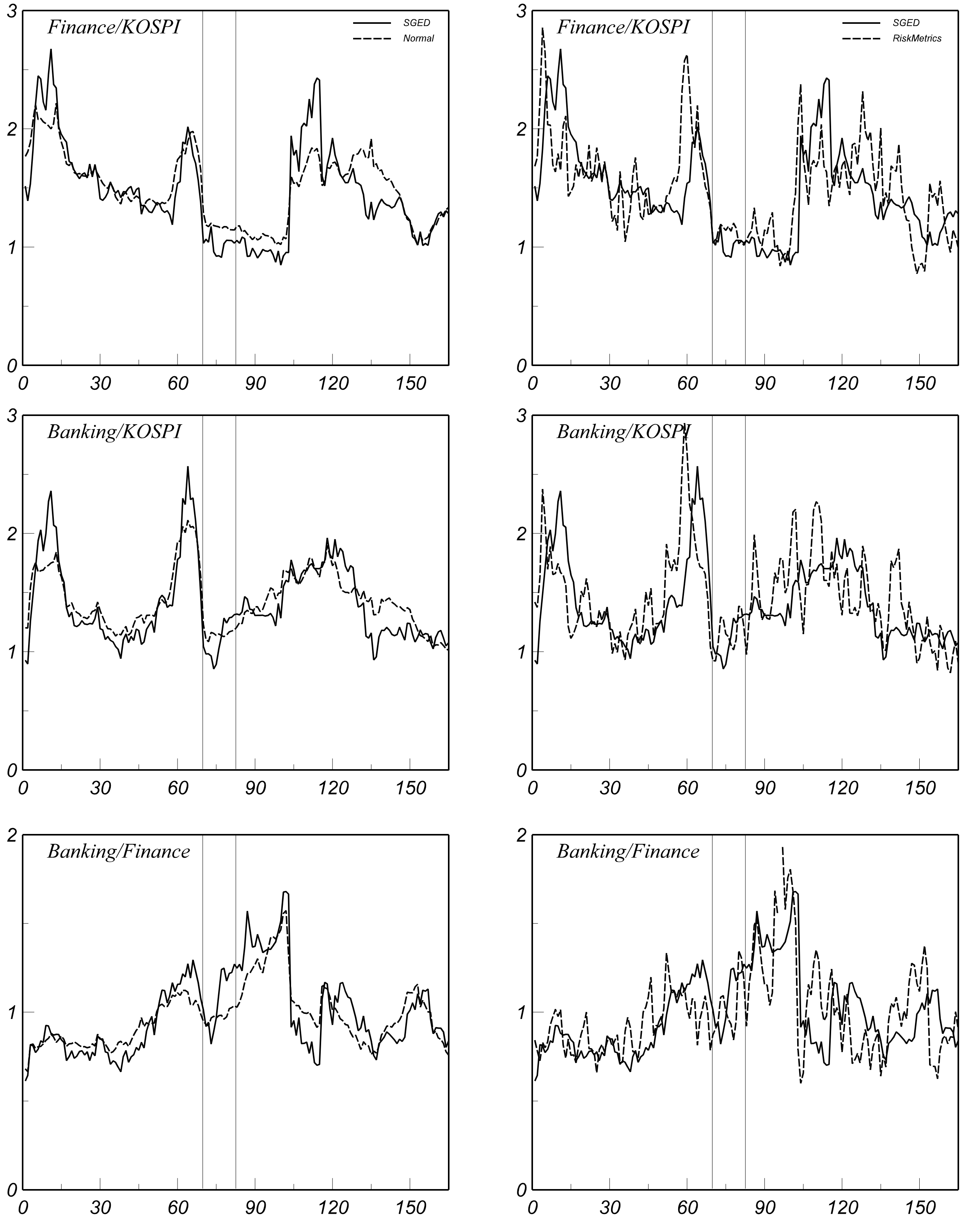


Figure 4. Comparison of VaR Ratios under GED, Normal and RiskMetrics

(wn=125, dn=10)



Appendix

Derivation of VaR and CVaR of Skewed GED

The density function of a Hansen-type skewed GED with a zero location parameter and unitary scale parameter is

$$f(y;k,\lambda) = \begin{cases} Ce^{-|y|^k/b_1}, & b_1 = 2(1-\lambda)^k \quad \textit{if} \;\; y<0 \\ Ce^{-|y|^k/b_2}, & b_2 = 2(1+\lambda)^k \quad \textit{if} \;\; y \geq 0 \end{cases} \tag{A.1}$$

where

$$C = \frac{k}{2^{(1+1/k)}\Gamma(1/k)}$$

and its cdf is

$$F(y;k,\lambda) = \begin{cases} \frac{1}{2}(1-\lambda)[1 - G(1/k, y_1^*)] & \textit{if} \;\; y<0 \\ \frac{1}{2}[(1-\lambda) + (1+\lambda)G(1/k, y_2^*)] & \textit{if} \;\; y \geq 0 \end{cases} \tag{A.2}$$

where $y_1^* = \dfrac{|y|^k}{2(1-\lambda)^k}$ and $y_2^* = \dfrac{|y|^k}{2(1+\lambda)^k}$, and

$$G(a,z) = \frac{1}{\Gamma(a)} \int_0^z e^{-t} t^{a-1} dt$$

is the incomplete gamma function with a shape parameter *a*. This can be computed by using proc ***cdfgam*(*a*,*z*)** in GAUSS software.

Note that $F(0)=(1-\lambda)/2$. Hence, the condition y<0 in the cdf is equivalent to $p \equiv F(y) < (1-\lambda)/2$. Using this, we can write the inverse cdf for a given p and λ as

$$G(1/k, y_p^*)] = \begin{cases} 1 - 2p/(1-\lambda) & \textit{if} \;\; 0<p \leq (1-\lambda)/2 \quad (\textit{i.e.}, \; y \leq 0) \\ [2p-(1-\lambda)]/(1+\lambda) & \textit{if} \;\; (1-\lambda)/2 < p \leq 1 \quad (\textit{i.e.}, \; y>0) \end{cases} \tag{A.3}$$

Once y_p^* is found from the inverse incomplete gamma function, the p-th quantile y_p of the skewed GED random variates can be computed from

$$y_p = \begin{cases} -(1-\lambda)[2y_p^*]^{1/k} & \textit{if} \;\; 0<p \leq (1-\lambda)/2 \\ (1+\lambda)[2y_p^*]^{1/k} & \textit{if} \;\; (1-\lambda)/2 < p \leq 1 \end{cases} \tag{A.4}$$

To find the mean of the truncated distribution

$$E(Y|Y<y_p) = \frac{1}{F(y_p)} \int_{-\infty}^{y_p} y f(y;k,\lambda) dy \tag{A.5}$$

The moments of this truncated distribution can be derived by using the following integrals for b>0

$$\int_{a_0}^{a_1} y^r e^{-|y|^k/b} dy = \frac{1}{k} b^{(r+1)/k} \int_{a_0^k/b}^{a_1^k/b} t^{[(r+1)/k]-1} e^{-t} dt \qquad \mathit{if}\ a_1 > a_0 \geq 0 \tag{A.6a}$$

which is derived by a change in variables ($t = y^k/b$). Similarly, for negative values of y we can write

$$\int_{a_0}^{a_1} y^r e^{-|y|^k/b} dy = (-1)^r \frac{1}{k} b^{(r+1)/k} \int_{(-a_1)^k/b}^{(-a_0)^k/b} t^{[(r+1)/k]-1} e^{-t} dt \qquad \mathit{if}\ a_0 < a_1 \leq 0 \tag{A.6b}$$

Applying these integral relationships we can write (A.5) in the case of $y_p \leq 0$ as

$$\begin{aligned} E(Y|Y<y_p) &= \frac{1}{F(y_p)} \int_{-\infty}^{y_p} y f(y;k,\lambda) dy = -\frac{1}{F(y_p)} \frac{C}{k} b_1^{2/k} \Gamma(2/k) \int_{(-y_p)^k/b_1}^{\infty} \frac{e^{-t} t^{2/k-1}}{\Gamma(2/k)} dt \\ &= -\frac{b_1^{2/k} C \Gamma(2/k)}{k F(y_p)} \left[1 - G\left(\frac{2}{k}, \frac{(-y_p)^k}{b_1} \right) \right], \qquad y_p \leq 0 \end{aligned} \tag{A.7a}$$

When $y_p \geq 0$, we have

$$\begin{aligned} E(Y|Y \leq y_p) &= \frac{1}{F(y_p)} \left(\int_{-\infty}^{0} y f(y;k,\lambda) dy + \int_{0}^{y_p} y f(y;k,\lambda) dy \right) \\ &= \frac{1}{F(y_p)} \left(-C \frac{b_1^{2/k} \Gamma(2/k)}{k} + \frac{b_2^{2/k} C \Gamma(2/k)}{k} G\left(\frac{2}{k}, \frac{y_p^k}{b_2} \right) \right) \\ &= \frac{C \Gamma(2/k)}{k F(y_p)} \left(-b_1^{2/k} + b_2^{2/k} G\left(\frac{2}{k}, \frac{y_p^k}{b_2} \right) \right), \qquad y_p \geq 0 \end{aligned} \tag{A.7b}$$

Now, we introduce the location and scale parameters through a linear transformation

$$X = \alpha + \theta Y$$

The VaR and the CVaR of X can be computed from the relationship

$$p = P(X \leq v) = P(Y \leq (v-\alpha)/\theta) \tag{A.8a}$$

$$E(X|X \leq v) = \alpha + \theta\, E(Y|Y \leq (v-\alpha)/\theta) \tag{A.8b}$$

Once y_p is found from (A.4) and the truncated mean from (A.7), the VaR of X can be computed from (A.8a) by $v = \alpha + \theta y_p$, and the CVaR of X can be computed from (A.8b).

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