DEPARTMENT OF ECONOMICS AND FINANCE

COLLEGE OF BUSINESS AND ECONOMICS

UNIVERSITY OF CANTERBURY

CHRISTCHURCH, NEW ZEALAND

Value-at-Risk for Country Risk Ratings*

Michael McAleer, Bernardo da Veiga, and Suhejla Hoti

WORKING PAPER

No. 29/2010

Department of Economics and Finance
College of Business and Economics
University of Canterbury
Private Bag 4800, Christchurch
New Zealand

Value-at-Risk for Country Risk Ratings*

Michael McAleer

Econometric Institute
Erasmus School of Economics
Erasmus University Rotterdam
The Netherlands
and

Tinbergen Institute
The Netherlands
and
Department of Economics and Finance
University of Canterbury
New Zealand

Bernardo da Veiga

School of Economics and Finance
Curtin University of Technology

Suhejla Hoti

Department of Treasury and Finance
Western Australia

Revised: May 2010

*The authors are most grateful to Robert Beauwens and two anonymous referees for helpful comments and suggestions. The first author wishes to acknowledge the financial support of the Australian Research Council, National Science Council, Taiwan, Center for International Research on the Japanese Economy (CIRJE), Faculty of Economics, University of Tokyo, and a Visiting Erskine Fellowship, College of Business and Economics, University of Canterbury, New Zealand.

Abstract

The country risk literature argues that country risk ratings have a direct impact on the cost of borrowings as they reflect the probability of debt default by a country. An improvement in country risk ratings, or country creditworthiness, will lower a country's cost of borrowing and debt servicing obligations, and vice-versa. In this context, it is useful to analyse country risk ratings data, much like financial data, in terms of the time series patterns, as such an analysis would provide policy makers and the industry stakeholders with a more accurate method of forecasting future changes in the risks and returns of country risk ratings. This paper considered an extension of the Value-at-Risk (VaR) framework where both the upper and lower thresholds are considered. The purpose of the paper was to forecast the conditional variance and Country Risk Bounds (CRBs) for the rate of change of risk ratings for ten countries. The conditional variance of composite risk returns for the ten countries were forecasted using the Single Index (SI) and Portfolio Methods (PM) of McAleer and da Veiga [10,11]. The results suggested that the country risk ratings of Switzerland, Japan and Australia are much mode likely to remain close to current levels than the country risk ratings of Argentina, Brazil and Mexico. This type of analysis would be useful to lenders/investors evaluating the attractiveness of lending/investing in alternative countries.

Keywords: Country risk, risk ratings, value-at-risk, risk bounds, risk management.

1. Introduction

A variety of univariate and multivariate conditional volatility models was used in Hoti and McAleer [6] to analyse the dynamics of the conditional volatility associated with country risk returns for 120 countries across eight geographical regions. This extensive analysis classified the countries according the persistence of shocks to risk returns and the correlation coefficients of the conditional shocks to risk returns. Similarly, Hoti [4] provided an analysis of economic, financial, political and composite risk ratings using univariate and multivariate volatility models for nine Eastern European countries. The empirical results enabled a comparative assessment of the conditional means and volatilities associated with country risk returns, defined as the rate of change in country risk ratings, across the countries. Moreover the estimated constant conditional correlation coefficients provided useful information as to whether these countries are similar in terms of shocks to the four risk returns.

Hoti and McAleer estimated and tested the constant conditional correlation asymmetric VARMA-GARCH models for four countries. The paper analysed the conditional means and volatilities of economic, financial, political and composite risk returns and evaluated the multivariate spillover effects of the four risk returns for a country. Indeed, significant multivariate spillover effects were found in the rate of change of country risk ratings (or risk returns) across economic, financial, political and composite risk returns. Moreover, Hoti [5] was the first attempt to model spillover effects for risk returns across different countries. The paper provided a novel analysis of four risk returns using multivariate conditional volatility models for six countries situated in the Balkan Peninsula. The empirical results showed that these models are able to capture the existence of country spillover effects in the country risk returns.

The purpose of this paper is to adapt the popular Value-at-Risk (VaR) approach in forecasting the conditional variance and Country Risk Bounds (CRBs) for the rate of change of risk ratings for ten representative countries. This paper demonstrates how this approach can be used not only by the countries wishing to attract foreign investments (or borrowing money), but also by the parties considering making such investments (or loans).

Empirical results suggest that the country risk ratings of Switzerland, Japan and Australia are much more likely to remain close to current levels than the country risk ratings of Argentina, Brazil and Mexico. This type of analysis would be useful to lenders/investors in evaluating the attractiveness of lending/investing in alternative countries.

The plan of the remainder of the paper is as follows. Section 2 describes country risk and country risk ratings. Section 3 extends the traditional VaR framework and introduces a new risk measure called Country Risk Bounds that is more useful in analysing country risk ratings. The models used are discussed in Section 4, while the data is described in Section 5. Section 6 presents the forecasting exercise and discusses the policy implications. Finally, some concluding remarks are given in Section 7.

2. Country Risk and Risk Ratings

The country risk literature distinguishes between the risk associated with a borrowing sovereign government and the risk associated with lending/investing in country as a whole, including individual borrowers residing in the country. While the later type of risk refers to country risk, the former is known as sovereign risk, which is the risk exposure vis-à-vis a sovereign government. Moreover, the literature holds that economic, financial and political risks affect each other.

Country risk may be prompted by a number of country-specific and regional/external factors. There are three major components of country risk, namely economic, financial and political risk. A primary function of country risk assessment is to anticipate payment problems by borrowers due to domestic and foreign economic, financial and political reasons. Country risk assessment evaluates economic, financial, and political factors, and their interactions in determining the risk associated with a particular country.

The importance of country risk analysis is underscored by the existence of numerous prominent country risk rating agencies, such as Moody's, Standard and

Poor's, and International Country Risk Guide, and Political Risk Services (for a critical survey of the country risk rating systems, see Hoti and McAleer [6,7]).

Country risk ratings are crucial for countries seeking foreign investment and selling government bonds on international financial markets, and for lending and investment decisions by large corporations and international financial institutions. Rating agencies provide qualitative and quantitative country risk ratings, combining information about economic, financial and political risk ratings into a composite risk rating. This is particularly important for developing countries, for which there is limited information available. Country risk ratings help developing countries to enter capital markets and provide economic, financial and political officials with essential tools to assess such risks.

Agency risk ratings play a central role in integrated capital markets. As discussed by PRS Group [12], country risk ratings as well as forecasts of country risk rating changes are very important for various parties in internationally oriented firms, lending institutions, insurance companies, and government offices. These parties include the president, vice president, business manager, project manager, project risk manager, director, strategic planner, finance officer, international officer, corporate security officer, economist, and market analyst. All these officials employ country risk measures and forecasts in different ways in order to anticipate and plan for the political, economic, and financial risks involved in international business operations.

However, failure by the rating agencies to predict a number of financial crises demands a thorough evaluation of agency rating systems. Rating systems have changed, especially after the South East Asian, Russian and South American crises of 1997-2002. These crises highlighted the need to accommodate factors such as contingent liabilities, adequacy of international reserves, relative likelihood of default on local currency against foreign currency sovereign debt, and assessment of individual debt instruments in selective default scenarios (see Bhatia [2]). Moreover, agency risk ratings may add to the instability of international financial markets. Amato and Furvine [1] argue that when rating agencies evaluate a risk rating, they overreact relative to the present state of the aggregate economy.

In view of the above, accurate forecasts of future changes in country risk are crucial. This paper is the first attempt in country risk literature to adapt the popular Value-at-Risk approach in forecasting changes in country risk ratings. The paper demonstrates how this approach can be used not only by countries wishing to attract foreign investments (or borrowing money), but also by parties considering such investments (or loans).

3. Country Risk Bounds

The traditional VaR risk approach measures the extent of an extraordinary loss in an ordinary day. VaR is a technique that helps quantify the potential size of losses, given a certain confidence level, and it is widely used in the banking industry to determine appropriate capital requirements that can be set aside to protect banks from adverse movements in the value of their trading portfolios. However, for country risk ratings both the potential maximum negative and positive returns are of interest.

From a lender's point of view, it is easy to see why predicting the maximum negative change in country risk rating is important. The most obvious reason is that large negative changes in country risk ratings can indicate a substantial increase in the likelihood of default. Therefore, lenders can employ the VaR analysis developed in this paper to help quantify the probability of default, which will aid lenders in deciding what rates to charge. Furthermore, debt covenants could be constructed in such a way as to take into account not only the current country risk rating but also the forecasted VaR threshold. Such covenant could, for example, stipulate higher interest rates if the forecasted VaR figure was to fall below a pre determined level.

However, for lenders, the size of potential positive changes in country risk ratings is also of importance. For example, lenders typically hold a diversified portfolio of loans, which includes a mixture of high and low risk loans. Substantial changes in the risk ratings of debtors will change the composition of the loan portfolio. Such change in composition, if matched by appropriate changes in interest rates, may be of concern for lenders as they can adversely change the risk/return profile of the loan portfolio and may require costly rebalancing transactions.

From the point of view of a borrowing country, the variable of interest is the likely terms and cost of future debt. A 2-sided VaR analysis can help borrowers quantify the extent to which their credit rating is likely to change in the future. Understanding the size of such potential shifts will be crucially important in determining future government expenditure, as substantial re-ratings can have a significant impact on the ability of a country to borrow money and service its debt. Therefore, for borrowing countries both the maximum expected positive and negative changes in country risk ratings are of interest, as they will help predict the probability of substantial country risk ratings changes.

In order to accommodate the above discussion we propose an extension of the VaR framework where both the upper and lower thresholds are considered. This measure will be henceforth known as Country Risk Bounds (CRBs). Formally, the upper CRB will be given by:

$$CRB_t^+ = E(Y_t \mid F_{t-1}) + z_t^+ \sigma_t \,,$$

while the lower CRB will be given by:

$$CRB_t^- = E(Y_t \mid F_{t-1}) + z_t^- \sigma_t \,,$$

where z_t^+ is the upper tail critical value at time t and z_t^- is the lower tail critical value at time t. This formulation is general and allows the use of asymmetric and time varying distributions.

4. Model Specifications

McAleer and da Veiga [11] showed that the variance of a portfolio can be estimated through Single Index (SI) or Portfolio Methods (PM) (see also McAleer and da Veiga [10]). The SI approach treats the portfolio as a single index and models its variance directly using an univariate volatility model, while the PM approach models the variance of each individual asset in the portfolio as well as the covariance between different subsections of the portfolio using multivariate volatility models. These variance and covariance forecasts are then combined to produce a variance forecast for the entire portfolio.

The data used in this paper are composite country risk ratings compiled by the International Country Risk Guide (ICRG) agency. These composite risk ratings are portfolios of political, economic and financial country risk ratings where political risk rating carries a 50% weight and economic and financial risk ratings each carry a 25% weight. Hence, following McAleer and da Veiga [11], the conditional variance of the composite risk ratings can be forecasted using the SI or PM approach.

There are a multitude of univariate and multivariate volatility models that can be used to forecast the variance of the composite risk ratings returns (for a comprehensive survey, see McAleer [9]). In this paper both the SI and PM versions of the Exponentially Weighted Moving Average (EWMA) model are used as they do not have to be estimated, and hence only requires a small number of observations to produce variance forecasts.

5. Data

The risk ratings and returns are discussed for ten developed and developing countries, namely Argentina, Australia, Brazil, China, France, Japan, Mexico, Switzerland, UK and the USA. These countries represent 4 geographical regions, namely South America (Argentina, Brazil), North and Central America (Mexico, USA), East Asia and the Pacific (Australia, China, Japan), and West Europe (France, Switzerland, UK). The ICRG country risk ratings for these countries are available from January 1984 to April 2005, the exception being China, for which data are available from December 1984. Of these countries, Argentina, Brazil, China and Mexico generally have a low risk rating for each of the four categories, which is consistent with low creditworthiness and high associated risk. While Switzerland, Australia and Japan generally have a high risk rating, which is consistent with high creditworthiness and low associated risk.

The mean risk ratings vary substantially across the ten countries and the four risk ratings. For the economic risk ratings, the mean ranges from 55.48 for Argentina to 86.53 for Switzerland. Three countries, namely Argentina, Brazil and Mexico, have mean risk ratings that are less than 60. Australia, China, France, UK and the USA have means of low to high 70s, while the means for Japan and Switzerland are higher than 82. The mean for financial ratings ranges from 52.01 for Argentina to 96.87 for Switzerland. As for the economic ratings, the lowest means are observed for Argentina, Brazil and Mexico, all being less than 69. Australia and China have means of low to high 70s, France, UK and the USA in the mid to high 70s. Only Japan and Switzerland have means that are higher than 95. For the political ratings, the mean ranges from 65.24 for China to 90.20 for Switzerland. Only the mean for Switzerland is above 90. Of the remaining 9 countries, Argentina, Brazil, China and Mexico have means of mid to high 60s, France a mean of 79.53, and Australia, Japan, UK and the USA means of low 80s. Finally, the mean for the composite ratings ranges from 59.75 for Argentina to 90.88 for Switzerland. Of the remaining 8 countries, Brazil, China and Mexico have means of low to high 60s, while Australia, France, Japan, UK and the USA have means of low to high 80s.

As discussed above, Argentina, Brazil and Mexico have the lowest mean ratings, while Switzerland has the highest mean ratings for all four risk categories. Moreover, there is a large difference between the minimum and maximum risk rating values for Argentina, Brazil, China and Mexico. Although SD varies substantially across the ten countries and four risk ratings, this primarily reflects differences in mean ratings. In general, financial risk ratings have the highest SDs, followed by the economic, political, composite risk ratings. Apart from economic risk ratings for Australia, UK and the USA and financial risk ratings for the USA, the risk ratings for the selected countries are all negatively skewed.

Risk returns are defined as the monthly percentage change in the respective risk rating. The means of all four risk returns for the ten countries are close to zero with standard deviations ranging from 1.36% (France) to 6.25% (Argentina) for economic risk returns, 1.22% (Japan) to 6.27% (Argentina) for financial risk returns, 0.75% (Switzerland) to 2.02% (Argentina) for political risk returns, and 0.60% (Switzerland) to 2.33% (Argentina) for composite risk returns. Of the ten countries, Argentina has the highest standard deviation for three of the four risk returns. There is no general pattern of skewness for the four risk returns for the ten countries, with all four returns being positively skewed for Switzerland. Apart from China and Switzerland, the financial risk ratings are negatively skewed. The political risk returns are positively skewed only in the case of the USA, while the composite risk returns are positively skewed only for Australia and Switzerland.

Significant differences are evident in the economic, financial and political risk ratings and risk returns for all ten countries. Moreover, the composite risk ratings and returns closely reflect the trends of the three component risk ratings and returns. A detailed analysis of the four risk ratings is given in Hoti and McAleer [7].

6. Forecasting and Policy Implications

In this section we describe the forecasting exercise to demonstrate the practical application of the CRBs framework developed here, in the context of managing the risks associated with risk ratings. As discussed above, the data used in this paper are ten country risk ratings and their associated returns. The sample period ranges from January 1984 to April 2005, corresponding to 256 country risk ratings and 255 risk returns for each country.

A rolling window is used to forecast 1-month ahead conditional variances and CRBs for country risk returns. In order to strike a balance between efficiency in calculation of conditional variances and a viable number of rolling regressions, the rolling window size is set at 55, which leads to a forecasting period October 1988 to April 2005.

A rolling window is a moving sub-sample within the entire sample data set. In the empirical example presented here, observations 1 to 55 of the data set, which corresponds to the January 1984 to September 1988, are used to calculate the conditional variance and CRBs for October 1988. Then, observations 2 to 56, which corresponds to the period February 1984 to October 1988, are used to calculate the conditional variance and CRBs for November 1988, followed by observations 3 to 57, and so on until the last rolling sample at the end of the total number of observations. This approach yields 200 out of sample forecasts.

The aim of this paper is to forecast the conditional variance and CRBs for the returns of composite risk ratings. As described above composite risk ratings are made up of political, financial and economic risk ratings, where political risk carries a weight of 50% while economic and financial risk carry a weight of 25% each. Hence, composite risk ratings are effectively a portfolio of economic, financial and political risk ratings. In this paper the EWMA model developed by Riskmetrics™ [13] is used to forecast the 1-month ahead conditional variance of country risk rating returns. Following McAleer and da Veiga [10,11], the variance of composite risk rating returns is forecasted using the Single Index (SI) approach and Portfolio Method (PM).

Figure 1 presents the forecasted conditional variances for each country risk rating returns using both SI and PM. Both models lead to very similar conditional variance forecast, with the PM having a tendency to yield slight higher variance forecasts for all countries except the USA.

Insert Figure 1 about here

Furthermore, Figure 2 plots the risk returns and CRBs for each country using a 95% level of confidence, while Tables 1 and 2 report the number of positive and negative observed violations at 90%, 95%, 98% and 99% levels of confidence for the SI and PM, respectively. As would be expected, the PM tends to give slightly wider bounds than the SI approach.

Insert Figure 2 about here

Insert Tables 1-2 about here

The basic test of model accuracy in the context of CRBs forecasts is conducted by comparing the number of observed violations with the expected number of violations implied by the chosen level of significance. For example, CRBs thresholds calculated assuming a 90% level of confidence should include 90% of observations, leading to violations 10% of the time. The probability of observing x violations in a sample of size T, under the null hypothesis, is given by:

$$\Pr(x) = C_x^T (\delta)^x (1-\delta)^{T-x} \tag{1}$$

where δ is the desired level of violations.

Christoffersen [3] referred to this test, as a test of Unconditional Coverage (UC). Therefore, the LR statistic for testing whether the number of observed violations, divided by T, is equal to δ is given by:

$$LR_{UC} = 2[\log(\hat{\delta}^{x}(1-\hat{\delta})^{N-x}) - \log(\delta^{x}(1-\delta)^{N-x})] \quad (2)$$

where $\hat{\delta} = x/N$, x is the number of violations, and N is the number of forecasts. The LR statistic is asymptotically distributed as $\chi^2(1)$ under the null hypothesis of correct UC.

The average CRB for each country and confidence level combination for the SI and PM approaches are given in Tables 3 and 4, respectively. As a symmetric distribution has been assumed in the calculation of the CRBs, only one figure is reported in the tables, which corresponds to the absolute value of the average upper and lower bounds. An average CRB gives an indication of the likely range of risk returns. For example Australia has an average CRB of 2.197% at the 99% level of confidence. This suggests that on average one can be 99% certain that Australian country risk returns will not vary by more than $\pm$ 2.197% on a monthly basis.

Insert Tables 3-4 about here

The results of the UC tests for the SI and PM approached are mixed (results are available upon request). On average both approaches appear to provide the correct unconditional coverage at the 95% and 90% level of confidence. However, at the 99% and 98% level of confidence both SI and PM appear to under-predict risk, and generally lead lo excessive violations. This result is to be expected given that the CRBs are estimated under the assumption of normality, while all returns are found to be highly non-normal, according to the Jarque-Bera test statistic.

Furthermore, a careful analysis of the results in Tables 1 and 2 suggests that the number of positive and negative violations can differ substantially for each country. This provides some evidence that the underlying distribution of risk returns may not be symmetric. However, there does not appear to be consistency of empirical results across the PM and SI methods. Consider, for example, the USA where the SI method yields far more positive violations than negative violations, while the PM method yields far more negative violations than positive violations. This result seems to indicate that the skewness of portfolio returns is not only a function of the skewness of the underlying assets, but also the way in which the portfolio is constructed and modelled. Future work will explore this important issue in greater detail.

The countries in Tables 3 and 4 are ranked from lowest to highest average CRBs. Switzerland, Japan and Australia have the lowest average CRB, while Argentina, Brazil and Mexico have the highest average CRB. It is worth noting that the relative rankings are invariant tothe choice of model. These results suggest that the country risk ratings of Switzerland, Japan and Australia are much mode likely to remain close to current levels than the country risk ratings of Argentina, Brazil and Mexico. This type of analysis would be useful to investors evaluating the attractiveness of investing in alternative counties.

7. Conclusion

This paper considered an extension of the Value-at-Risk (VaR) framework where both the upper and lower thresholds are considered. The purpose of the paper was to forecast the conditional variance and Country Risk Bounds (CRBs) for the rate of change of risk ratings for ten countries. The conditional variance of composite risk returns for the ten countries were forecasted using the Single Index (SI) and Portfolio Methods (PM) of McAleer and da Veiga [10,11].

Both models led to very similar conditional variance forecasts, with PM having a tendency to yield slightly higher variance forecasts for all countries, except the USA. The CRBs for each country were calculated using a 90%, 95%, 98% and 99% level of confidence. As would be expected, PM in general gave slightly wider bounds than the SI approach. An interesting result was that the number of violations in the upper and lower tails was often different, suggesting that the country risk returns may follow an asymmetric distribution. Therefore, future research might improve the accuracy of risk returns threshold forecasts by considering asymmetric distributions.

The average CRB for each country and the confidence level combination for the SI and PM approaches showed that Switzerland, Japan and Australia have the lowest average CRB, while Argentina, Brazil and Mexico have the highest average CRB. Moreover, the relative rankings are invariant to the choice of model. The results suggested that the country risk ratings of Switzerland, Japan and Australia are much mode likely to remain close to current levels than the country risk ratings of Argentina, Brazil and Mexico. This type of analysis would be useful to lenders/investors evaluating the attractiveness of lending/investing in alternative countries.

References

[1] J.D. Amato, C.H. Furfine, Are credit ratings procyclical?, *Bank for International Settlements Working Paper* 129 (2003).

[2] A.V. Bhatia, Sovereign credit ratings methodology: an evaluation, *International Monetary Fund Working Paper* 02/170 (2002).

[3] P.F. Christoffersen, Evaluating interval forecasts, *International Economic Review*, 39 (1998) 841-862.

[4] S. Hoti, Comparative analysis of risk ratings for the East European region, *Mathematics and Computers in Simulation*, 68 (2005a) 449-462.

[5] S. Hoti, Modelling country spillover effects in country risk ratings, *Emerging Markets Review*, 6 (2005b) 324-345.

[6] S. Hoti, M. McAleer, An empirical assessment of country risk ratings and associated models, *Journal of Economic Surveys*, 18(4) (2004) 539-588.

[7] S. Hoti, M. McAleer, *Modelling the Riskiness in Country Risk Ratings*, Contributions to Economic Analysis Series, Number 273, Amsterdam, Elsevier (2005a).

[8] S. Hoti, M. McAleer, Modelling spillover effects for country risk ratings and returns, *Risk Letters*, 1(1) (2005b) 11-17.

[9] M. McAleer, Automated inference and learning in modeling financial volatility, *Econometric Theory*, 21(2005) 232-261.

[10] M. McAleer, B. da Veiga, Forecasting value-at-risk with a parsimonious portfolio spillover GARCH (PS-GARCH) model, *Journal of Forecasting*, 27 (2008a)1-19.

[11] M. McAleer, B. da Veiga, Single index and portfolio models for forecasting, value-at-risk thresholds, *Journal of Forecasting*, 27 (2008b) 217-235.

[12] Political Risk Services, *PRS Methodology: The Coplin-O'Leary System*, http://www. prsgroup.com/PDFS/prsmethodology.pdf (2007).

[13] Riskmetrics^{TM}, *J.P. Morgan Technical Document*, 4th Edition, New York, J.P. Morgan (1996).

Table 1. Single index CRBs violations

	Level of Confidence							
	99%		98%		95%		90%	
Country	PV	NV	PV	NV	PV	NV	PV	NV
Argentina	3	5	5	6	6	8	10	11
Australia	3	5	5	6	6	8	10	11
Brazil	4	1	5	6	7	9	10	10
China	1	1	2	1	10	4	18	5
France	5	1	7	3	8	4	13	8
Japan	6	7	6	8	6	9	9	14
Mexico	4	5	4	6	6	10	8	11
Switzerland	5	6	8	7	10	9	15	12
UK	2	2	2	2	6	7	10	10
USA	6	2	6	2	6	2	9	7

Notes:
(1) Positive violations (PV) occur when the actual return is greater than the positive CRB threshold.
(2) Negative violations (NV) occur when the actual return is smaller than the negative CRB threshold.
(3) The level of confidence is 2-tailed.

Table 2. Portfolio method CRBs violations

	Level of Confidence							
	99%		98%		95%		90%	
Country	PV	NV	PV	NV	PV	NV	PV	NV
Argentina	5	5	5	7	7	8	12	9
Australia	1	1	2	1	9	3	16	5
Brazil	2	2	2	2	6	5	10	10
China	6	1	6	2	6	4	11	7
France	3	5	4	6	5	8	6	10
Japan	3	2	4	5	6	8	9	10
Mexico	5	2	6	2	7	3	8	5
Switzerland	4	6	5	7	5	9	10	14
UK	3	4	5	6	6	7	8	13
USA	3	8	6	9	7	10	8	12

Notes:
(1) Positive violations (PV) occur when the actual return is greater than the positive CRB threshold.
(2) Negative violations (NV) occur when the actual return is smaller than the negative CRB threshold
(3) The level of confidence 2-tailed.

Table 3. Average CRBs using the single index approach

Country	Level of Confidence			
	99%	98%	95%	90%
Switzerland	1.528%	1.382%	1.163%	0.976%
Japan	1.985%	1.795%	1.510%	1.267%
Australia	2.116%	1.914%	1.610%	1.351%
France	2.353%	2.128%	1.790%	1.502%
UK	2.415%	2.185%	1.838%	1.542%
USA	2.669%	2.415%	2.031%	1.705%
China	3.105%	2.809%	2.363%	1.983%
Mexico	3.438%	3.110%	2.616%	2.196%
Brazil	4.485%	4.056%	3.412%	2.864%
Argentina	5.122%	4.633%	3.897%	3.271%

Notes:
(1) The Average CRB measures the average confidence interval around the risk returns, given each level of confidence.
(2) The level of confidence is 2-tailed.

Table 4. Average CRBs using the portfolio method

Country	Level of Confidence 99%	98%	95%	90%
Switzerland	1.581%	1.430%	1.203%	1.010%
Japan	2.039%	1.844%	1.551%	1.302%
Australia	2.197%	1.987%	1.671%	1.403%
France	2.396%	2.167%	1.823%	1.530%
UK	2.454%	2.219%	1.867%	1.567%
USA	2.866%	2.592%	2.180%	1.830%
China	3.233%	2.924%	2.460%	2.065%
Mexico	3.505%	3.170%	2.667%	2.238%
Brazil	4.562%	4.126%	3.471%	2.913%
Argentina	5.693%	5.149%	4.331%	3.635%

Notes:
(1) The Average CRB measures the average confidence interval around the risk returns, given each level of confidence.
(2) The level of confidence is 2-tailed.

Figure 1. Conditional variance forecasts for risk returns

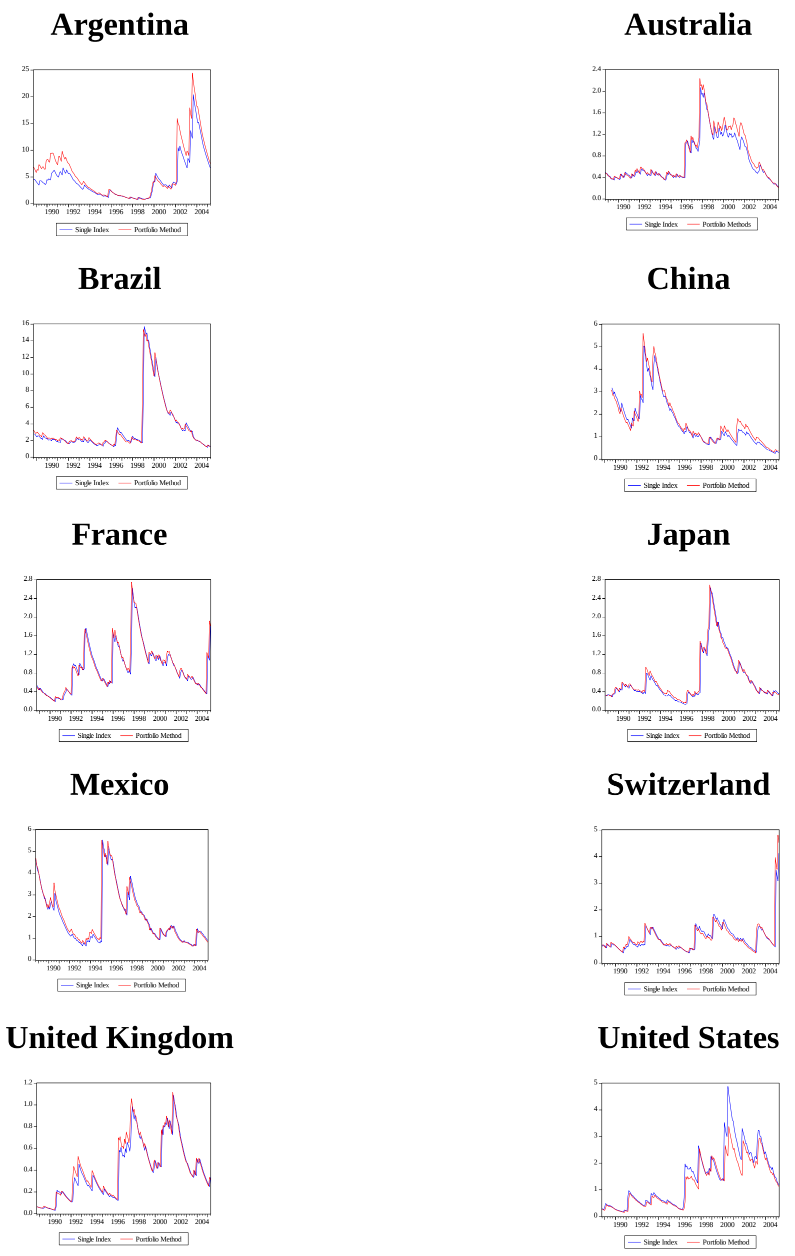
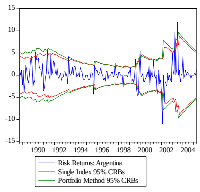
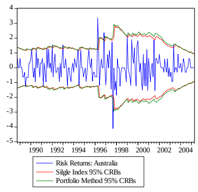


Figure 2. Risk returns and 95% CRBs

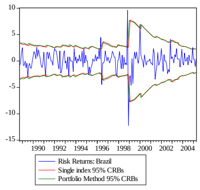
Argentina



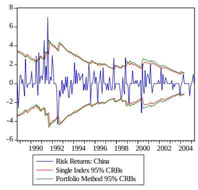
Australia



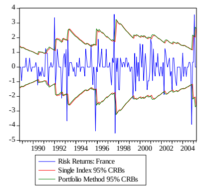
Brazil



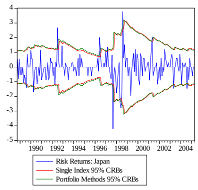
China



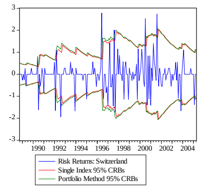
France



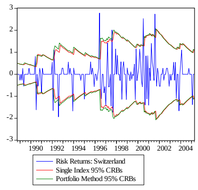
Japan



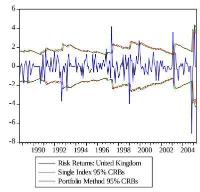
Mexico



Switzerland



United Kingdom



United States