Optimal Risk Management Before, During and After the 2008-09 Financial Crisis

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Abstract

In this paper we advance the idea that optimal risk management under the Basel II Accord will typically require the use of a combination of different models of risk. This idea is illustrated by analyzing the best empirical models of risk for five stock indexes before, during, and after the 2008-09 financial crisis. The data used are the Dow Jones Industrial Average, Financial Times Stock Exchange 100, Nikkei, Hang Seng and Standard and Poor's 500 Composite Index. The primary goal of the exercise is to identify the best models for risk management in each period according to the minimization of average daily capital requirements under the Basel II Accord. It is found that the best risk models can and do vary before, during and after the 2008-09 financial crisis. Moreover, it is found that an aggressive risk management strategy, namely the supremum strategy that combines different models of risk, can result in significant gains in average daily capital requirements, relative to the strategy of using single models, while staying within the limits of the Basel II Accord.

Keywords: Optimal risk management, average daily capital requirements, alternative risk strategies, value-at-risk forecasts, combining risk models.

JEL Classifications: G32, G11, G17, C53, C22

1. Introduction

The Basel II Accord (Basel Committee on Banking Supervision (1996)) was designed to monitor and encourage sensible risk taking by using appropriate models of risk to calculate Value-at-Risk (VaR) and subsequent daily capital charges.

VaR is defined as an estimate of the probability and size of the potential expected financial loss over a given period, and is a standard tool in risk management. It has become especially important following the 2005 amendment to the Basel Accord (Basel Committee on Banking Supervision (2005) and Basel Committee on Banking Supervision (2009)),[1] whereby banks and other Authorized Deposit-taking Institutions (ADIs) were permitted and encouraged to use internal models to forecast daily VaR (see Jorion (2000) for a detailed discussion).

Risk management is important both for regulatory authorities and for ADIs. Financial regulators want ADIs to have sufficient liquidity and solvency. ADIs want to maximize profits from their investments in financial assets and remain in good standing with their regulators.

In this paper we define risk management in terms of choosing sensibly from a variety of risk models. This approach includes the criteria for selection of optimal risk models, together with considering the strategy of combining alternative risk models. The choice of risk models to be considered may vary over time, even daily.

The amendment to the initial Basel Accord was designed to encourage and reward institutions with superior risk management systems. A back-testing procedure, whereby actual returns are compared with the corresponding VaR forecasts, was introduced to assess the quality of the internal models used by ADIs. In cases where internal models lead to a greater number of violations than could reasonably be expected, given the confidence level, the ADI is required to hold a higher level of capital (see Table 6 in Appendix 1) for the penalties imposed under the Basel II Accord). Penalties imposed on ADIs affect profitability directly through higher

[1] The 2005 document contains the January 1996 text of the "Amendment to the Capital Accord to incorporate market risks" modified to reflect the following textual changes: (i) Modification to the Amendment to the Capital Accord to incorporate market risks (September 1997 press release); and (ii) The Application of Basel II to Trading Activities and the Treatment of Double Default Effects.

capital charges, and indirectly through the imposition of a more stringent external model to forecast VaR.

Excessive conservatism can have a negative impact on the profitability of ADIs as higher capital charges are subsequently required. Therefore, it is sensible for ADIs to consider a strategy that allows an endogenous decision as to how many times they should violate in any financial year (for further details, see McAleer and da Veiga (2008a, 2008b), McAleer (2005, 2009), Caporin and McAleer (2009), McAleer et al. (2009a, 2009b), and Jiménez-Martín et al. (2009)).

In this paper we emphasize the idea that optimal risk management requires the use of different risk models over time. This appreoach is illustrated using Standard and Poor's 500 (S&P500) index, Dow Jones Industrial Average (DJIA), Financial Times Stock Exchange 100 (FTSE) index, Nikkei (NK) index, and Hang Seng (HSI) index, from 3 January 2000 to 14 July 2009. The optimal models of risk management are identified according to the minimization of average daily capital charges under the Basel II Accord. A risk management strategy is proposed, namely choosing the supremum of the forecasted VaR of alternative risk models, that is found to be optimal in most of the examples presented.

The remainder of the paper is organized as follows. In Section 2 we present the five indices for the empirical analysis. Section 3 presents the different models of risk that are optimal for each index and for each time period. Section 4 presents some conclusions.

2. Description of the Stock Indexes

For purposes of illustrating the major point, we chose the following stock indices: Dow Jones Industrial Average (DJIA), Financial Times Stock Exchange 100 (FTSE), Hang Seng Index (HS), Nikkei index, and Standard and Poor's 500 (S&P500) Composite index, from 3 January 2000 to 15 July 2009. The indexes were selected for comparability with previous studies (see McAleer et al. (2009a, 2009b)) and also for containing a significant amount of variability.

In Figure 1 we show the daily levels of the five indices. It is apparent that they have similar patterns of variability over time. However, a closer look at the correlation coefficients in Table 1 reveals that, while S&P500 has very high correlations with DJIA, FTSE and Nikkei, the correlations between Nikkei and HSI of 0.634, and between FTSE and HSI of 0.698, are relatively low.

When we turn our attention to the daily returns (see Figure 2 and Table 2), we observe the high (0.966) correlation between DJIA and S&P500, two indices in similar markets. However, the correlations between the other indices are lower which, in some cases, are as low as 0.112. This suggests that the returns behave somewhat differently in the four areas of the sample (namely, the USA,, United Kingdom, Hong Kong and Japan).

Moreover, the changes in the index level for the whole period vary substantially across the indices, from a high of 2.7% for HS to -26.4% for DJIA, -36.4% for FTSE, -37.7% for S&P500, and -51.3% for Nikkei.

Figure 3 and Table 3 show the volatilities of the returns, which are calculated as the standard deviations of the returns of each index. Turning to Table 3, we see that the correlation between the volatilities of DJIA and S&P500 is high (at 0.948), which is hardly surprising as they both refer to the US market. However, the correlations between the volatilities of the remainder of the indexes are somewhat smaller, with a maximum of 0.493 between DJIA and FTSE and a minimum of 0.195 between DJIA and Nikkei.

From the above we can conclude that there is a substantial amount of heterogeneity among the indices, so that we could learn from such diversity.

3. Optimal Risk Models Before, During and After the 2008-09 Financial Crisis

In this section it is illustrated that the best risk models for a given index may vary across time. We also illustrate the idea that the strategy that combines different risk models can be optimal for risk management under the Basel II Accord. In order to do so, we first define the best risk model as the model of VaR that gives the highest number of days in minimizing capital charges over a given period within the Basel II limits. In almost all cases, such a model also gives the minimum average daily capital charges (DCC) for the period considered (see McAleer et al. (2009b) for further details).

We take into account the restriction, under the Basel II limits, that the number of violations should be less than 10 within the previous 250 days (see Appendix 1), or proportionately if the period consists of fewer than 250 days. A violation is said to occur when the actual loss in a given day is larger than the forecast VaR for that day.

In this paper we use seven alternative models of risk for predicting VaR. The specific models chosen are well known and widely used in the literature. In ascending order of complexity, except for the last case, these risk models are GARCH, GARCH-t, EGARCH, EGARCH-t, GJR, GJR-t, and Riskmetrics (1996) (see McAleer et al. (2009a) for a detailed description of each model).

For the sake of exposition it is assumed that, for each stock index, an ADI follows passively the strategy of investing in the index. We then calculate the VaR and CR implied by each of the seven models of risk, and each of the five stock indexes for each of the three periods (namely, before, during and after the 2008-09 financial crisis). The empirical findings are summarized in Table 4.

When we consider only the basic strategies rather than combinations of models, in the second column is given the best model before the financial crisis. In the third column, we have the percentage of days for which it was the best model during the period considered. In the fourth column, we have the average DCC of each model before the financial crisis. This pattern is repeated in columns 5 to 10. During the 2008-09 financial crisis, GARCH, EGARCH and EGARCH-t are the best models. After the financial crisis, the best risk model was EGARCH across all the indexes. Thus, it is observed that the best model changed for all the indices during and after the 2008-2009 financial crisis. The precise dates of the financial crisis for each index are given in Table 7 of Appendix 2.

ADIs need not restrict themselves to using only one of the available risk models. McAleer et al. (2009b) proposed a risk management strategy that consists in choosing from among different combinations of alternative risk models to forecast VaR. We first consider a combination of models that might be characterized as an aggressive risk strategy, namely the supremum (SUP), and another that might be regarded as a conservative risk strategy, namely the infinum (INF).

The supremum VaR strategy, which is calculated for the individual models of volatility, reflects an aggressive risk management strategy since it chooses the supremum of the VaR for each individual model (namely, the smallest in absolute value as it is negative). The infinum strategy chooses the infinum of the VaR (namely, the largest in absolute value), which is calculated for individual models of volatility,reflects a conservative risk management strategy. Given the two combined strategies, we obtain the empirical results that are given in Table 5.

It can be seen that the supremum (SUP) strategy is optimal in 11 of 15 cases. In only 4 of 15 cases is the single model strategy found to be optimal. It can be observed that, in general, the average DCC values in Table 5 are lower than thir counterparts in Table 4.

These empirical findings suggest strongly that using combinations of risk models can lead to substantially lower daily average capital requirements than using only single models, while staying within the limits of violations of the Basel II Accord. A complementary strategy to the one of using the aggressive supremum strategy or the conservative infinum strategy is to use the DYLES strategy proposed in McAleer et al. (2009a).

4. Conclusions

Under the Basel II Accord, ADIs have to communicate their risk estimates to the relevant monetary authorities, using a variety of VaR models to estimate and forecast risk. ADIs are subject to a back-testing procedure that compares the daily VaR with the subsequently realized returns. Under the Basel II Accord, ADIs that fail the back-test can be subject to the imposition of standard models that can lead to higher daily capital costs.

In this paper we defined risk management in terms of choosing optimally from a variety of conditional volatility (or risk) models, and considered combining alternative risk models. These issues were illustrated using five major stock market indices, namely the Dow Jones Industrial Average (DJIA), Financial Times Stock Exchange 100 (FTSE) index, Nikkei (NK) index, Hang Seng (HSI) index, and Standard and Poor’s 500 (S&P500) Composite index, from 3 January 2000 to 15 July 2009.

The two main empirical findings of the paper are as follows:

1- **Optimal risk management models change with the financial crisis.**

Alternative risk models were found to be optimal before, during and after the 2008-09 financial crisis for the different indices considered. The feasible, sensible and optimal strategy of choosing different models of daily risk is an implication of the empirical results.

2- **Optimal risk management within Basel II requires to use combinations of models.**

In this paper we proposed a general strategy for constructing risk management models that used combinations of several models for forecasting VaR. An aggressive risk management strategy, namely choosing the supremum of the forecasted VaR of alternative risk models, was found to be optimal in most of the examples considered.

An explanation as to why a particular model might be optimal in over a specified period for a given index is an open question that remains for further research.

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Figure 1

Daily data for DJIA, FTSE, HS, NIKKEI and S&P500

from 3 January 2000 to 14 July 2009

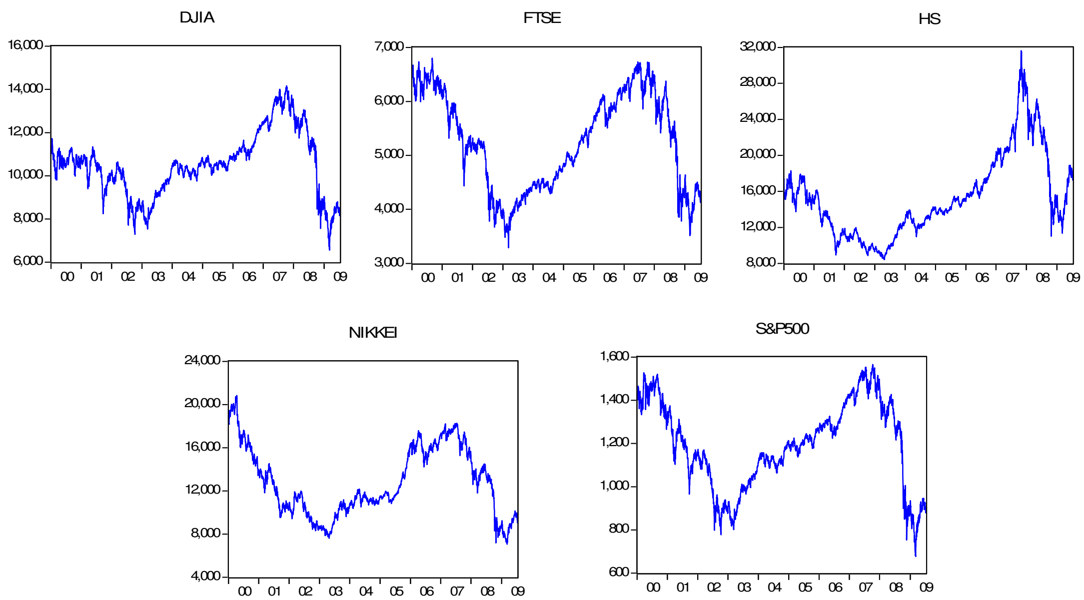

Table 1. Correlations between Indices

Index	DJIA	FTSE	HS	NIKKEI	S&P500
DJIA	1.00				
FTSE	0.834	1.000			
HSI	0.820	0.698	1.000		
NIKKEI	0.786	0.916	0.634	1.000	
S&P500	0.915	0.952	0.724	0.914	1.000

Figure 2

Daily returns for DJIA, FTSE, HS, NIKKEI and S&P500

from 3 January 2000 to 14 July 2009

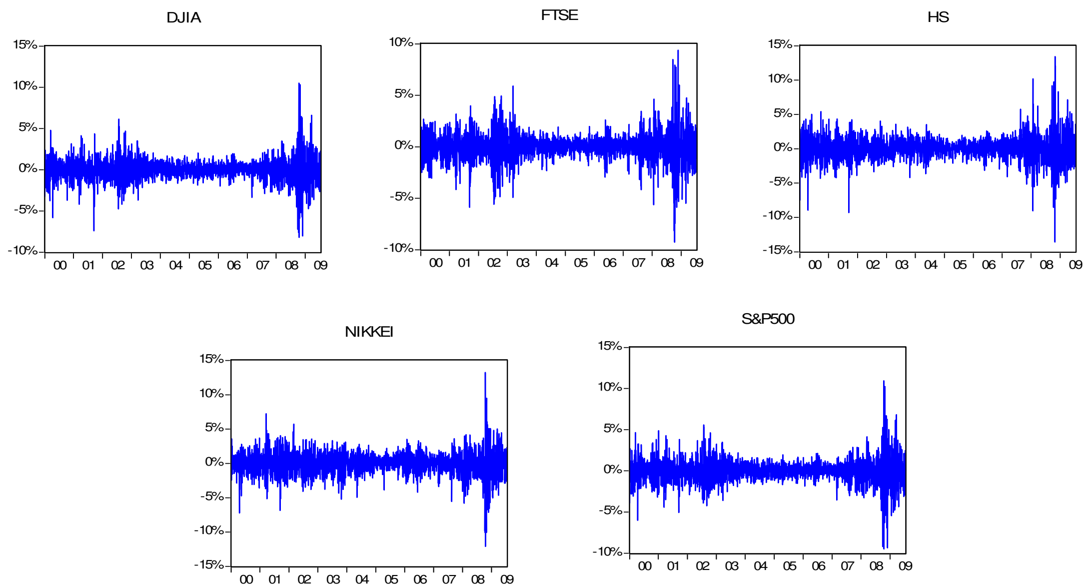

Table 2. Correlations of Returns

Index	DJIA	FTSE	HS	NIKKEI	S&P500
DJIA	1.000				
FTSE	0.482	1.000			
HS	0.184	0.365	1.000		
NIKKEI	0.112	0.303	0.581	1.000	
S&P500	0.966	0.494	0.198	0.111	1.000

Figure 3

Daily volatility of DJIA, FTSE, HS, NIKKEI and S&P500

from 3 January 2000 to 14 July 2009

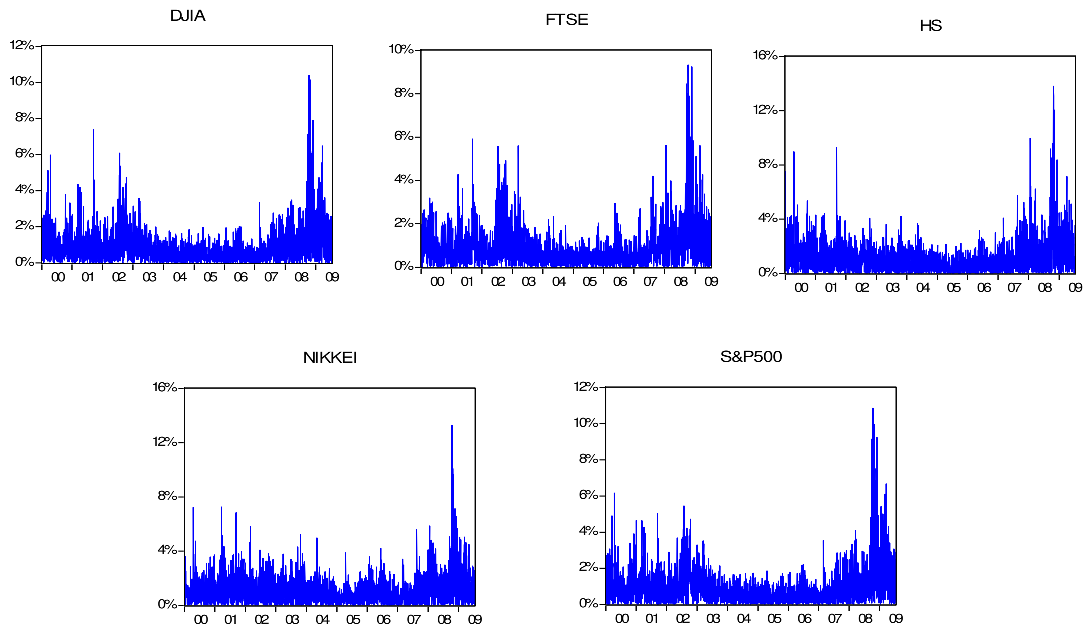

Table 3. Correlations of Volatilities

Index	DJIA	FTSE	HS	NIKKEI	S&P500
DJIA	1.000				
FTSE	0.493	1.000			
HS	0.296	0.372	1.000		
NIKKEI	0.195	0.307	0.476	1.000	
S&P500	0.948	0.492	0.297	0.197	1.000

Table 4

Best Single Risk Models for Forecasting VaR for Each Index

Index	Before crisis			During crisis			After crisis		
	Best	%	Avg	Best	%	Avg	Best	%	Avg
DJIA	GARCH	49.7	8.2	GARCH	81.4	17.5	EGARCH	86.9	12.4
FTSE	GARCH	42.2	8.5	EGARCH	84.2	17.3	EGARCH	83.3	12.5
HSI	EGARCH_t	0.00	11.0	GARCH	66.1	10.1	EGARCH	53.5	15.9
NIKKEI	GJR	44.6	10.4	EGARCH	45.4	17.9	EGARCH	87.9	12.41
S&P500	GARCH	46.0	8.5	EGARCH_t	12.0	20.0	EGARCH	87.0	12.4

Notes: % denotes the percentage of days that the VaR model provides the minimum capital charges for the analyzed period.
Avg denotes the average of the DCC for the sub-period.

Table 5

Best Combination and Single Risk Models for Forecasting VaR for Each Index

Index	Before crisis			During crisis			After crisis		
	Best	%	Avg	Best	%	Avg	Best	%	Avg
DJIA	SUP	99.0	7.71	GARCH	58.3	17.5	SUP	100	11.9
FTSE	SUP	87.8	8.02	SUP	100	16.9	SUP	95.8	12.0
HS	INF	0.0	12.5	SUP	100	9.5	SUP	51.3	15.6
NIKKEI	GJR	35.0	10.4	SUP	75	17.5	SUP	100	11.9
S&P500	SUP	56.7	8.2	EGARCH_t	8.0	20.0	SUP	98.9	11.9

Notes: % denotes the percentage of days that the VaR model provides the minimum capital charges for the analyzed period.
Avg denotes the average of the DCC for the sub-period.

Appendix 1. Forecasting Value-at-Risk and Daily Capital Charges

The Basel II Accord stipulates that daily capital charges (DCC) must be set at the higher of the previous day's VaR or the average VaR over the last 60 business days, multiplied by a factor (3+*k*) for a violation penalty, wherein a violation involves the actual negative returns exceeding the VaR forecast negative returns for a given day:

$$DCC_t = \sup\left\{-\left(3+k\right)\overline{\mathrm{VaR}}_{60}, \quad -\mathrm{VaR}_{t-1}\right\} \tag{1}$$

where

DCC = daily capital charges, which is the higher of $-\left(3+k\right)\overline{\mathrm{VaR}}_{60}$ and $-\mathrm{VaR}_{t-1}$,
VAR_t = Value-at-Risk for day *t*,
$VAR_t = \hat{Y}_t - z_t \cdot \hat{\sigma}_t$,
$\overline{\mathrm{VaR}}_{60}$ = mean VaR over the previous 60 working days,
$\hat{Y}_t$ = estimated return at time t,
z_t = 1% critical value of the distribution of returns at time t,
$\hat{\sigma}_t$ = estimated risk (or square root of volatility) at time t,
$0 \le k \le 1$ is the Basel II violation penalty (see Table 6).

The multiplication factor (or penalty), *k*, depends on the central supervisory authority's assessment of the ADI's risk management practices and the results of a simple back test. It is determined by the number of times actual losses exceed a particular day's VaR forecast (Basel Committee on Banking Supervision (1996)). The minimum multiplication factor of 3 is intended to compensate for various errors that can arise in model implementation, such as simplifying assumptions, analytical approximations, small sample biases and numerical errors that tend to reduce the true risk coverage of the model. Increases in the multiplication factor are designed to increase the confidence level that is implied by the observed number of violations to the 99 per cent confidence level, as required by the regulators (for a detailed discussion of VaR, as well as exogenous and endogenous violations (for further details, see McAleer (2009), Jiménez-Martin et al. (2009), and McAleer et al. (2009a)).

Table 6

Basel II Accord Penalty Zones

Zone	Number of Violations	*k*
Green	0 to 4	0.00
Yellow	5	0.40
	6	0.50
	7	0.65
	8	0.75
	9	0.85
Red	10+	1.00

Note: The number of violations is given for 250 business days. The penalty structure under the Basel II Accord is specified for the number of violations and not their magnitude, either individually or cumulatively.

Appendix 2

Level and Dates of the Recession for Each Index

Table 7. Dates from Peak to Trough

Index	peak_value	peak_date	trough_value	trough_date
DJIA	11782.35	11/8/2008	6547.050	9/3/2009
FTSE	5636.610	29/8/2008	3512.090	3/3/2009
HS	22862.60	1/8/2008	11015.84	27/10/2008
NIKKEI	13430.91	11/8/2008	7054.980	10/3/2009
S&P500	1305.323	11/8/2008	676.5302	9/3/2009

Note: The peak and the trough of each index are considered at the beginning and the end of the 2008-09 financial crisis.