Has the Basel Accord Improved Risk Management During the Global Financial Crisis?*

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Abstract

The Basel II Accord requires that banks and other Authorized Deposit-taking Institutions (ADIs) communicate their daily risk forecasts to the appropriate monetary authorities at the beginning of each trading day, using one or more risk models to measure Value-at-Risk (VaR). The risk estimates of these models are used to determine capital requirements and associated capital costs of ADIs, depending in part on the number of previous violations, whereby realised losses exceed the estimated VaR. In this paper we define risk management in terms of choosing from a variety of risk models, and discuss the selection of optimal risk models. A new approach to model selection for predicting VaR is proposed, consisting of combining alternative risk models, and we compare conservative and aggressive strategies for choosing between VaR models. We then examine how different risk management strategies performed during the 2008-09 global financial crisis. These issues are illustrated using Standard and Poor's 500 Composite Index.

Key words and phrases: Value-at-Risk (VaR), daily capital charges, violation penalties, optimizing strategy, risk forecasts, aggressive or conservative risk management strategies, Basel Accord, global financial crisis.

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

1. Introduction

The global financial crisis of 2008-09 has left an indelible mark on economic and financial structures worldwide, and left an entire generation of investors wondering how things could have become so severe (see, for example, Borio (2008)). There have been many questions asked about whether appropriate regulations were in place, especially in the US, to permit the appropriate monitoring and encouragement of (possibly excessive) risk taking.

The Basel II Accord was designed to monitor and encourage sensible risk taking using appropriate models of risk to calculate Value-at-Risk (VaR) and forecast daily capital charges. VaR is defined as an estimate of the probability and size of the potential loss to be expected over a given period, and is now a standard tool in risk management. It has become especially important following the 1995 amendment to the Basel Accord, 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). The last decade has witnessed a growing academic and professional literature comparing alternative modelling approaches to determine how to measure VaR, especially for large portfolios of financial assets.

When the Basel I Accord was concluded in 1988, no capital requirements were defined for market risk. However, regulators soon recognized the risks to a banking system if insufficient capital is held to absorb the large sudden losses from huge exposures in capital markets. During the mid 90's, proposals were tabled for an amendment to the 1988 Accord, requiring additional capital over and above the minimum required for credit risk. Finally, a market risk capital adequacy framework was adopted in 1995 for implementation in 1998. The 1995 Basel I Accord amendment provides a menu of approaches for determining market risk capital requirements, ranging from a simple, to intermediate and advanced approaches. Under the advanced approach (the internal model approach), banks are allowed to calculate the capital requirement for market risk using their internal models. The use of internal models was only introduced in 1998 in the European Union. The 26 June 2004 Basel II framework, implemented in many countries in 2008 (though not yet formally in the USA) enhanced the requirements for market risk management by including, for example, oversight rules, disclosure, management of counterparty risk in trading portfolios.

In the 1995 amendment, p. 16, a similar capital requirement system was recommended, but the specific penalties were left to each national supervisor. We consider that the penalty structure contained in Table 1 of this paper belongs only to Basel II, and was not part of Basel I or its 1995 amendment.

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 1 for the penalties imposed under the Basel II Accord. Penalties imposed on ADIs affect profitability directly through higher capital charges, and indirectly through the imposition of a more stringent external model to forecast VaR[1]. This is one reason why financial managers may prefer risk management strategies that are passive and conservative rather than active and aggressive.

Excessive conservatism can have a negative impact on the profitability of ADIs as higher capital charges are subsequently required. Therefore, ADIs should perhaps consider a strategy that allows an endogenous decision as to how many times ADIs should violate in any financial year (for further details, see McAleer and da Veiga (2008a, 2008b), McAleer (2008), Caporin and McAleer (2010) and McAleer et al. (2010)).

However, in this paper we adopt a different approach based on an alternative design of optimal strategies. Since ADIs typically want to maximize their profit within the rules of Basel II, choosing the forecasting model of VaR that minimizes daily capital charges while keeping the number of violations within the limits of Table 1, is required.

We observe that the risk model that minimizes daily capital charges has changed before, during and after the global financial crisis. Since no single model is optimal over time, we have devised as an alternative to single models, using combinations of them. Combining forecasting models is common in the time series literature but it has been rarely used for forecasting VaR for risk management purposes (Chiriac and Pohlmeier, 2010, which was released after the first version of this paper, propose to combine models but their benchmark criteria for model comparison is different).

[1] In the 1995 amendment (page 16), a similar capital requirement system was recommended, but specific penalties were left to each national supervisor. We interpret the penalty structure contained in Table 1 of this paper as belonging only to Basel II, and not as part of Basel I or its 1995 amendment.

This paper considers market[2] risk management in terms of choosing sensibly and optimally from a variety of risk models. The main contribution of this paper is to propose combining alternative models of market risk for purposes of risk management in the context of Basel II. We also propose some examples of combinations of strategies, such as conservative and aggressive strategies, and discuss how to choose between them.

From a practical perspective, the paper also examines how the new market risk management strategies performed during the 2008-09 global financial crisis and beyond. The paper then forecasts VaR and daily capital charges for the different market risk management strategies considered. These issues are illustrated using Standard and Poor's 500 Composite Index.

The Basel II accord has been in operation in Europe only from 2008. The effects of the global financial crisis should probably not be attributed to any failings of Basel II as it was not implemented in the USA, which was the epicentre of the crisis (see, for example, Cannata and Quagliariello (2009)).

The remainder of the paper is organized as follows. In Section 2 we present the main ideas of the Basel II Accord Amendment as it relates to forecasting VaR and daily capital charges. Section 3 reviews some of the most well known models of volatility that are used to forecast VaR and calculate daily capital charges, and presents aggressive and conservative bounds on risk management strategies. In Section 4 the data used for estimation and forecasting are presented. Section 5 analyses the forecast values of VaR and daily capital charges before, during and after the 2008-09 global financial crisis, and Section 6 summarizes the main conclusions.

2. 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

[2] Market risk is defined as the risk of losses in the on and off-balance sheet positions arising from movements in market prices. The risks subject to this requirement pertain to interest rate related instruments and equities in the trading book, and foreign exchange risk and commodities risk throughout the bank (Basel Committee on Banking Supervision (2006)).

(3+*k*) for a violation penalty, wherein a violation involves the actual negative returns exceeding the VaR forecast negative returns for a given day:[3]

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

where

DCC_t = daily capital charges, which is the higher of $-(3+k)\,\overline{\mathrm{VaR}}_{60}$ 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 1).

[Table 1 goes here]

The multiplication factor[4] (or penalty), *k,* depends on the central 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, 2006)). 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 (see Stahl (1997)). 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

[3] Our aim is to investigate the likely performance of the Basel II regulations. In this section we carry out our analysis applying the Basel II formulae to a period that includes the 2008-09 global financial crisis, during which the Basel II Accord regulations were not fully implemented.

[4] Formula (1) is contained in the 1995 amendment to Basel I, while Table 1 appears for the first time in the Basel II Accord in 2004.

discussion of VaR, as well as exogenous and endogenous violations, see McAleer (2009), Jiménez-Martin et al. (2009), and McAleer et al. (2010)).

In calculating the number of violations, ADIs are required to compare the forecasts of VaR with realised profit and loss figures for the previous 250 trading days. In 1995, the 1988 Basel Accord (Basel Committee on Banking Supervision (1988) was amended to allow ADIs to use internal models to determine their VaR thresholds (Basel Committee on Banking Supervision (1995)). However, ADIs that proposed using internal models are required to demonstrate that their models are sound. Movement from the green zone to the red zone arises through an excessive number of violations. Although this will lead to a higher value of *k*, and hence a higher penalty, a violation will also tend to be associated with lower daily capital charges.[5]

Value-at-Risk refers to the lower bound of a confidence interval for a (conditional) mean, that is, a "worst case scenario on a typical day". If interest lies in modelling the random variable, Y_t, it could be decomposed as follows:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t . \tag{2}$$

This decomposition states that Y_t comprises a predictable component, $E(Y_t \mid F_{t-1})$, which is the conditional mean, and a random component, ε_t. The variability of Y_t, and hence its distribution, is determined by the variability of ε_t. If it is assumed that ε_t follows a conditional distribution such that:

$$\varepsilon_t \sim D(\mu_t, \sigma_t^2)$$

where μ_t and σ_t are the conditional mean and standard deviation of ε_t, respectively, these can be estimated using a variety of parametric, semi-parametric or non-parametric methods. The VaR threshold for Y_t can be calculated as:

$$VaR_t = E(Y_t \mid F_{t-1}) - \alpha\sigma_t , \tag{3}$$

[5] The number of violations in a given period is an important guidance (but not the only one) for the regulators to approve a given VaR model.

where α is the critical value from the distribution of ε_t to obtain the appropriate confidence level. It is possible for σ_t to be replaced by alternative estimates of the conditional standard deviation in order to obtain an appropriate VaR (for useful reviews of theoretical results for conditional volatility models, see Li et al. (2002) and McAleer (2005), who discusses a variety of univariate and multivariate, conditional, stochastic and realized volatility models).

Some empirical studies (see, for example, Berkowitz and O'Brien (2001), Gizycki and Hereford (1998), and Pérignon et al. (2008)) have indicated that some financial institutions overestimate their market risks in disclosures to the appropriate regulatory authorities, which can imply a costly restriction to the banks trading activity. ADIs may prefer to report high VaR numbers to avoid the possibility of regulatory intrusion. This conservative risk reporting suggests that efficiency gains may be feasible. In particular, as ADIs have effective tools for the measurement of market risk, while satisfying the qualitative requirements, ADIs could conceivably reduce daily capital charges by implementing a context-dependent market risk disclosure policy. For a discussion of alternative approaches to optimize VaR and daily capital charges, see McAleer (2009) and McAleer et al. (2010).

The next section describes several volatility models that are widely used to forecast the 1-day ahead conditional variances and VaR thresholds.

3. Models for Forecasting VaR

As discussed previously, ADIs can use internal models to determine their VaR thresholds. There are alternative time series models for estimating conditional volatility. In what follows, we present several conditional volatility models to evaluate strategic market risk disclosure, namely GARCH, GJR and EGARCH, with *Gaussian*, *Student t,* and *Generalized Gaussian* distributions errors, where the degrees of freedom are estimated.

These models were chosen because they are well known and are widely used in the literature. For an extensive discussion of the theoretical properties of several of these models, see Ling and McAleer (2002a, 2002b, 2003a) and Caporin and McAleer (2010). As an alternative to estimating the parameters, we also consider the exponential weighted moving average (EWMA) method by *Riskmetrics*^{TM} (1996) and Zumbach, (2007) that calibrates the unknown parameters.

We include a section on these models to present them in a unified framework and notation, and to make explicit the specific versions we are using. Apart from EWMA, the models are presented in increasing order of complexity.

3.1 GARCH

For a wide range of financial data series, time-varying conditional variances can be explained empirically through the autoregressive conditional heteroskedasticity (ARCH) model, which was proposed by Engle (1982). When the time-varying conditional variance has both autoregressive and moving average components, this leads to the generalized ARCH(p,q), or GARCH(p,q), model of Bollerslev (1986). It is very common to impose the widely estimated GARCH(1,1) specification in advance.

Consider the stationary AR(1)-GARCH(1,1) model for daily returns, y_t:

$$y_t = \varphi_1 + \varphi_2 y_{t-1} + \varepsilon_t, \qquad |\varphi_2| < 1 \tag{4}$$

for $t = 1,...,n$, where the shocks to returns are given by:

$$\begin{aligned} \varepsilon_t &= \eta_t \sqrt{h_t}, \quad \eta_t \sim iid(0,1) \\ h_t &= \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \end{aligned} \tag{5}$$

and $\omega > 0, \alpha \geq 0, \beta \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. The stationary AR(1)-GARCH(1,1) model can be modified to incorporate a non-stationary ARMA(p,q) conditional mean and a stationary GARCH(r,s) conditional variance, as in Ling and McAleer (2003b).

3.2 GJR

In the symmetric GARCH model, the effects of positive shocks (or upward movements in daily returns) on the conditional variance, h_t, are assumed to be the same as the negative shocks (or downward movements in daily returns). In order to accommodate asymmetric behaviour, Glosten, Jagannathan and Runkle (1992) proposed a model (hereafter GJR), for which GJR(1,1) is defined as follows:

$$h_t = \omega + (\alpha + \gamma I(\eta_{t-1}))\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{6}$$

where $\omega > 0, \alpha \geq 0, \alpha + \gamma \geq 0, \beta \geq 0$ are sufficient conditions for $h_t > 0$, and $I(\eta_t)$ is an indicator variable defined by:

$$I(\eta_t) = \begin{cases} 1, & \varepsilon_t < 0 \\ 0, & \varepsilon_t \geq 0 \end{cases} \tag{7}$$

as η_t has the same sign as ε_t. The indicator variable differentiates between positive and negative shocks, so that asymmetric effects in the data are captured by the coefficient γ. For financial data, it is expected that $\gamma \geq 0$ because negative shocks have a greater impact on risk than do positive shocks of similar magnitude. The asymmetric effect, γ, measures the contribution of shocks to both short run persistence, $\alpha + \gamma/2$, and to long run persistence, $\alpha + \beta + \gamma/2$. Although GJR permits asymmetric effects of positive and negative shocks of equal magnitude on conditional volatility, the special case of leverage, whereby negative shocks increase volatility while positive shocks decrease volatility (see Black (1976) for an argument using the debt/equity ratio), cannot be accommodated, at least in practice.

3.3 EGARCH

An alternative model to capture asymmetric behaviour in the conditional variance is the Exponential GARCH, or EGARCH(1,1), model of Nelson (1991), namely:

$$log h_t = \omega + \alpha \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta log h_{t-1}, \quad |\beta| < 1 \tag{8}$$

where the parameters α, β and γ have different interpretations from those in the GARCH(1,1) and GJR(1,1) models.

EGARCH captures asymmetries differently from GJR. The parameters α and γ in EGARCH(1,1) represent the magnitude (or size) and sign effects of the standardized residuals, respectively, on the conditional variance, whereas α and $\alpha + \gamma$ represent the effects of positive and negative shocks, respectively, on the conditional variance in GJR(1,1). Unlike GJR, EGARCH can accommodate leverage, depending on two sets of restrictions imposed on the size and sign parameters.

As noted in McAleer et al. (2007), there are some important differences between EGARCH and the previous two models, as follows: (i) EGARCH is a model of the logarithm of the conditional variance, which implies that no restrictions on the parameters are required to ensure $h_t > 0$; (ii) moment conditions are required for the GARCH and GJR models as they are dependent on lagged unconditional shocks, whereas EGARCH does not require moment conditions to be established as it depends on lagged conditional shocks (or standardized residuals); (iii) Shephard (1996) observed that $|\beta| < 1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1); (iv) as the standardized residuals appear in equation (7), $|\beta| < 1$ would seem to be a sufficient condition for the existence of moments; and (v) in addition to being a sufficient condition for consistency, $|\beta| < 1$ is also likely to be sufficient for asymptotic normality of the QMLE of EGARCH(1,1).

The three conditional volatility models given above are estimated under the following distributional assumptions on the conditional shocks: (1) normal, and (2) *Student t*, with estimated degrees of freedom. As the models that incorporate the t distributed errors are estimated by QMLE, the resulting estimators are consistent and asymptotically normal, so they can be used for estimation, inference and forecasting.

3.4 Exponentially Weighted Moving Average (EWMA)

As an alternative to estimating the parameters of the appropriate conditional volatility models, *Riskmetrics*^{TM} (1996) developed a model which estimates the conditional variances and covariances based on the exponentially weighted moving average (EWMA) method, which is, in effect, a restricted version of the ARCH(∞) model. This approach forecasts the conditional variance at time *t* as a linear combination of the lagged conditional variance and the squared unconditional shock at time $t-1$. The EWMA model calibrates the conditional variance as:

$$h_t = \lambda h_{t-1} + (1-\lambda)\varepsilon_{t-1}^2 \tag{9}$$

where λ is a decay parameter. *Riskmetrics*™ (1996) suggests that λ should be set at 0.94 for purposes of analysing daily data. As no parameters are estimated, there is no need to establish any moment or log-moment conditions for purposes of demonstrating the statistical properties of the estimators.

4. Data

The data used for estimation and forecasting are the closing daily prices for Standard and Poor's Composite 500 Composite Index (S&P500), which were obtained from the Ecowin Financial Database for the period 3 January 2000 to 8 August 2012. Although it is unlikely that an ADI's typical market risk portfolio tracks only the S&P500 Composite Index, which is not a traded index (unlike its options or futures counterparts), the S&P Composite Index is used as an illustration of the broad movements of profits and losses of the equity portfolios of ADIs.

If P_t denotes the market price, the returns at time t (R_t) are defined as:

$$R_t = \log\left(P_t / P_{t-1}\right). \tag{10}$$

[Insert Figure 1 here]

Figure 1 shows the S&P500 returns, for which the descriptive statistics are given in Table 2. The extremely high positive and negative returns are evident from September 2008 onward, and have continued well into 2009 and during the European sovereign-debt crisis, which started in May 2010. The mean is close to zero, and the range is between +11% and -9.5%. The Jarque-Bera Lagrange multiplier test rejects the null hypothesis of normally distributed returns. As the series displays high kurtosis, this would seem to indicate the existence of extreme observations, as can be seen in the histogram, which is not surprising for financial returns data.

[Insert Table 2 here]

Several measures of volatility are available in the literature. In order to gain some intuition, we adopt the measure proposed in Franses and van Dijk (1999), where the true volatility of returns is defined as:

$$V_t = \left(R_t - E\left(R_t \mid F_{t-1}\right)\right)^2, \tag{11}$$

where F_{t-1} is the information set at time *t*-1.

[Insert Figure 2 here]

Figure 2 shows the S&P500 volatility, as the square root of V_t in equation (11). The series exhibits clustering that needs to be captured by an appropriate time series model. The volatility of the series appears to be high during the early 2000s, followed by a quiet period from 2003 to the beginning of 2007. Volatility increases dramatically after August 2008, due in large part to the worsening global credit environment. This increase in volatility is even higher in October 2008. In less than 4 weeks in October 2008, the S&P500 index plummeted by 27.1%. In less than 3 weeks in November 2008, starting the morning after the US elections, the S&P500 index plunged a further 25.2%. Overall, from late August 2008, US stocks fell by an almost unbelievable 42.2% to reach a low on 20 November 2008.

Since the end of 2008, there have been further significant shocks, especially those initiated by the European sovereign debt crisis, which started in May 2010. However, these shocks have not been as great in magnitude, although they may have similar long lasting effects, as the 2008-09 global financial crisis.

An examination of daily movements in the S&P500 index back to 2000 suggests that large changes by historical standards are 4% in either direction. From January 2000 to August 2008, there was a 0.31% chance of observing an increase of 4% or more in one day, and a 0.18% chance of seeing a reduction of 4% or more in one day. Therefore, 99.5% of movements in the S&P500 index during this period had daily swings of less than 4%. Prior to September 2008, the S&P500 index had only 7 days with massive 4% gains, but since September 2008, there have been 18 more such days. On the downside, before the current stock market meltdown, the S&P500 index had only 4 days with huge 4% or more losses, whereas during the recent panic, there were a further 25 such days. As mentioned previously, the changes since the end of 2008 have been significant though less severe in magnitude.

This comparison is between more than 99 months and a shorter period of 36 months. During this time span of the global financial crisis, the 4% or more gain days chances increased five times while the chances of 4% or more loss days multiplied by 18 times. Such movements in the S&P500 index are unprecedented.

Alternative models of volatility can be compared on the basis of statistical significance, goodness of fit, forecasting VaR, calculation of daily capital charges, and optimality on a daily or temporally aggregated basis. As the focus of forecasting VaR is to calculate daily capital charges, subject to appropriate penalties, the most severe of which is temporary or permanent suspension from investment activities, the goodness of fit criterion used is the calculation of daily and mean capital charges, both before and after the 2008-09 global financial crisis.

5. Forecasting VaR and Calculating Daily Capital Charges

In this section we conduct a hypothetical exercise to analyze the performance of existing state-of-the-art and the proposed risk management strategies, as permitted under the Basel II framework, when applied to the S&P500 Composite Index. Before doing so, we will discuss briefly the performance of the three major estimated models, namely GARCH(1,1), GJR(1,1) and EGARCH(1,1), for the full sample period.

The GARCH(1,1) estimates under the three densities, namely Normal, Student t and Generalized Normal, in Table 4, are similar, with the ARCH (or alpha) effect being around 0.8, and the GARCH (or beta) effect being around 0.91, such that the sum exceeds 0.99. Similar results are obtained for the asymmetric GJR(1,1) model in Table 5, with the asymmetry coefficient, gamma, being significant for all three densities, and with a similar order of magnitude. The estimates for EGARCH(1,1) are also similar across the three densities for the full sample period.

[Insert Tables 4-5 here]

The forecast values of VaR and daily capital charges are analysed before, during and after the 2008-09 global financial crisis considering alternative risk management strategies. In Figure 3, VaR forecasts are compared with S&P500 returns, where the vertical axis represents returns, and the horizontal axis represents the days from 2 January 2008 to 3 August 2012. The S&P500 Composite Index returns are given as the upper blue line that fluctuates around zero.

ADIs need not restrict themselves to using only one of the available risk models. In this paper we propose a risk management strategy that consists in choosing from among different combinations of alternative risk models to forecast VaR. We first discuss a combination of models that can be characterized as an aggressive strategy and another that can be regarded as a conservative strategy, as given in Figure 3.[6]

The upper red line represents the infinum of the VaR calculated for the individual models of volatility, which reflects an aggressive risk management strategy, whereas the lower green line represents the supremum of the VaR calculated for the individual models of volatility, which reflects a conservative risk management strategy. These two lines correspond to combinations of alternative risk models.

[Insert Figure 3 here]

As can be seen in Figure 3, VaR forecasts obtained from the different models of volatility have fluctuated, as expected, during the first few months of 2008. It has been relatively low, at below 5%, and relatively stable between April and August 2008. Around September 2008, VaR started increasing until it peaked in October 2008, between 10% and 15%, depending on the model of volatility considered. This is essentially a four-fold increase in VaR in a matter of one and a half months. In the last two months of 2008, VaR decreased to values between 5% and 8%, which is still twice as large as it had been just a few months earlier. Therefore, volatility has increased substantially during the global financial crisis, and has remained relatively high after the crisis, especially during the European sovereign debt crisis from May 2010.

Figure 4 includes daily capital charges based on VaR forecasts and the mean VaR for the previous 60 days, which are the two lower thick lines. The red line corresponds to the aggressive risk management strategy based on the supremum of the daily VaR forecasts of the alternative models of volatility, and the green line corresponds to the conservative risk management strategy based on the infinum of the VaR forecasts of the alternative models of volatility[7].

Before the global financial crisis, there is a substantial difference between the two lines corresponding to the aggressive and conservative risk management strategies. However, at the onset of the global financial crisis, the two lines virtually coincide, which suggests that the averaged rolling window term in the Basel II formula, which typically dominates the calculation of daily capital charges, is excessive.

[6] This is a novel possibility. Technically, a combination of forecast models is also a forecast model. In principle, the adoption of a combination of forecast models by an ADI to produce a combined forecast, is not forbidden by the Basel Accords, although it is subject to regulatory approval.
[7] Note that VaR figures are negative.

After the global financial crisis had begun, there is a substantial difference between the two strategies, arising from divergence across the alternative models of volatility, and hence between the aggressive and conservative risk management strategies.

[Insert Figure 4 here]

It can be observed from Figure 4 that daily capital charges always exceed VaR (in absolute terms). Moreover, immediately after the global financial crisis had started, a significant amount of capital was set aside to cover likely financial losses. This is a positive feature of the Basel II Accord, since it can have the effect of shielding ADIs from possible significant financial losses.

The Basel II Accord would seem to have succeeded in covering the market losses of ADIs before, during and after the global financial crisis for a portfolio that replicates S&P500. Therefore, it is likely to be useful when extended to countries to which it does not currently apply.

[Insert Figure 5 here]

Figure 5 shows the accumulated number of violations for three strategies over a period of 250 days. Table 3 gives the percentage of days for which daily capital charges are minimized, the mean daily capital charges, the total number of violations, the normalized number of violation rate (that is, the ratio of NoV*250 to number of days) and the accumulated losses[8] (AcLoss) for the alternative models of volatility. The upper red line in Figure 5 corresponds to the aggressive risk management strategy, which yields a normalized number of violations of 10.24, thereby exceeding the limit of 10 in 250 working days. The lower green line corresponds to the conservative risk management strategy, which gives only 2.09. This small number of violations is well within the Basel II limits and will keep the ADIs in the green zone of Table 1, but may lead to higher daily capital charges. This conservative strategy may be optimal in our case, if one decides to stay in the green zone.

It may be useful to consider other strategies that lie somewhat in the middle of the previous two, such as the DYLES strategy, developed in McAleer et al. (2010), which seems to work well in

[8] López (1999) suggested measuring the accuracy of the VaR forecast on the basis of the distance between the observed returns and the forecasted VaR values if a violation occurs: $\Psi_{t+1} = \begin{cases} \left| R_{t+1} - VaR_{t+1|t} \right| & if\ R_{t+1} < 0\ and\ R_{t+1} < VaR_{t+1|t} \\ 0 & otherwise \end{cases}$, a preferred VaR model is the one that minimizes the total loss value, $\Psi_{t+1} = \Sigma_{t=1}^{T} \Psi_t$.

practice, or the median strategy, which was found to be optimal, in a different context, in McAleer et al. (2011).

It is also worth noting from Table 3 and Figure 6, which gives the duration of the minimum daily capital charges for three alternative models of volatility, that two models of risk, including the conservative risk management strategy, do not minimize daily capital charges for even one day. On the other hand, the aggressive risk management strategy minimizes the mean daily capital charge over the year relative to its competitors, and also has the second highest frequency of minimizing daily capital charges. The Riskmetrics and EGARCH model with t distribution errors also minimize daily capital charges frequently.

[Insert Figure 6 here]

In terms of choosing the appropriate risk model for minimizing DCC, the simulations results reported here would suggest the following:

(1) Before the global financial crisis from 3 January 2008 to 6 June 2008, the best model for minimizing daily capital charges is GARCH (coinciding with the Upperbound). For the period 6 June 2008 to 16 July 2008, GJR was best and, for only 5 days, EGARCH was the best. This is a period with relatively low volatility and few extreme values.

(2) Riskmetrics is the best model during the beginning of the crisis, from 16 July 2008 to 15 September 2009. The S&P500 reached a peak on 12 August 2008, after which it started to decrease. In the second half of September 2008, the volatility on returns began to increase considerably.

(3) From 24 September 2008 to the end of 2009, the best model was EGARCH_T. This is a period with considerably high volatility and a large number of extreme values of returns. EGARCH can capture asymmetric volatility, thereby providing a more accurate measure of risk during large financial turbulence.

(4) During the rest of the sample, the Upperbound seems to be the strategy that minimizes the DCC most of the days, but not the only one.

The global financial crisis has affected the best risk management strategies by changing the optimal model for minimizing daily capital charges. Here we proposed combinations of models to accommodate this situation. Our results suggest that some of these combinations might have provided adequate coverage against market risk of a portfolio that replicates S&P500, during the period 2008-09, which includes the global financial crisis.

6. Conclusion

Alternative risk models were found to be optimal in terms of minimizing daily capital charges before and during the global financial crisis. Volatility increased four-fold during the 2008-09 global financial crisis and the European sovereign debt crisis starting from May 2010, and remained relatively high after the crisis, as illustrated using the S&P500 Composite Index. As the risk model that optimizes daily capital charges has been changing during that period, this suggests that, as in time series, the forecasts of VaR could be improved using a combination of models rather than a single model.

In this paper we proposed the idea of constructing risk management strategies that used combinations of several models for forecasting VaR. It was found that, in our case, an aggressive risk management strategy yielded the lowest mean capital charges, and had the highest frequency of minimizing daily capital charges throughout the forecasting period, but which also tended to violate too often. Such excessive violations can have the effect of leading to unwanted publicity, and temporary or permanent suspension from trading as an ADI. On the other hand, a conservative risk management strategy would have far fewer violations, and a correspondingly higher mean daily capital charges. This strategy will be the preferred one if the ADIs want to stay in the green zone of the Basel II Accord penalties.

The area between the bounds provided by the aggressive and conservative risk management strategies would seem to be a fertile area for future research. A risk management strategy that used combinations of alternative risk models for predicting VaR and minimizing daily capital charges, namely the median, was found to be optimal in McAleer et al. (2012a, 2012b). A risk model that uses the DYLES strategy established in McAleer et al. (2010) may also be a useful risk management strategy.

The recommended policy changes to practice by ADIs are straightforward as the methods suggested in this paper are practical, are simple to understand and implement, are easy to monitor and regulate, are leads to accurate forecasts, in general.

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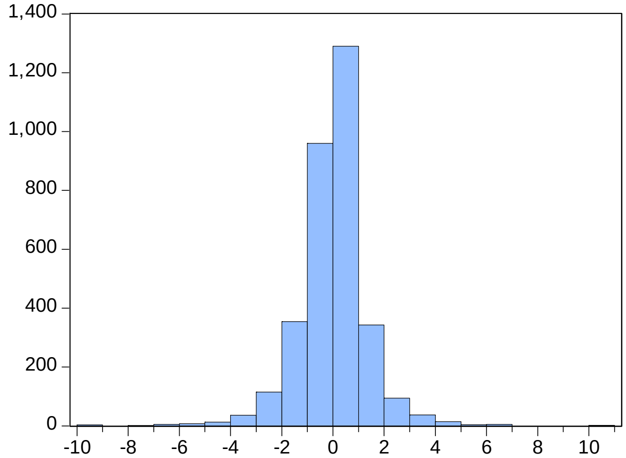
Table 1: Basel Accord Penalty Zones

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.

Table 2. Descriptive Statistics for S&P500 Returns

3 January 2000 – 03 August 2012



Series: S&P500 Returns
Sample 3/01/2000 3/08/2012
Observations 3283

Mean	-0.000184
Median	0.017670
Maximum	10.95792
Minimum	-9.469733
Std. Dev.	1.340072
Skewness	-0.154533
Kurtosis	10.57462
Jarque-Bera	7861.464
Probability	0.000000

Table 3. Percentage of Days Minimizing Daily Capital Charges, Mean Daily Capital Charges, Number of Violations, Normalized Number of Violations and Accumultated lossses for for Alternative Models of Volatility

MODEL	% of days minimizing DCC	Mean DCC	NoV	Norm. NoV	AcLoss
RSKM	18.4 %	12.10	31	6.48	21.30
GARCH	1.0%	12.02	35	7.32	21.84
GJR	3.0%	11.82	33	6.90	18.18
EGARCH	11.7%	11.35	41	8.57	28.11
GARCH_t	0.0%	12.97	10	2.09	7.60
GJR_t	12.1%	12.38	14	2.93	8.08
EGARCH_t	15.8%	11.76	17	3.55	11.23
GARCH_g	5.9%	12.38	21	4.39	13.58
GJR_g	9.3%	11.45	20	4.18	12.67
EGARCH_g	6.2%	11.75	27	5.64	19.09
Lowerbound	0.0%	13.43	10	2.09	5.88
Upperbound	16.7%	11.14	49	10.24	33.29

Table 4

GARCH(1,1) Estimates

Density	Parameter	All	Std. Error
Normal	α	0.083**	0.0068
	β	0.909**	0.0072
	$\alpha + \beta$	0.992	

Density	Parameter	All	Std. Error
Student-t (6.85)	α	0.083**	0.0098
	β	0.914**	0.0093
	$\alpha + \beta$	0.998	

Density	Parameter	All	Std. Error
Generalized Normal	α	0.083**	0.0105
	β	0.913**	0.0105
	$\alpha + \beta$	0.996	

Notes: All denotes the full sample period. The entries in parentheses for the Student-t distribution are the estimated degrees of freedom.
** These estimates are statistically significant at the 1% level.

Table 5

GJR(1,1) Estimates

Density	Parameter	All	Std-error
Normal	α	-0.024**	0.0054
	γ	0.152**	0.0102
	β	0.9366**	0.0059
	$\alpha+\beta+\gamma/2$	0.989	

Density	Parameter	All	Std-error
Student-t (8.37)	α	-0.027**	0.0075
	γ	0.154**	0.0138
	β	0.940**	0.0070
	$\alpha+\beta+\gamma/2$	0.990	

Density	Parameter	All	Std-error
Generalized Normal	α	-0.026**	0.0081
	γ	0.153**	0.0147
	β	0.938**	0.0080
	$\alpha+\beta+\gamma/2$	0.989	

Notes: All denotes the full sample period. The entries in parentheses for the Student-t distribution are the estimated degrees of freedom.

** These estimates are statistically significant at the 1% level.

Table 6

EGARCH(1,1) Estimates

Density	Parameter	All	Std-error
Normal	α	0.101**	0.0107
	γ	-0.123**	0.0078
	β	0.982**	0.0017

Density	Parameter	All	Std-error
Student-t (7.72)	α	0.096**	0.0139
	γ	-0.129**	0.0108
	β	0.987**	0.0021

Density	Parameter	All	Before
Generalized Normal	α	0.101**	0.0156
	γ	-0.128**	0.0114
	β	0.986**	0.0024

Notes: All denotes the full sample period. The entries in parentheses for the Student-t distribution are the estimated degrees of freedom.
** These estimates are statistically significant at the 1% level.

Figure 1. Daily Returns on the S&P500 Index

3 January 2000 – 3 August 2012

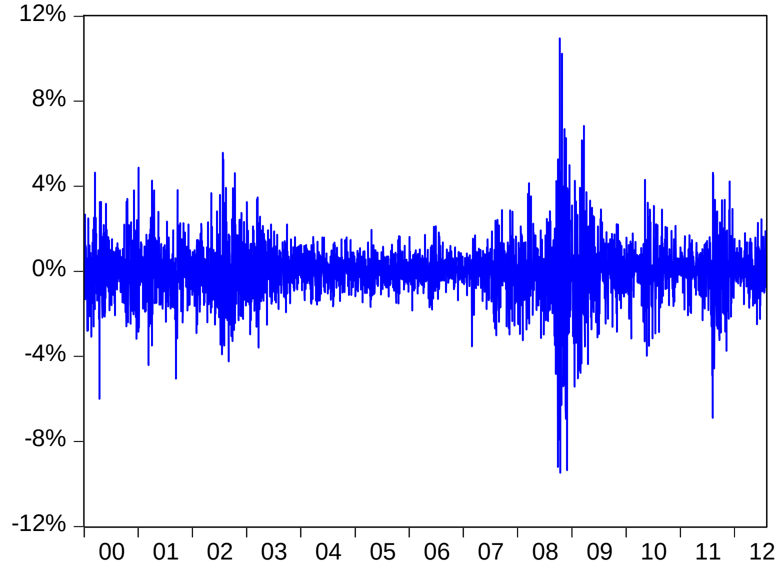


Figure 2. Daily Volatility in S&P500 Returns

3 January 2000 – 3 August 2012

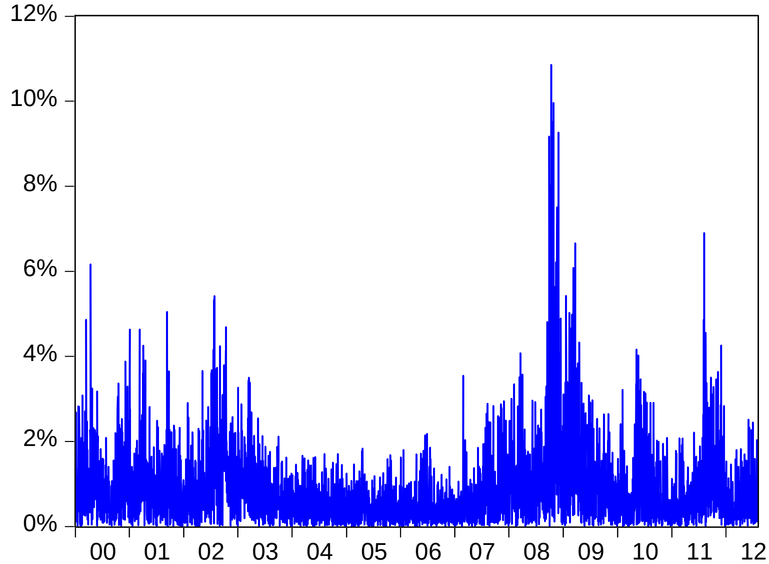
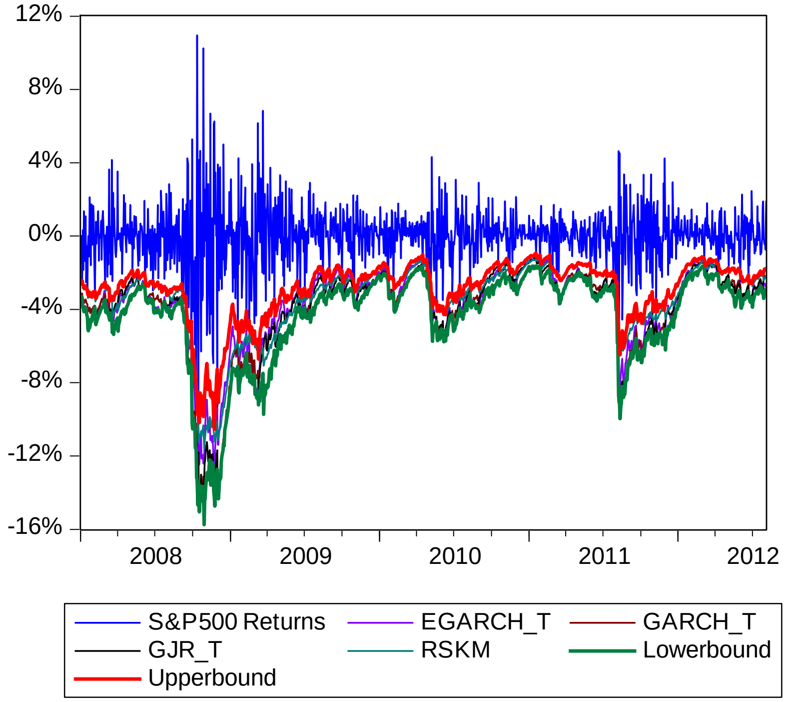


Figure 3. VaR for S&P500 Returns

2 January 2008 – 3 August 2012



Note: The upper blue line represents daily returns for the S&P500 index. The upper red line represents the infinum of the VaR forecasts for the different models described in Section 3. The lower green line corresponds to the supremum of the forecasts of the VaR for the same models.

Figure 4. VaR and Mean VaR for the Previous 60 Days to Calculate Daily Capital Charges for S&P500 Returns, 3 January 2008- 3 August 2012

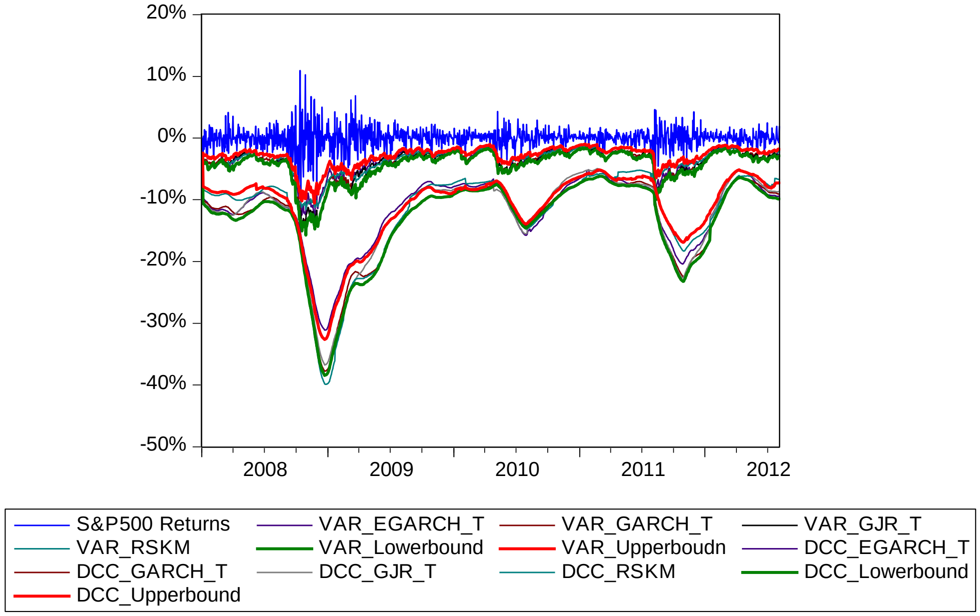


Figure 5. Number of Violations Accumulated Over 250 Days,

3 January 2008- 3 August 2012

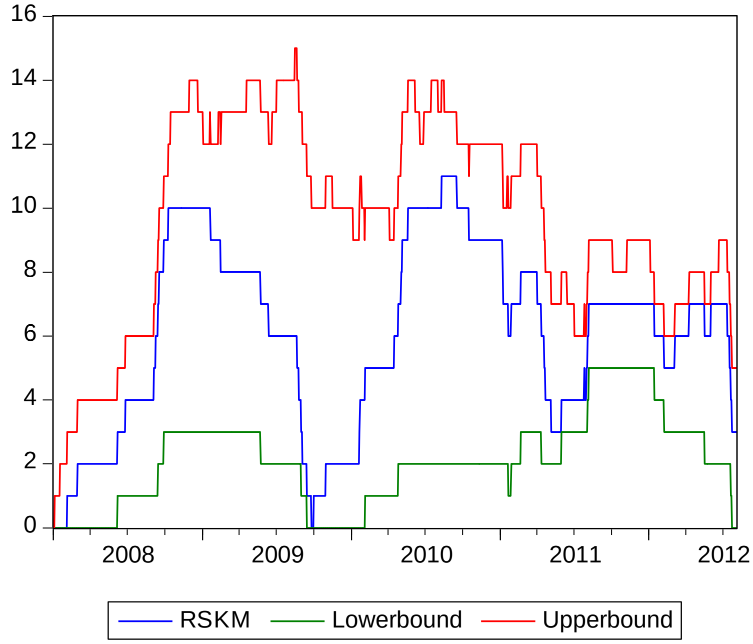
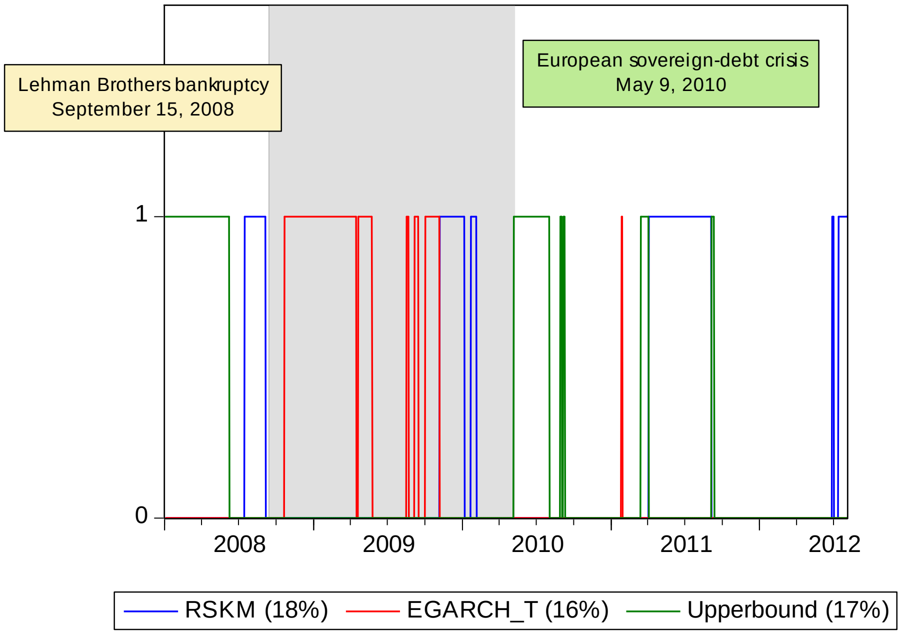


Figure 6. Duration of Minimum Daily Capital Charges

for Alternative Models of Volatility,

3 January 2008- 3 August 2012



Note: One in the figura means that the model minizmizes DCC in that day.