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How Effective are the Basel Accord Penalties?

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Abstract

The internal models amendment to the Basel Accord allows banks to use internal models to forecast Value-at-Risk (VaR) thresholds, which are used to calculate the required capital that banks must hold in reserve as a protection against negative changes in the value of their trading portfolios. As capital reserves lead to an opportunity cost to banks, it is likely that banks could be tempted to use models that underpredict risk, and hence lead to low capital charges. In order to avoid this problem the Basel Accord introduced a backtesting procedure, whereby banks using models that led to excessive violations are penalised through higher capital charges. This paper investigates the performance of five popular volatility models that can be used to forecast VaR thresholds under a variety of distributional assumptions. The results suggest that, within the current constraints and the penalty structure of the Basel Accord, the lowest capital charges arise when using models that lead to excessive violations, thereby suggesting the current penalty structure is not severe enough to control risk management. In addition, an alternative penalty structure is suggested to be more effective in aligning the interests of banks and regulators.

Keywords: Value-at-Risk (VaR), GARCH, risk management, violations, forecasting, simulations, Basel Accord penalties.

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

1. Introduction

On June 26, 1974 Herstatt, a German bank, had received large payments of DEM in Frankfurt in exchange for USD payments that were to be made in New York later that day due to time zone differences. However, before the USD payments were made, Herstatt was forced into liquidation by German regulators. The Herstatt fiasco led the G-10 countries to form a committee called the Basel Committee on Banking Supervision which was initially intended to deal with the role of regulators in cross-jurisdictional situations and to investigate ways of harmonizing international banking regulations.

In 1988 the Basel Committee issued the Basel Capital Accord, which prescribes minimum capital requirements that Authorized Deposit Taking Institutions (ADIs) must meet as a protection against credit risk. This became law in all G-10 countries by 1992, with the exception of Japan, where an extended transition period was granted.

In 1993 the Basel Accord was amended to require ADIs also to hold capital in reserve against market risk, based on the Value-at-Risk (VaR) approach. The VaR procedure is designed to forecast the maximum expected loss over a target horizon, given a statistical confidence limit (see Jorion (2000) for a detailed discussion of VaR methods). Initially, the Basel Accord stipulated a standardized approach which all institutions were required to adopt in calculating their VaR thresholds. This approach suffered from several deficiencies, the most notable of which were its assumption of no diversification benefits, which led to conservatism (and hence to greater opportunity costs), and its failure to reward institutions with superior risk management expertise. In view of these drawbacks a further amendment, called the Market Risk amendment, was proposed in 1995 and subsequently adopted in 1996.

The Market Risk amendment to the Basel Accord allows ADIs to use internal models to measure and forecast market risk. The forecasted market risk, or volatility, forms a basis for the calculation of VaR which, in turn, is used to determine the required capital charges.

In order to maintain discipline and ensure that ADIs have in place adequate models of market risk, a backtesting procedure is used to count the number of times the actual losses exceeded the forecasted VaR over the previous 250 business days. As VaR models are designed to provide 99% coverage (or lead to violations 1% of the time), the Basel Accord specifies penalties that increase the required capital charge if too many violations are detected.

A three-zone approach is used to measure the accuracy of the forecasting model, as shown in Table 1. ADIs that fall in the Green zone are deemed to have models that are adequately accurate, and do not incur penalties from regulators. Once in the Yellow zone, regulators will impose a penalty which will increase the required capital charge and will be required to justify the excessive number of violations: the greater is the number of violations, the more likely it is that ADIs will be penalized and required to revise their model. Finally, if an ADI enters the Red zone, the model used is deemed to be unacceptably inaccurate, and the ADI will be required to adopt a more stringent model that will lead to fewer violations and larger capital charges.

Under the internal models amendment to the Basel Accord, the capital charge must be set at the higher of the previous day's VaR or the average VaR over the last 60 days, multiplied by a factor (3+k). Finally, if a bank's model is found to be inadequate as it leads to an excessive number of violations, the bank may be required to adopt the standardized approach, which can lead to higher capital charges. Hence, it is vitally important that the model used does not lead to backtesting results that fall in the yellow zone and (especially) red zone, lest regulators find the model to be inadequate and require the bank to adopt the standardized approach.

McAleer and da Veiga (2008a, 2008b) have argued that, within the constraints of the Basel Accord, ADIs should choose the model that leads to the lowest possible capital charge, conditional on the model not leading to the ADI falling in the Red zone (or upper

Table 1: Basel Accord Penalty Zones

Zone	Number of Violations	Increase in *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 capital charge is given as the average VaR over the last 60 trading days, multiplied by a factor (3+*k*).

(dark) Yellow zone). Such an approach will ensure that the opportunity cost associated with capital charges are minimized, while maximizing the benefits associated with minimal regulatory intervention, Furthermore, ADIs that have good risk management systems in place will benefit from superior reputation, lower cost of debt, and perhaps stronger demand for its deposit facilities.

Therefore, the maximization problem faced by ADIs with regard to their VaR forecasts can be formulated as follows. Let

$$VaR_t = \widehat{r}_{i,t} - \widehat{z}_{i,t}\widehat{\sigma}_{i,t} \quad (1)$$

where $\widehat{r}_{i,t}$ is the forecasted return from model *i* at time *t*, $\widehat{z}_{i,t}$ is the forecasted critical value from model *i* at time *t*, and $\widehat{\sigma}_{i,t}$ is the forecasted standard deviation from model *i* at time *t*:

$$Vio_t = \begin{cases} 1 & r_t < VaR_t \\ 0 & r_t \geq VaR_t \end{cases} \quad (2)$$

$$Vio_t^{250} = \sum_{\tau=1}^{250} Vio_{t-\tau} \quad (3)$$

and

$$k = \begin{cases} 0 & 0 < Vio_t^{250} \leq 4 \\ 0.4 & Vio_t^{250} = 5 \\ 0.5 & Vio_t^{250} = 6 \\ 0.65 & Vio_t^{250} = 7 \\ 0.75 & Vio_t^{250} = 8 \\ 0.85 & Vio_t^{250} = 9 \\ 1 & Vio_t^{250} \geq 10 \end{cases} \quad (4)$$

Let

$$CC_t^* = \left[\sum_{\tau=1}^{60} \frac{VaR_{t-\tau}}{60}\right][3+k] \quad (5)$$

$$VaR_{t-1}^P = \left[\sum_{\tau=1}^{60} \frac{VaR_{t-\tau}}{60}\right] \quad (6)$$

$$\Omega_t = \begin{cases} 0 & VaR_{t-1} \leq VaR_{t-1}^P \\ 1 & VaR_{t-1} > VaR_{t-1}^P \end{cases} \quad (7)$$

Therefore, the Basel Accord capital charges are given by:

$$CC_t = (1-\Omega_t)VaR_{t-1} + \Omega_t CC_{t-1}^* \quad (8)$$

Therefore, ADIs must solve the following problem:

$$Min \quad CC_t = (1-\Omega_t)VaR_{t-1} + \Omega_t CC_{t-1}^* \quad (9)$$

over the choice of model and distributional assumption, subject to:

$$Vio_t^{250} \leq \vartheta \quad (10)$$

where ϑ is the upper bound allowed by regulators. Other constraints could be included to take into account other concerns of regulators and ADIs.

McAleer and da Veiga (2008a, 2008b) found that models that led to an excessive number of violations also tend to yield lower capital charges, compared with models that led to the correct number of violations (see also da Veiga et al. (2008), Jiménez-Martín et al. (2009), and McAleer et al. (2009a, 2009b, 2009c)). These results suggest that ADIs are likely to have an incentive to choose models that understate their true market risk exposure, as capital charges represent a cost to ADIs. This finding suggests that the penalty structure associated with the Basel Accord backtesting procedure is not severe enough. Lucas (2001) first presented this finding and showed that, under the current penalty structure, ADIs are likely to underreport risk by 25%. This finding is consistent with Berkowitz and O'Brien (2002) where it was found that commercial banks tend to underestimate risk and lead to excessive, and serially correlated, violations.

The aim of the paper is to investigate this issue further and to develop backtesting procedures that will better align the interests of both regulators and ADIs. Section 2 presents an empirical analysis that compares the capital charges produced by various models and shows that, under the current penalty structure, ADIs have an incentive to underpredict risk. A simulation exercise is presented in Section 3, and some concluding remarks are given in Section 4.

2. Empirical Analysis

In this section the VaR thresholds for the S&P500 index are forecasted for the period 14 January 1986 to 28 March 2005. In order to remain consistent with the Basel Accord, a 10-day holding period return is used. The data are plotted in Figure 1. The returns display significant clustering, which needs to be analysed using an appropriate conditional volatility model.

Figure 2 gives the histogram and descriptive statistics for the S&P500 returns. The series has mean and median close to zero, and a standard deviation of 3.2%. The returns range from 14.3% to -37.7%, which correspond to the 1987 crash. Furthermore, the returns series are negatively skewed, display excess kurtosis, and are highly non-normal according to the Jarque-Bera test statistic.

Figure 1: S&P500 10-day Returns

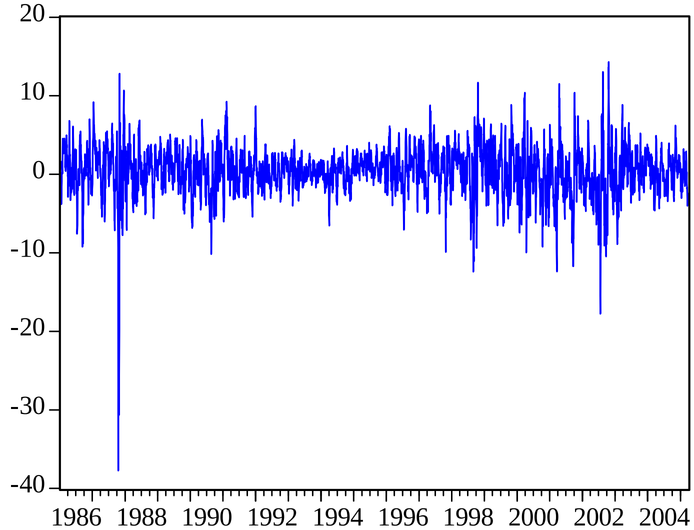
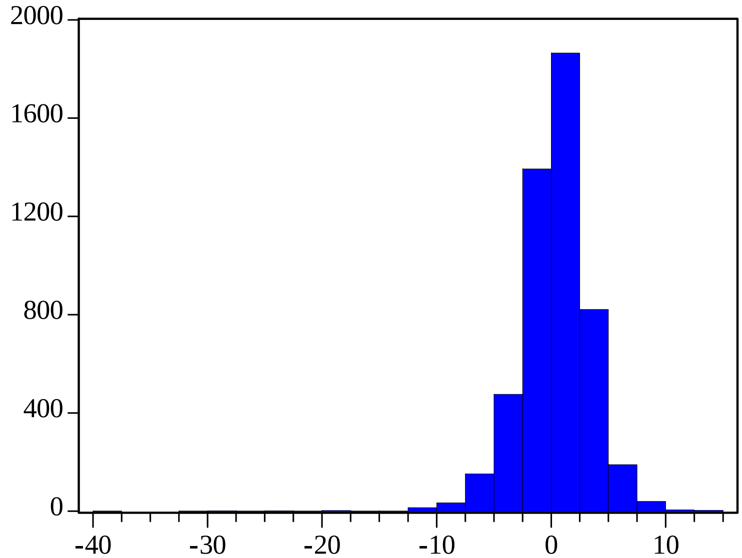


Figure 2: Histogram and Descriptive Statistics for S&P500 10-day Returns



Series: S&P500	
Sample 14/01/1986 28/03/2005	
Observations 5010	
Mean	0.345282
Median	0.516317
Maximum	14.29652
Minimum	-37.72015
Std. Dev.	3.169252
Skewness	-1.513332
Kurtosis	16.03120
Jarque-Bera	37360.61
Probability	0.000000

VaR thresholds are forecasted using the Riskmetrics^{TM}, ARCH, GARCH, GJR and EGARCH models, for a rolling window of 2000 observations, which yield 3010 forecasts, as there are 5010 observations in the sample period. Furthermore, the VaR thresholds are calculated under three distributional assumptions, namely normal, student t and generalized error distribution (GED).

The critical values are also obtained through bootstrapping. Figures 3 to 6 plot the estimated critical values used in this section. The t distribution generally gives the widest confidence intervals, while the normal distribution gives the narrowest. In order to remain consistent with the Basel Accord, a 99% level of confidence is used.

Table 1 presents the results of the forecasting exercise, and are ranked according to the number of violations. A general trend is that the VaR thresholds obtained under the assumption of normality generally lead to the highest number of violations, the greatest time spent out of the Green zone, and lowest Basel Accord capital charges. Using a t distribution leads to the lowest number of violations, the least amount of time spent out of the Green zone, and the highest Basel Accord capital charges.

The results obtained using the GED and bootstrapped critical values are very similar, lying between those obtained for the t and normal distributions. It is interesting to note that using a t distribution often leads to results that fail the UC test due to insufficient violations, thereby suggesting that the VaR thresholds obtained are excessively conservative.

Figure 3: Normal Distribution 99% Critical Values

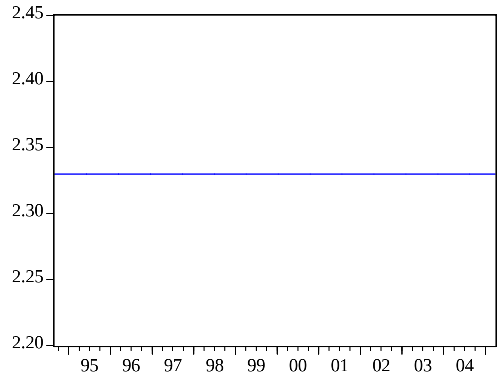


Figure 6: Bootstrap 99% Critical Values

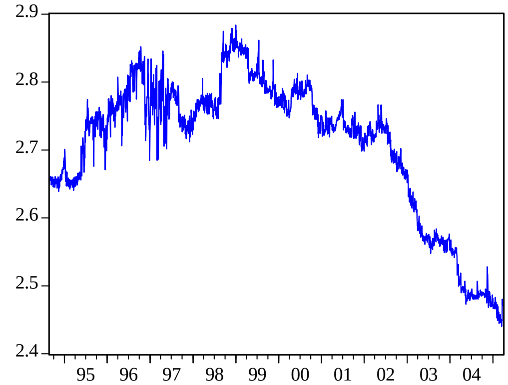


Figure 4: GED 99% Critical Values

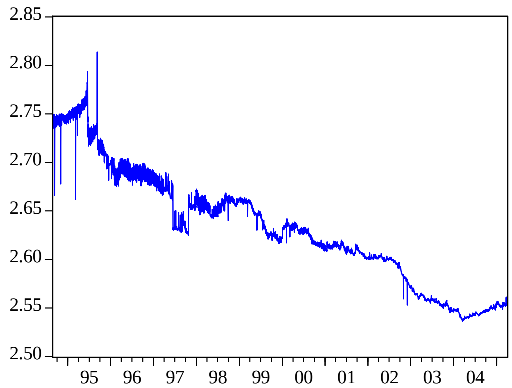


Figure 5: t Distribution 99% Critical Values

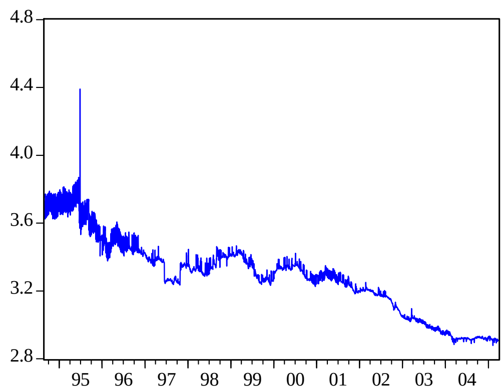


Table 1: VaR Threshold Forecast Results

Model	No. of Violations	Capital Charges				Proportion out of Green	Statistical Tests		
		Basel Accord	New Penalty				UC	Ind	CC
			$\nu=1$	$\nu=2$	$\nu=3$				
ARCH N	80	8.099	10.484	14.203	17.92	67%	**24.93***	0.032	**24.96***
Riskmetrics^{TM} N	59	7.882	9.482	11.809	14.136	57%	**9.501***	3.719	**13.22***
GARCH N	47	7.928	9.200	11.096	12.993	42%	3.554	2.257	5.811
GJR N	45	7.656	8.635	10.128	11.622	33%	2.809	2.481	5.29
ARCH GED	43	8.542	9.931	12.027	14.123	41%	2.137	0.167	2.304
ARCH BS	42	8.448	9.821	11.882	13.943	41%	1.834	0.21	2.044
EGARCH N	42	7.536	8.516	9.977	11.483	35%	1.834	0.258	2.092
Riskmetrics^{TM} GED	35	8.271	8.768	9.459	10.151	19%	0.331	1.09	1.421
Riskmetrics^{TM} BS	31	8.483	8.737	9.099	9.460	12%	0.011	1.84	1.851
GJR GED	30	8.307	8.974	9.927	10.88	21%	0.000	1.619	1.619
EGARCH GED	28	8.123	8.591	9.241	9.892	15%	0.066	0.269	4.152
GJR BS	27	8.509	8.989	9.656	10.322	15%	0.145	2.371	2.516
EGARCH BS	25	8.301	8.18	8.815	9.111	8%	0.404	0.212	0.335
GARCH GED	22	8.308	8.536	8.853	9.170	9%	1.055	4.488	5.543
GARCH BS	21	8.591	8.778	9.033	9.289	6%	1.35	0.147	1.497
EGARCH t	15	9.710	9.710	9.710	9.710	0%	**4.079**	0.073	0.616
Riskmetrics^{TM} t	14	10.095	10.095	10.095	10.095	0%	**4.718**	0.061	**4.779**
GARCH t	13	10.353	10.353	10.353	10.353	0%	**5.415**	0.053	5.468
GJR t	13	10.095	10.095	10.095	10.095	0%	**5.415**	0.053	5.468
ARCH t	11	11.542	11.555	11.572	11.589	0.3%	**7.031***	0.044	**7.075***

Notes: The Unconditional Coverage (UC) test is asymptotically distributed as $\chi^2(1)$. The Serial Independence (Ind) and Conditional Coverage tests are asymptotically distributed as $\chi^2(2)$ Entries in **bold** denote significance at 5% and * denotes significance at 1%. As there are 3010 days in the forecasting period, the expected number of violations at the 1% level is 30.

The results reported in Table 1 clearly show that the current penalty structure proposed by the Basel Accord rewards ADIs that use models that under report risk and lead to an excessive number of violations. Therefore, the current penalty structure does not align the interests of regulators with those of ADIs. In order to relieve this problem, we suggest that the penalty structure should be much more severe. In this paper we modify the Basel Accord capital charges to be given by:

$$CC_t = (1-\Omega_t)VaR_{t-1} + \Omega_t CC^*_{t-1} \tag{10}$$

where

$$CC^*_t = \left[\sum_{\tau=1}^{60} \frac{VaR_{t-\tau}}{60}\right]\left[3 + \nu I(k)e^k\right] \tag{11}$$

$$I(k) = \begin{cases} 0 & k = 0 \\ 1 & k \neq 0 \end{cases} \tag{12}$$

where ν is a scaling factor chosen by regulators. In this paper, ν has been set equal to one, two and three.

The capital charges given by the new penalty structures are presented in Table 1. Under the Basel Accord penalty structure, the minimum capital charge, at 7.54%, is given by the EGARCH model when it is estimated under the assumption of normality. This case leads to backtesting results that lie outside the Green zone 35% of the time. The new penalty structure, which is substantially more severe than the Basel Accord penalty, performs better in terms of aligning the interests of ADIs and regulators. Using the new penalty structure, the minimum capital charges are given by the EGARCH model using bootstrapped critical values, which lead to backtesting results that lie outside the Green zone only 8% of the time.

More importantly, under the existing penalty structure, models that lead to excessive violations, such as the Riskmetrics^{TM} and ARCH models under the assumption of normality, lead to some of the lowest capital charges, while leading to backtesting results that fall out of the green zone 57% and 67% of the time, respectively. The new penalty structures reverse this trend, and lead to substantially higher capital charges for models that yield excessive violations than models that have the correct coverage.

Figure 7 plots the relationship between the number of violations and capital charges given by each model under the current Basel Accord penalty structure. As previously stated, the minimum point corresponds to the EGARCH model estimated under the assumption of normality, which leads to an average capital charge of 7.54%. Figure 7 also fits a second-order polynomial to the data, with the values given in parenthesis being the t ratios corresponding to the parameter estimates. The capital charges are minimised under the current penalty structure when violations occur approximately 1.86% of the time, at nearly twice the correct number of violations.

The relationship between the number of violations and capital charges given by each model under the new penalty structures are given in Figure 8 for $\nu = 1$, Figure 9 for $\nu = 2$ and Figure 10 for $\nu = 3$. The minimum capital charges, according to the estimated equations, occur when violations occur approximately 1.36% of the time for $\nu = 1$, approximately 0.80% of the time for $\nu = 2$, and approximately 0.30% of the time for $\nu = 3$. Based on the above analysis, it would appear that the penalty structure using $\nu = 2$ is superior to the others as it would lead ADIs to choose models that lead to violations approximately 0.8% of the time, which is closest to the target level of violations at the 1% level of significance.

Figure 7: Relationship Between Number of Violations and Capital Charges for the Basel Accord Penalty Structure

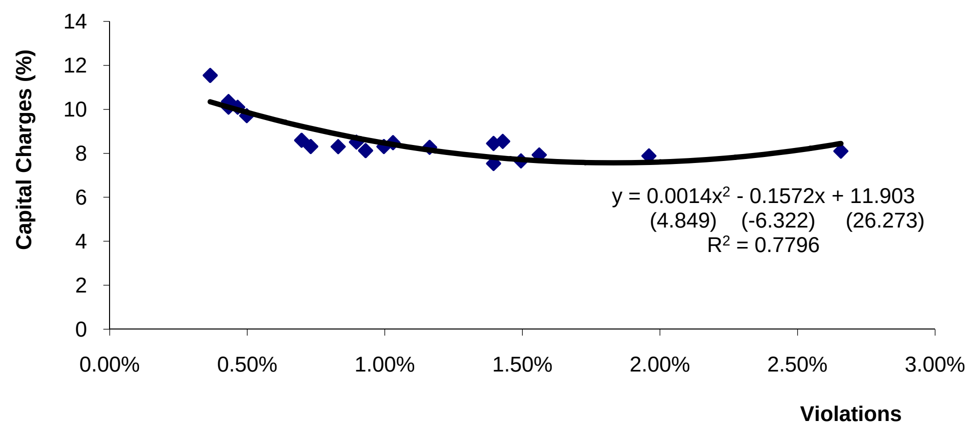


Figure 8: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 1$)

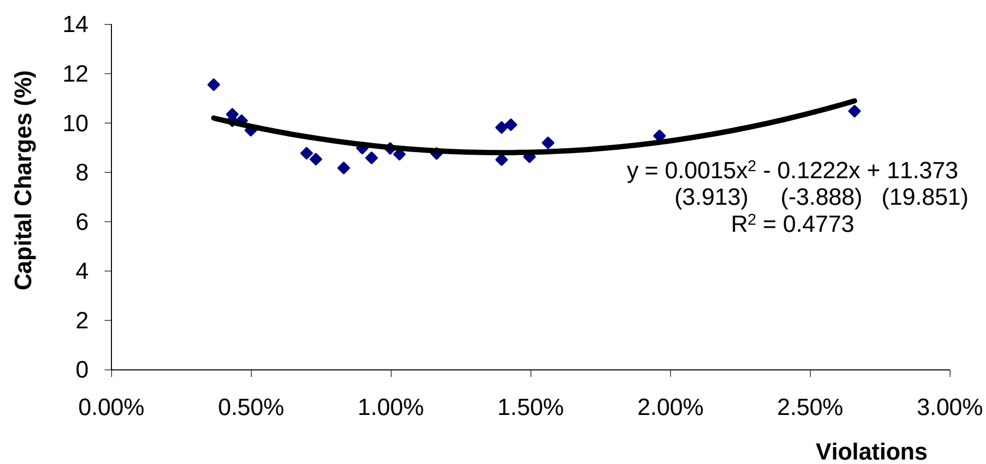


Figure 9: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 2$)

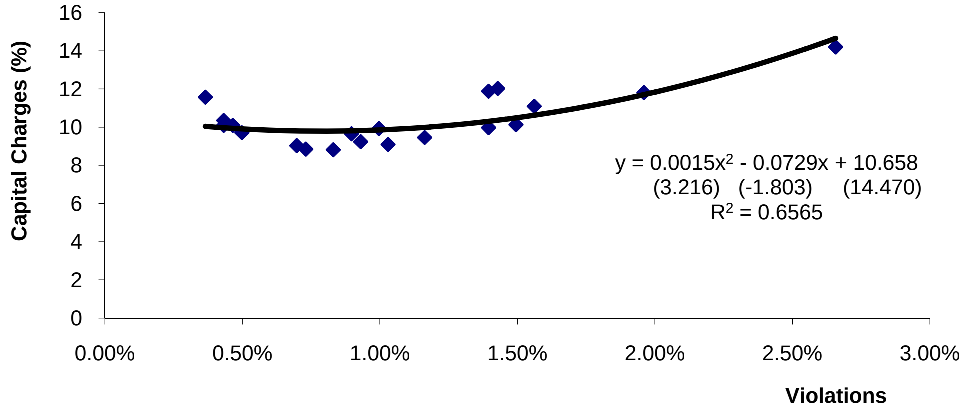
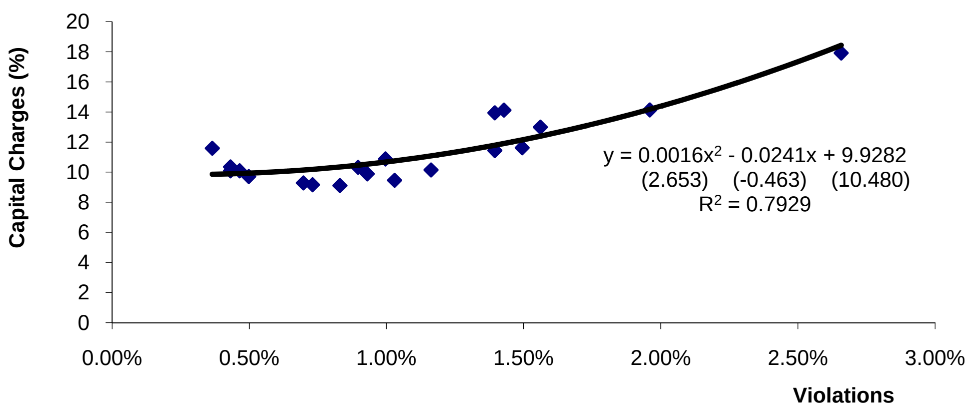


Figure 10: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 3$)



3. Simulation Exercise

A careful analysis of the results presented in Table 1 shows that differences between different types of models, under the same distributional assumption, is much smaller than the differences between the same model under different distributional assumptions. This result suggests that the within the class of conditional volatility models, the most important consideration for ADIs is the distribution for purposes of calculating the critical values. In this section, we use simulated data to analyse the importance of choosing the correct critical value. The returns are simulated using a GARCH model and a t distribution with 10 degrees of freedom. A total of 20,000 returns are simulated. Figure 11 plots the simulated returns.

In order to analyse the Current Basel Accord penalty structure, the industry standard Riskmetrics™ model is used to forecast the conditional variance for the simulated returns series. As the Riskmetrics™ model is calibrated using a simple formula, and thereby does not require estimation, ADIs must choose what critical value to use. In this paper we analyse the importance of choosing the correct critical value by estimating VaR threshold, and then calculating average capital charges for a range of critical values. The critical values that are chosen range from 1 to 7, with increments of 0.01. As the correct critical value for returns that follow a t distribution with 10 degrees of freedom is 2.764, it is expected that critical values lower (higher) than 2.764 will lead to a greater (lower) number of violations than expected at the 1% critical value.

Figure 12 gives the relationship between the number of violations and the Basel Accord capital charges. Each point on this graph corresponds to the results obtained for one critical value. These results suggest that the Basel Accord capital charges are a decreasing function of the number of violations. In short, banks are likely to have an incentive to choose models that will lead to the maximum number of violations permitted by regulators.

Figure 11: Simulated Returns Assuming a t distribution with 10 Degrees of Freedom

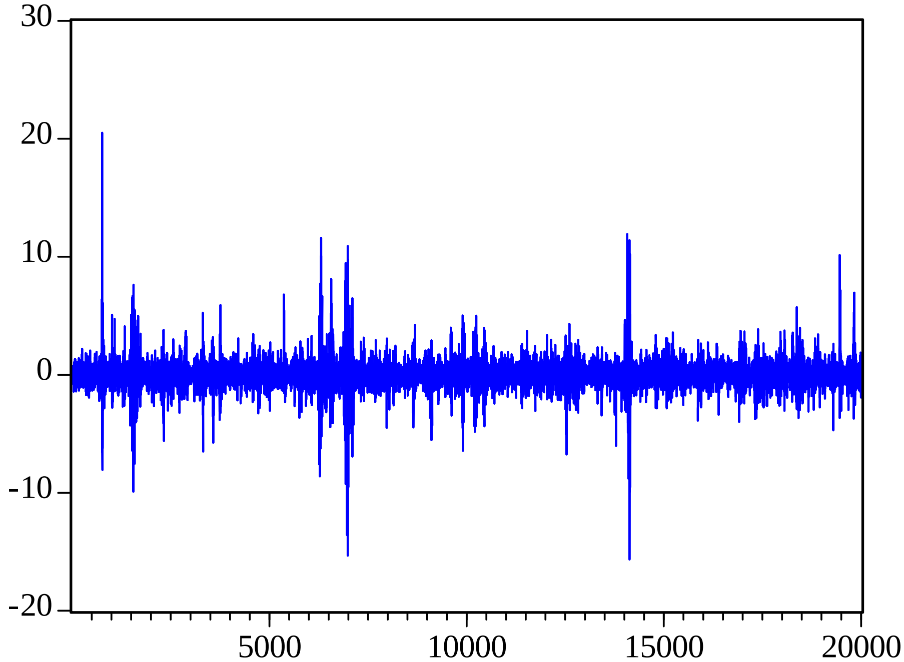


Figure 12: Relationship Between Number of Violations and Capital Charges for the Basel Accord Penalty Structure

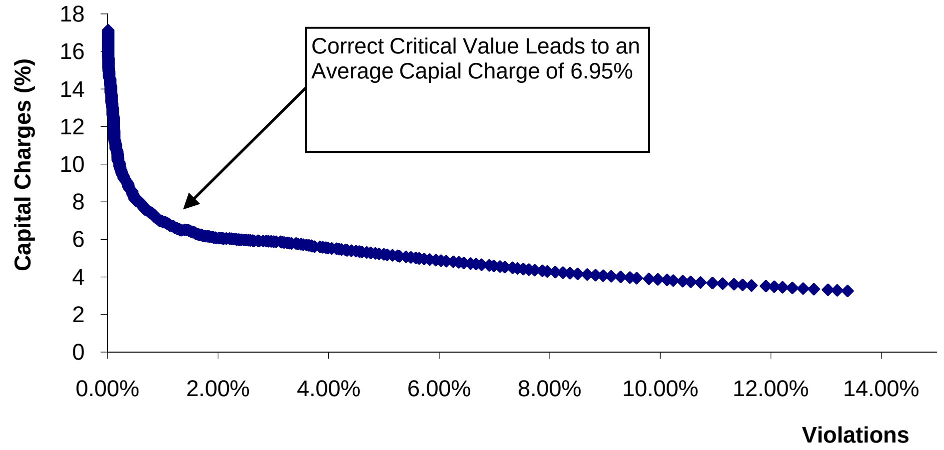


Figure 13: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 1$)

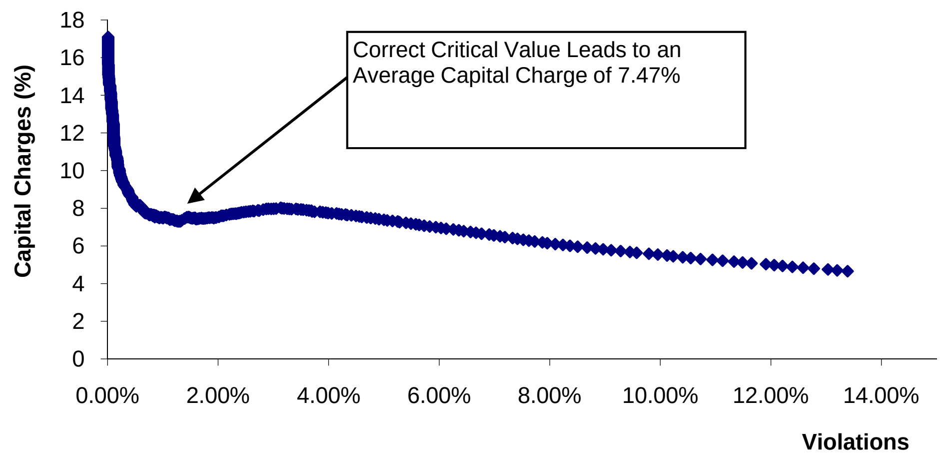


Figure 14: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 2$)

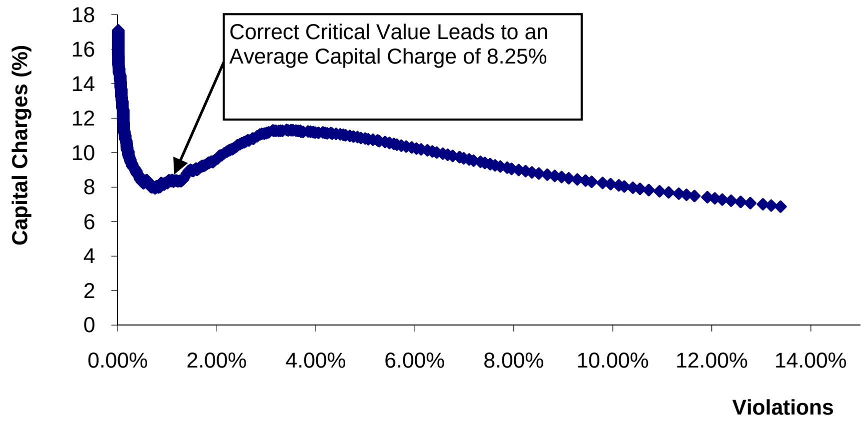
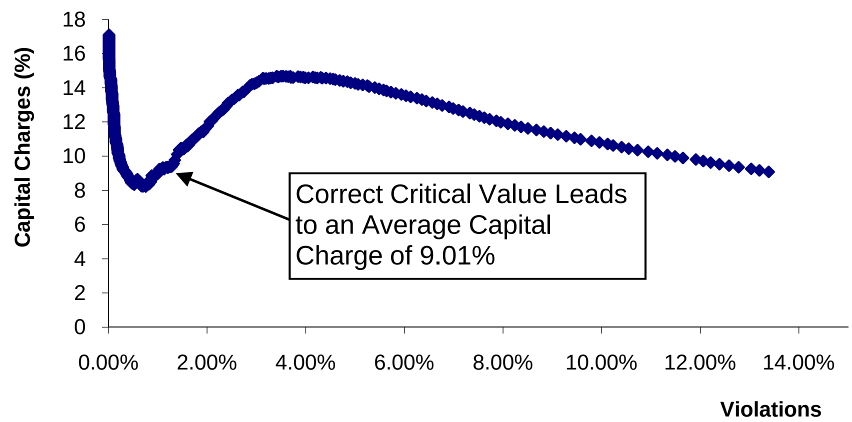


Figure 15: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 3$)



Figures 13 to 15 give the relationship between the number of violations and the capital charges obtained under the new penalty structure, which produces a minimum of between 0 and 4% of violations. If it is assumed that regulators will place an upper bound on the maximum number of violations allowed before a model is deemed to be inadequate, then the new penalty structure is superior to the existing one as it would lead ADIs to choose models that provide more conservative VaR forecasts.

4. Concluding Remarks

In this paper the ability of the current penalty structure proposed in the Basel Accord to align the interests of regulators with those of ADIs was investigated. In accordance with the findings of Lucas (2001), the current Basel Accord penalty structure was found to be highly inadequate. In particular, the results suggest that the Basel Accord penalty structure provided an incentive for ADIs to underreport risk, thereby lowering the required capital charges.

In order to demonstrate that more severe penalties for violations are needed, this paper presented a simple new penalty structure. The results showed that the new penalty structure was substantially more effective in aligning the interests of ADIs with those of regulators by awarding ADIs incentives to choose more conservative VaR models. Through a simulation exercise, it was shown that the new penalty structure creates a relationship between capital charges and the number of violations where a minimum is achieved. This suggests that if regulators place an upper bound on the permitted number of violations before an ADI is required to change their model, the new penalty structure is superior in aligning the interests of both ADIs and regulators.

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