Market Risk Management of Banks:
Implications from the Accuracy of Value-at-Risk Forecasts

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Abstract

This paper adopts the backtesting criteria of the Basle Committee to compare the performance of a number of simple value-at-risk (VaR) models. These criteria provide a new standard on forecasting accuracy. Currently central banks in major money centers, under the auspices of the Basle Committee of the Bank of International settlement, adopt the VaR system to evaluate the market risk of their supervised banks. Banks are required to report VaRs to bank regulators with their internal models. These models must comply with the Basle's backtesting criteria. If a bank fails the VaR backtesting, it will be imposed a higher capital requirements. VaR is a function of volatility forecasts. Past studies mostly conclude that ARCH and GRACH models provide better volatility forecasts. However, this paper finds that ARCH-based and GARCH-based VaR models consistently fail to meet with the Basle's backtesting criteria. These findings suggest that the use of ARCH-based and GARCH-based models to forecast their VaRs is not a reliable way to manage a bank's market risk.

1. Introduction

Modeling and forecasting volatility of financial time series have been a popular research topic for the past several years. There are two major reasons for this development. The first reason is the rapid growth of financial derivatives that requires volatility forecasts to calculate their fair prices. The second reason is the growing concern of risk management among financial institutions. Currently central banks in major money centers, led by the Basle Committee on Banking Supervision (see Basle Committee 1996a) of the Bank of International Settlement, require their supervised banks to measure market risk of their assets and trading books with value-at-risk (VaR). In order to constrain the risk-taking activities of banks, the Basle Committee links capital requirements on banks to the size of their VaRs. In brief, large VaRs result in more capital charges.

VaR can be interpreted as a function of volatility forecasts. By definition, VaR is an estimate (or forecast) of the amount that could be lost on a portfolio of assets. Consider a portfolio of assets whose returns follow a normal distribution. VaR of the portfolio can be expressed as:

$$VaR = MV_p \cdot |min\{E(R_p) - k \cdot s_{p}, 0\}| \quad (1)$$

where MV_p is the market value of the portfolio; $E(R_p)$ is the expected portfolio return; k stands for the critical value for a required confidence level; and s_p is the volatility forecast of the portfolio returns. Equation (1) ensures that VaR is a measure on the expected maximum trading loss of the portfolio. The size of the expected maximum trading loss depends on $E(R_p)$, k and s_p. For simplicity, many banks estimate daily VaRs by assuming daily $E(R_p)$ equal to zero. In this case, daily VaRs can be written as:

$$VaR = MV_p \cdot k \cdot s_p \quad (2)$$

Both equations (1) and (2) show that VaR is positively related to volatility forecast (s_p). Larger volatility forecasts result in not only larger VaRs but also more capital charges imposed by central banks. In most circumstances, no commercial bank wants to have a higher capital requirement. An increase in capital charge increases the equity-asset ratio of a bank. As equity tends to have higher required rate of returns than debt or other sources of capital, the average cost of capital of the bank will rise. This may result in low profitability of the bank in terms of return on equity (ROE) and exert downward pressure on the bank's stock prices.

Forecasting VaRs can include simulation-based methods and parametric methods. These methods require some inputs of volatility forecasts. Previous studies on volatility forecasts, such as Akgiray (1989), Pagan and Schewert (1990), Ballie and Bollerslev (1992), West and Cho (1995), Brailsford and Ford (1966), Chu and Frend (1996), Frances and Dijk (1996), Andersen and Bollerslev (1997), Brooks (1998), and Taylor (1999), generally forecast volatility by different time series models and measure predictive accuracy by mean absolute forecast errors or mean squared forecast errors. In all these studies, forecast error is defined as absolute gap between actual volatility (measured by a squared daily return) and forecasted volatility. A general conclusion from these studies is that GARCH-based models tend to have better performance in forecasting volatility than other time series models.

Daily VaRs of banks and their internal VaR models are not publicly available information. In order to study the reliability of different VaR models, this paper selects a portfolio of stocks as a proxy of the net asset of a bank and then applies a number of VaR models to forecast its daily VaRs. The stock portfolio to be selected is the Australia's All Ordinary Index (AOI). The AOI is a well-diversified portfolio of Australian companies. Australia economy has a wide range of business sectors, including mining of natural resources, exports of agricultural products, financial services, manufacturing, telecommunication and etc. This makes the AOI subject to various market risks in both the local and global markets, namely commodity risk, currency risk, interest rate risk and stock market risk. The risk feature of the AOI is somewhat similar to that of a global bank that exposes itself vigorously to different financial markets.

In this paper, we employ nine univariate time series models to generate volatility forecasts. They are random walk, AR(1), ARMA(1,1), ARCH(1), GARCH(1,1), AR(1)-ARCH(1), ARMA(1,1)-ARCH(1), AR(1)-GARCH and ARMA(1,1)-GARCH(1,1), are used to forecast the VaRs of the AOI returns and volatilities. These forecasts are then transformed to VaR forecasts. Previous research seldom evaluates the performance of VaR forecasts provided by ARCH-based and GARCH-based models.[1] This paper assesses the predictive accuracy of the VaR models by two criteria. The first assessment criterion is whether a model is able to comply with the backtesting criteria laid out by the Basle Committee (see Basle Committee 1996b). The second assessment criterion is the size of VaRs. These two criteria are more "practical" measures on predictive accuracy of VaR models. Banks will have additional capital charges as penalty if their VaR models fail to meet the backtesting criteria. Meanwhile, banks are required to have higher capital charges when they report larger VaRs. Therefore, banks prefer VaR models that are able to pass in backtesting and to provide small VaRs.

Using 4,000 daily returns of the AOI as the sample, this paper finds that the ARCH-based and the GARCH-based VaR models consistently fail to comply with the Basle's backtesting criteria. This finding suggest that the use of ARCH-based and GARCH-based models to forecast VaRs is not a reliable way to manage a bank's market risk. This paper proceeds as follows. Section 2 introduces the Basle's backtesting criteria on a VaR model and its VaR-based capital requirements. Section 3 describes the data and the VaR models to be used. Section 4 compares the accuracy of VaRs provided by the models. Section 5 concludes the paper.

[1] Hendricks (1996) and Jackson and Perraudin (1998) evaluate different VaR models. These studies compare simulation-based VaR models and parametric VaR models with moving average volatility and do not include any ARCH-based or GARCH-based models.

2. The Basle's Backtesting Criteria on VaR Models

The Basle Committee does not specify strictly how banks should forecast VaRs. Banks are allowed to use internal VaR models. However, they are inclined to underestimate their VaRs since this helps reduce their capital charges. For this reason, the Basle Committee sets some requirements on VaR models used by banks to ensure their reliability (see Basle Committee 1996). The requirements are as follows:

a) Banks must use at least one year of data to estimate one-day and ten-day VaRs.

b) Capital charge is equal to the three times (this is known as capital multiplier) the 60-day moving average of 1% ten-day VaR estimates, or 1% ten-day VaR on the current day, whichever is higher.

In addition, the Basle Committee (1996b) provides the following criteria for backtesting an internal VaR model:

a) One-day VaRs are compared with actual one-day trading outcomes.

b) One-day VaRs are required to be correct in 99% of backtesting days. There should be at least 250 days (around 1-year data) for backtesting.

c) A VaR model fails in backtesting when it provides 5% or more incorrect VaRs.

d) If a bank provides a VaR model that fails in backtesting, it will have their capital multiplier adjusted upward. This means that its capital charges will be larger.

Furthermore, the Basle Committee (1996b) defines accuracy of a VaR forecast by an actual loss smaller than a VaR forecast. Mathematically, it can be written as:

(3) $VaR_{t+1} \geq$ *Actual trading Loss at time t+1*, *where* VaR_{t+1}*: VaR forecast at time t+1 made at time t.*

The Basle Committee requires that the above condition must holds at least in 99% of backtesting days. This definition of predictive accuracy provides a new standard on the accuracy of VaR forecasts.

3. Data, Forecasting Models and Relative VaRs

The sample in this study is the AOI from February 1983 to June 1999. A total of 4,000 daily returns are obtained. In order to check the robustness of the findings, the whole period is divided into four subperiods of equal number of observations. Daily AOI returns (R_t) are computed with the following formula:

(4) $$R_t = \log\left(\frac{P_t}{P_{t-1}}\right)\cdot 100\%$$, where P_t*: AOI at time t*

This paper applies nine commonly-used univariate time series models to produce one-step-ahead return forecasts ($\hat{R}_{t+1}$) and volatility forecasts ($\hat{s}_{t+1}$) of the AOI. These models are summarized as follows:

Forecasting Model	One-step-ahead Return Forecast: $\hat{R}_{t+1}$	One-step-ahead Volatility Forecast: $\hat{s}_{t+1}$
Random Walk	$\hat{R}_{t+1} = \hat{b}_0$	$(\hat{s}_{t+1})^2 = \hat{g}_0$
AR(1)	$\hat{R}_{t+1} = \hat{b}_0 + \hat{b}_1 \cdot R_t$	$(\hat{s}_{t+1})^2 = \hat{g}_0$
ARMA(1,1)	$\hat{R}_{t+1} = \hat{b}_0 + \hat{b}_1 \cdot R_t + \hat{b}_2 \cdot e_t$	$(\hat{s}_{t+1})^2 = \hat{g}_0$
ARCH(1)	$\hat{R}_{t+1} = \hat{b}_0$	$(\hat{s}_{t+1})^2 = \hat{g}_0 + \hat{g}_1 \cdot (e_t)^2$
AR(1)-ARCH(1)	$\hat{R}_{t+1} = \hat{b}_0 + \hat{b}_1 \cdot R_t$	$(\hat{s}_{t+1})^2 = \hat{g}_0 + \hat{g}_1 \cdot (e_t)^2$
ARMA(1,1)-ARCH(1)	$\hat{R}_{t+1} = \hat{b}_0 + \hat{b}_1 \cdot R_t + \hat{b}_2 \cdot e_t$	$(\hat{s}_{t+1})^2 = \hat{g}_0 + \hat{g}_1 \cdot (e_t)^2$
GARCH(1,1)	$\hat{R}_{t+1} = \hat{b}_0$	$(\hat{s}_{t+1})^2 = \hat{g}_0 + \hat{g}_1 \cdot (e_t)^2 + \hat{g}_2 \cdot (\hat{s}_t)^2$
AR(1)-GARCH(1,1)	$\hat{R}_{t+1} = \hat{b}_0 + \hat{b}_1 \cdot R_t$	$(\hat{s}_{t+1})^2 = \hat{g}_0 + \hat{g}_1 \cdot (e_t)^2 + \hat{g}_2 \cdot (\hat{s}_t)^2$
ARMA(1,1)-GARCH(1,1)	$\hat{R}_{t+1} = \hat{b}_0 + \hat{b}_1 \cdot R_t + \hat{b}_2 \cdot e_t$	$(\hat{s}_{t+1})^2 = \hat{g}_0 + \hat{g}_1 \cdot (e_t)^2 + \hat{g}_2 \cdot (\hat{s}_t)^2$

The parameters in the above models are estimated at time t with observations of AOI returns from *t-249* to t. This complies with the Basle's requirement that VaRs must be estimated with data of not less than 250 days. All estimates are updated every trading day with observations of the most recent 250 days. Thus, the volatility forecasts of the random walk, AR(1) and ARMA(1,1) are simple standard deviation of forecast errors in the last 250 days.

The above return and volatility forecasts are transformed to VaR forecasts in the following way. Since banks can hold either long or short positions on any financial assets, this paper considers both long and short positions of the AOI portfolio. This papers uses relative VaRs (denoted by RV_{t+1}) to measure the size of VaRs. RVs is simply the maximum trading loss in return. Using RV instead of nominal VaRs help generalize conclusions from our analysis to portfolios or banks of different size. Mathematically, RVs are obtained by:

(5) *Buying Long the AOI:* $RV_{t+1} = |\min\{\hat{R}_{t+1} - k \cdot \hat{s}_{t+1},\ 0\}|$

(6) *Selling Short the AOI:* $RV_{t+1} = \max\{\hat{R}_{t+1} + k \cdot \hat{s}_{t+1},\ 0\}$

Equation (5) predicts the maximum loss (in return) for long positions in the next period, in which trading loss occurs when the AOI falls. Equation (6) predicts the maximum loss (in return) for short positions in the next period, in which trading loss occurs when the AOI rises. The $\hat{R}_{t+1}$ and $\hat{\sigma}_{t+1}$ in the equations are obtained from the nine forecasting models. The k is the critical value for a required confidence level. This paper adopts a k (where $k = 2.575$) that corresponds a 99% two-tailed confidence level. Through this transformation, all the nine forecasting models become VaR models. Slightly modifying equation (3), this paper defines accuracy of RVs by

$$(7) \qquad RV_{t+1} \geq \textit{Actual trading loss (in return) at time } t+1$$

The following section will discuss the performance of RVs produced by the nine VaR models according to equation (7).

4. Forecasting Performance

Performance of Return Forecasts

Table 1 provides summary statistics on the daily AOI returns and return forecasts provided by the random walk, AR(1) and ARMA(1,1) models. Column (8) shows the mean square error (MSE) of the return forecasts, while Column (9) shows their mean absolute error (MAE). The first section shows the results in the whole period, while the others show the results of four subperiods. From both the MSE and MAE, we find no forecasting model consistently having superior performance in forecasting AOI returns in all the sample periods.

Insert Table 1 around here

Size of Relative VaRs

Table 2 shows the relative VaRs (RVs) provided by the nine VaR models at 99% confidence level. The size of the RVs is a major concern since it can determine banks' capital charges. On the basis of equations (5) and (6), we obtain RVs for both long and short positions. They are shown respectively in Columns (5) and (6). The "Average RV" in Column (4) is mean of RV(Long) and RV(Short).
From Columns (4), (5) and (6), we find that the ARCH(1) and GARCH(1,1) models have remarkably large RVs in the whole period. However, this result is not robust because we do not find the same result in Periods 1, 3 and 4. Excluding Period 2, we find that the random walk, AR(1) and the ARMA(1,1) models generally have larger RVs than other models.

Accuracy of Relative VaRs

Equation (7) has set the criterion of a correct RV forecast. The Basle Committee requires that a VaR model should be correct in 99% of backtesting days. A VaR model will fail if it provides 5% or more incorrect VaR forecasts. This pass/fail measure sets an objective standard for comparing the performance of the nine VaR models[2]. We assume that a bank holds either a long or a short position on the AOI. When a RV for either a long or position cannot satisfy equation (7), we define it as an incorrect RV forecast. In other words, correct RVs imply that trading outcomes, being assumed to be normally distributed, must lie within a 99% confidence interval.

Table 3 shows the percentage of correct RVs and their size. Banks generally want a pass (i.e. not less than 95% correct VaR forecasts) in backtesting their VaR models and small VaRs provided by the models. Column (3) shows the number of correct RV forecasts and Column (4) shows the percentage of correct

[2] There are a number of theoretical and empirical studies on techniques for evaluating VaR models, such as Kupiec (1995), Crnkovic and Drachman (1995), Christoffersen (1996), Jackson, Maude and Perraudin (1997) and Lopez (1998). This paper follows primarily the Basle's evaluation system (1996b) since it has economic meanings for bank risk management.

RVs. From Column (4), we find that the random walks, AR(1) and ARMA(1,1) models have more than 95% correct RVs. This implies that these models pass the backtesting. However, those ARCH-based and GARCH-based models all fail in backtesting. Same results are found in all the subperiods. That is, ARCH-based and GARCH-based models generally fail, while other models pass. Column (5) exhibits the size of correct RVs. Smaller RVs would suggest less capital requirements in relative terms. It is obvious that the ARCH-based and GARCH-based models generally have smaller size of RVs in all the periods, except in Period 2. Combining all the above results, we can conclude that ARCH-based and GARCH-based models can produce smaller VaRs but they tend to fail in backtesting.

Insert Table 3 around here

Size of Forecast Errors of Relative VaRs

For those incorrect RVs, we measure the size of their errors by RV errors (VEs). A VE is the absolute difference between an actual trading loss (in return) and a RV. Two summary statistics on VEs are provided, namely mean absolute VE (MAVE) and mean squared VE (MSVE). Table 4 shows the MAVE and MSVE of the incorrect RV forecasts of both long and short positions. From the MAVE and MSVE in the whole period, we find some mixed results. No model has consistently large forecast errors. In all the subperiods, there is no remarkable evidence that some VaR models have consistently larger size of VEs.

Insert Table 4 around here

5. Summary and Implications

This paper addresses the issue of using value-at-risk (VaR) for banking regulation and supervision. In order to limit the risk-taking behavior of banks and reduce the likelihood of bank failures, many central banks, coordinated by the Basle Committee of the Bank of International Settlement, paid much attention to developing the VaR system in the past ten years. VaR is a measure on market risk, estimating the maximum trading loss that a bank can encounter. Currently central banks in major money centers require their supervised banks to report VaRs. Banks can use their internal VaR models but their models must comply with the backesting criteria set by the Basle Committee. If a bank fails in backtesting, it will have additional capital charges as penalty.

This paper mainly adopts the Basle's backtesting criteria to compare the performance of a number of simple VaR models. The Basle's backtesting criteria have economic implications to banks and provide a new standard for forecasting accuracy. We deliberately select the Australia's All Ordinary Index (AOI) as the sample. The AOI is a well-diversified asset portfolio that is subject to a wide range of market risks, including commodity risk, currency risk, interest rate risk and stock market risk. The VaR models in this paper are univariate time-series models. They may not be the VaR models practically adopted by banks. In most cases, banks use simulation methods or parametric methods to obtain the VaRs of their ever-changing portfolios of assets, liabilities and off-balance-sheet items. In practice, we do not know exactly which assets banks are holding. For this reason, we select a stock portfolio, i.e. the AOI, to act as the proxy measure for a bank's portfolio. The VaR models in this paper, the simulation-based methods and the parametric models all require some inputs on volatility forecasts to produce VaRs. Consider that a simple bank that holds only one asset and the asset returns follow normal distribution. In this case, the VaR models in this paper, the simulation-based methods and the parametric methods tend to provide similar VaRs. Thus, the accuracy of the VaR models in this paper will have implications for the accuracy of the VaR models used by banks.

Past studies mostly conclude that ARCH and GRACH models can provide better volatility forecasts. Although VaR is just a function of volatility forecasts, this paper finds that ARCH-based and GARCH-based VaR models consistently fail to pass in backtesting. This finding is robust across the whole and different subperiods in our study. This finding implies that the use of ARCH-based and GARCH-based models is not a reliable way for a bank to forecast VaRs and to manage its market risk.

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Table 1 AOI Returns and Return Forecasts in the Whole Sample Period and Subperiods

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample Period	**Forecasting Model**	**Obs**	**Mean**	**SD**	**Minimum**	**Maximum**	**MSE of Point Forecast**	**MAE of Point Forecast**
Whole Period	Actual AOI Returns	4000	0.019	0.439	-12.491	2.635		
February 11, 1983	Forecasts [Random Walk Model]	4000	0.019	0.030	-0.070	0.106	0.275	0.193
To	Forecasts [AR(1) Model]	4000	0.017	0.196	-11.489	0.507	0.278	0.229
June 11, 1999	Forecasts [ARMA(1,1) Model]	4000	0.018	0.201	-10.682	1.663	0.279	0.224
Period 1	Actual AOI Returns	1000	0.046	0.347	-1.586	1.627		
February 11, 1983	Forecasts [Random Walk Model]	1000	0.038	0.022	-0.017	0.078	0.261	0.122
To	Forecasts [AR(1) Model]	1000	0.041	0.093	-0.434	0.507	0.257	0.118
July 27, 1986	Forecasts [ARMA(1,1) Model]	1000	0.041	0.108	-0.524	0.713	0.256	0.118
Period 2	Actual AOI Returns	1000	0.003	0.637	-12.491	2.431		
July 25, 1986	Forecasts [Random Walk Model]	1000	0.012	0.042	-0.070	0.106	0.324	0.408
to	Forecasts [AR(1) Model]	1000	0.000	0.373	-11.489	0.268	0.335	0.549
March 24, 1991	Forecasts [ARMA(1,1) Model]	1000	0.005	0.374	-10.682	1.663	0.335	0.522
Period 3	Actual AOI Returns	1000	0.014	0.331	-1.322	1.104		
May 25, 1991	Forecasts [Random Walk Model]	1000	0.010	0.025	-0.038	0.078	0.254	0.110
To	Forecasts [AR(1) Model]	1000	0.012	0.056	-0.258	0.275	0.255	0.109
March 24, 1995	Forecasts [ARMA(1,1) Model]	1000	0.012	0.065	-0.280	0.303	0.256	0.109
Period 4	Actual AOI Returns	1000	0.014	0.365	-3.235	2.635		
March 25, 1995	Forecasts [Random Walk Model]	1000	0.015	0.011	-0.020	0.047	0.261	0.134
To	Forecasts [AR(1) Model]	1000	0.014	0.046	-1.127	0.154	0.263	0.141
June 11, 1999	Forecasts [ARMA(1,1) Model]	1000	0.014	0.077	-1.440	0.337	0.267	0.146

Table 2 Size of Relative VaRs (RVs) of Different Forecasting Models

(1)	(2)	(3)	(4)	(5)	(6)
			Relative VaR (RV)		
Sample	**Model**	**Obs**	**Average RV**	**RV (Long)**	**RV(Short)**
Whole Period	Random Walk Model	4000	1.035	1.016	1.053
	AR(1) Model	4000	1.015	0.997	1.034
	ARMA(1,1) Model	4000	1.007	0.987	1.026
	ARCH (1) Model	4000	3.273	3.254	3.292
	AR(1)-ARCH(1) Model	4000	1.211	1.194	1.228
	ARMA(1,1)-ARCH(1) Model	4000	1.211	1.193	1.229
	GARCH (1, 1) Model	4000	3.280	3.261	3.298
	AR(1)-GARCH(1,1) Model	4000	1.253	1.236	1.270
	ARMA(1,1)-GARCH(1,1) Model	4000	1.253	1.235	1.270
Period 1	Random Walk Model	1000	0.904	0.866	0.942
	AR(1) Model	1000	0.877	0.836	0.918
	ARMA(1,1) Model	1000	0.872	0.831	0.913
	ARCH (1) Model	1000	0.319	0.281	0.357
	AR(1)-ARCH(1) Model	1000	0.300	0.259	0.341
	ARMA(1,1)-ARCH(1) Model	1000	0.300	0.259	0.341
	GARCH (1, 1) Model	1000	0.329	0.290	0.367
	AR(1)-GARCH(1,1) Model	1000	0.313	0.272	0.354
	ARMA(1,1)-GARCH(1,1) Model	1000	0.313	0.272	0.354
Period 2	Random Walk Model	1000	1.444	1.432	1.456
	AR(1) Model	1000	1.411	1.407	1.415
	ARMA(1,1) Model	1000	1.386	1.377	1.395
	ARCH (1) Model	1000	12.090	12.078	12.102
	AR(1)-ARCH(1) Model	1000	3.909	3.909	3.909
	ARMA(1,1)-ARCH(1) Model	1000	3.909	3.904	3.914
	GARCH (1, 1) Model	1000	12.071	12.059	12.083
	AR(1)-GARCH(1,1) Model	1000	4.032	4.032	4.033
	ARMA(1,1)-GARCH(1,1) Model	1000	4.033	4.030	4.035
Period 3	Random Walk Model	1000	0.881	0.871	0.891
	AR(1) Model	1000	0.860	0.848	0.872
	ARMA(1,1) Model	1000	0.859	0.847	0.871
	ARCH (1) Model	1000	0.296	0.286	0.307
	AR(1)-ARCH(1) Model	1000	0.291	0.278	0.303
	ARMA(1,1)-ARCH(1) Model	1000	0.291	0.278	0.303
	GARCH (1, 1) Model	1000	0.303	0.293	0.313
	AR(1)-GARCH(1,1) Model	1000	0.297	0.285	0.309
	ARMA(1,1)-GARCH(1,1) Model	1000	0.297	0.285	0.309
Period 4	Random Walk Model	1000	0.910	0.895	0.925
	AR(1) Model	1000	0.914	0.900	0.928
	ARMA(1,1) Model	1000	0.911	0.896	0.925
	ARCH (1) Model	1000	0.387	0.372	0.402
	AR(1)-ARCH(1) Model	1000	0.344	0.330	0.358
	ARMA(1,1)-ARCH(1) Model	1000	0.344	0.329	0.359
	GARCH (1, 1) Model	1000	0.415	0.401	0.430
	AR(1)-GARCH(1,1) Model	1000	0.369	0.355	0.383
	ARMA(1,1)-GARCH(1,1) Model	1000	0.369	0.355	0.383

Table 3 Percentage of Correct RV Forecasts and their Size

(1)	(2)	(3)	(4)	(5)
		Correct RV Forecasts		
Sample	Model	Number	Percentage	Size
Whole Period	Random Walk Model	3928	98.20%	1.037
	AR(1) Model	3920	98.00%	1.015
	ARMA(1,1) Model	3915	97.88%	1.008
	ARCH (1) Model	2754	68.85%	4.624
	AR(1)-ARCH(1) Model	2725	68.13%	1.647
	ARMA(1,1)-ARCH(1) Model	2716	67.90%	1.652
	GARCH (1, 1) Model	2725	68.13%	4.692
	AR(1)-GARCH(1,1) Model	2679	66.98%	1.744
	ARMA(1,1)-GARCH(1,1) Model	2666	66.65%	1.751
Period 1	Random Walk Model	977	97.70%	0.905
	AR(1) Model	974	97.40%	0.878
	ARMA(1,1) Model	975	97.50%	0.873
	ARCH (1) Model	668	66.80%	0.337
	AR(1)-ARCH(1) Model	656	65.60%	0.314
	ARMA(1,1)-ARCH(1) Model	656	65.60%	0.314
	GARCH (1, 1) Model	672	67.20%	0.353
	AR(1)-GARCH(1,1) Model	647	64.70%	0.335
	ARMA(1,1)-GARCH(1,1) Model	649	64.90%	0.333
Period 2	Random Walk Model	988	98.80%	1.444
	AR(1) Model	983	98.30%	1.405
	ARMA(1,1) Model	982	98.20%	1.383
	ARCH (1) Model	792	79.20%	15.172
	AR(1)-ARCH(1) Model	791	79.10%	4.856
	ARMA(1,1)-ARCH(1) Model	791	79.10%	4.859
	GARCH (1, 1) Model	796	79.60%	15.090
	AR(1)-GARCH(1,1) Model	773	77.30%	5.137
	ARMA(1,1)-GARCH(1,1) Model	765	76.50%	5.187
Period 3	Random Walk Model	981	98.10%	0.882
	AR(1) Model	983	98.30%	0.861
	ARMA(1,1) Model	982	98.20%	0.860
	ARCH (1) Model	641	64.10%	0.311
	AR(1)-ARCH(1) Model	631	63.10%	0.304
	ARMA(1,1)-ARCH(1) Model	627	62.70%	0.304
	GARCH (1, 1) Model	635	63.50%	0.326
	AR(1)-GARCH(1,1) Model	632	63.20%	0.321
	ARMA(1,1)-GARCH(1,1) Model	630	63.00%	0.321
Period 4	Random Walk Model	982	98.20%	0.913
	AR(1) Model	980	98.00%	0.916
	ARMA(1,1) Model	976	97.60%	0.913
	ARCH (1) Model	653	65.30%	0.448
	AR(1)-ARCH(1) Model	647	64.70%	0.383
	ARMA(1,1)-ARCH(1) Model	642	64.20%	0.384
	GARCH (1, 1) Model	622	62.20%	0.530
	AR(1)-GARCH(1,1) Model	627	62.70%	0.450
	ARMA(1,1)-GARCH(1,1) Model	622	62.20%	0.453

Table 4 Absolute and Squared Errors of Incorrect RV Forecasts

		Long Position		Short Position	
(1)	(2)	(3)	(4)	(5)	(6)
Sample	Model	MAVE	MSVE	MAVE	MSVE
Whole Period	Random Walk Model	0.693	3.570	0.260	0.195
(Sample Size	AR(1) Model	0.697	3.557	0.274	0.302
= 4000)	ARMA(1,1) Model	0.638	3.210	0.271	0.298
	ARCH (1) Model	0.247	0.389	0.194	0.072
	AR(1)-ARCH(1) Model	0.247	0.383	0.191	0.066
	ARMA(1,1)-ARCH(1) Model	0.246	0.381	0.192	0.068
	GARCH (1, 1) Model	0.253	0.378	0.198	0.077
	AR(1)-GARCH(1,1) Model	0.244	0.346	0.196	0.075
	ARMA(1,1)-GARCH(1,1) Model	0.247	0.349	0.194	0.074
Period 1	Random Walk Model	0.161	0.075	0.272	0.141
(Sample Size	AR(1) Model	0.175	0.093	0.208	0.096
= 1000)	ARMA(1,1) Model	0.189	0.097	0.280	0.151
	ARCH (1) Model	0.216	0.093	0.203	0.078
	AR(1)-ARCH(1) Model	0.212	0.091	0.198	0.074
	ARMA(1,1)-ARCH(1) Model	0.214	0.092	0.195	0.075
	GARCH (1, 1) Model	0.223	0.098	0.195	0.074
	AR(1)-GARCH(1,1) Model	0.201	0.084	0.187	0.064
	ARMA(1,1)-GARCH(1,1) Model	0.207	0.087	0.183	0.064
Period 2	Random Walk Model	2.153	14.740	0.663	0.440
(Sample Size	AR(1) Model	1.900	12.930	0.405	0.368
= 1000)	ARMA(1,1) Model	1.894	12.943	0.293	0.243
	ARCH (1) Model	0.410	1.788	0.183	0.077
	AR(1)-ARCH(1) Model	0.423	1.805	0.171	0.049
	ARMA(1,1)-ARCH(1) Model	0.411	1.783	0.180	0.055
	GARCH (1, 1) Model	0.446	1.799	0.191	0.080
	AR(1)-GARCH(1,1) Model	0.411	1.531	0.187	0.079
	ARMA(1,1)-GARCH(1,1) Model	0.393	1.480	0.188	0.081
Period 3	Random WalkModel	0.131	0.030	0.136	0.029
(Sample Size	AR(1) Model	0.133	0.030	0.152	0.032
= 1000)	ARMA(1,1) Model	0.131	0.026	0.149	0.031
	ARCH (1) Model	0.203	0.072	0.199	0.072
	AR(1)-ARCH(1) Model	0.195	0.066	0.201	0.072
	ARMA(1,1)-ARCH(1) Model	0.195	0.067	0.196	0.068
	GARCH (1, 1) Model	0.196	0.068	0.202	0.074
	AR(1)-GARCH(1,1) Model	0.196	0.065	0.202	0.074
	ARMA(1,1)-GARCH(1,1) Model	0.200	0.067	0.195	0.070
Period 4	Random Walk Model	0.462	0.603	0.407	0.562
(Sample Size	AR(1) Model	0.473	0.569	0.444	0.890
= 1000)	ARMA(1,1) Model	0.379	0.438	0.397	0.790
	ARCH (1) Model	0.220	0.101	0.188	0.064
	AR(1)-ARCH(1) Model	0.227	0.114	0.185	0.063
	ARMA(1,1)-ARCH(1) Model	0.230	0.115	0.191	0.066
	GARCH (1, 1) Model	0.224	0.101	0.201	0.080
	AR(1)-GARCH(1,1) Model	0.227	0.107	0.204	0.082
	ARMA(1,1)-GARCH(1,1) Model	0.232	0.110	0.206	0.081

NB:
MAVE: Mean absolute errors of incorrect RV forecasts
MSVE: Mean squared errors of incorrect RV forecasts