Measuring the forecasting accuracy of models: evidence from industrialised countries

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Abstract: This paper uses the approach suggested by Akrigay (1989), Tse and Tung (1992) and Dimson and Marsh (1990) to examine the forecasting accuracy of stock price index models for industrialised markets. The focus of this paper is to compare the Mean Absolute Percentage Error (MAPE) of three models, that is, the Random Walk model, the Single Exponential Smoothing model and the Conditional Heteroskedastic model with the MAPE of the benchmark Naïve Forecast 1 case. We do not evidence that a single model to provide better forecasting accuracy results compared to other models.

Keywords: forecasting accuracy; stock price returns; industrialised countries; random walk; single exponential smoothing; conditional heteroskedastic.

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1 Introduction

In finance literature, investors are supposed to behave rationally by seeking to minimise risk and maximise returns. The investor's focus on gaining excess returns has led academia and practitioners alike to seek forecasting models and mechanisms to smooth stock price volatility and capture stock returns. However, various academic efforts have resulted in the invention of a number of forecasting models to exploit abnormal returns. These forecasting models have been observed to provide different results based on different regulations and circumstances.

The regulations are important to investors and other practitioners as these protect them from abnormal stock market reaction to unusual corporate events that lead to crisis or panic. With respect to the models that are widely used for forecasting purposes of the stock price indices, these can identify the impact of a crisis especially on a certain time and give an analogous forecasting. However, as the practice has shown, the GARCH-M model developed by Bollerslev (1987) is a good model to 'withstand' abnormal events and the model can react analogously in periods of different picks. GARCH-M model is used in our study in order to see if simple models or more sophisticated ones are preferred for forecasting accuracy to the stock indices around the world.

Our study attempts to examine the forecasting accuracy of three models for selected industrialised stock markets around the world. In particular, the focus of our study is to compare the Mean Absolute Percentage Error (MAPE) of three models, that is, the Random Walk model (RWM), the Single Exponential Smoothing model (SESM) and the Conditional Heteroskedastic Model (CHM) with the MAPE of the benchmark Naïve Forecast 1 case.

Not only sophisticated models which account for clustering in the data, but also less sophisticated such as the Random Walk and the SESMs are used in order to catch each pattern that exists in the data set. If the data follows a pattern in which the previous week-day's returns are important to forecast the next week-day returns, then the RWM is the preferred model for these stock exchanges. It is worth mentioning that if this is the case, it would not be important to use the GARCH-M model here. However, theory has shown that the ARCH family models are very important for forecasting the accuracy of the stock price behaviour both in the asset return case as well the stock index case.

On the other hand, the SESM is also more advanced than the RWM because the first gives different importance to the data sets and investors can see their stock price return to change values steadily. However, this does not mean that the RWM is an old tool which does not have any value. The simplest models some times might work better in a stock market than the more sophisticated ones, as these depend on the nature of the stock exchange which we look at. Thus, based on the previous theoretical analysis, we do not know if the GARCH-M or the SESM is superior in forecasting as compared to the RWM. The present study tries to fill this caveat as well to compare the MAPE of the above aforementioned models with the MAPE of the Naïve Forecast 1 case.

We follow a simple approach in order to provide investors with some insights with respect to the advantages of the forecasting accuracy of the aforementioned models. We are aware that there are more sophisticated forecasting techniques in the literature; however, this is a noteworthy attempt to compare the importance of each of the three aforementioned models.

This paper is structured as follows. Section 2 contains the literature review on forecasting modelling approaches. Section 3 describes the data and methodology of the present study. Section 4 presents the empirical findings. Finally, conclusions are provided in Section 5.

2 Literature review

In this section, we discuss the empirical findings on forecasting accuracy models in association with the RWM, the ARCH family models and the Black-Scholes model with applications to cash markets, high frequency data and derivatives. We also mention some of the factors that influence the predictability of stock price returns through calm and volatile periods.

Wiggins (1987) solved the call option valuation problem, given a fairly general continuous stochastic process for return volatility. Statistical estimates for volatility process parameters were calculated for several individual stocks and indices. The resulting estimated option values did not differ dramatically from Black-Scholes values in most cases, although there was some evidence that for longer-maturity index options, Black-Scholes overvalued out-of-the-money calls in relation to in-the-money calls.

The forecasting accuracy of simple models examined by Scheinkman and LeBaron (1989) supported the idea that the behaviour of the statistics seem to leave no doubt that past weekly returns help predict future ones, even though they are uncorrelated. Furthermore, it seemed that a substantial part of the variation on weekly returns was coming from non-linearities as opposed to randomness. In other words, the data were not incompatible with a theory where some of the variation would come from non-linearities as opposed to randomness and were not compatible with a theory that predicted that the returns were generated by independent and identically distributed (i.i.d.) random variables. In contrast to Scheinkman and LeBaron (1989) and Tse and Tung (1992) found evidence strongly in favour of an Exponentially Weighted Moving Average (EWMA) model for both the Japanese and Singaporean stock markets.

More sophisticated studies by Akrigay (1989) revealed evidence about the time-series behaviour of stock prices. Specifically, daily return series exhibited significant levels of second-order dependence that could not be modelled as linear white-noise processes. A reasonable return-generating process was empirically shown to be a first-order autoregressive process with conditionally heteroskedastic innovations. In particular, generalised autoregressive conditional heteroskedastic GARCH processes fitted the data very satisfactory. Various out of sample forecasts of monthly return variances were generated and compared statistically. Forecasts based on the GARCH model were found to be superior.

Nelson (1991) showed that in data at high frequencies, an ARCH model may perform well in estimating the conditional variance of a process, even when the ARCH model was severely mispecified. While such models might perform reasonably well at filtering (i.e., at estimating unobserved instantaneous conditional variances), they might perform disastrously at medium-and long-term forecasting of the process and its volatility. In addition, Nelson and Foster (1995) developed a conditional heteroskedastic process under which a mis-pecified ARCH model performed successfully both tasks, that is, filtering and forecasting. The ARCH model specified, correctly, the functional form of the first two conditional moments of all state variables. They applied these approaches to a diffusion model employed in the options pricing literature, the stochastic model of Wiggins (1987).

Haugen and Baker (1995) found that the determinants of the cross-section of expected stock returns were stable in their identity and were influenced from period to period and from country to country. Their results suggested that first stocks with higher expected and realised rates of returns were unambiguously lower in risk than stocks with lower returns. Second, the important determinants of expected stock returns were strikingly common to major equity markets of the world. Overall, the results seemed to reveal a major failure in the efficient market hypothesis.

Pesaran and Timmerman (1995) analysed the robustness of the predictability of the US stock returns and addressed the issue of whether this predictability could have been historically exploited by investors to earn profits in excess of a buy-and-hold strategy in the market index. They found that the predictive power of various economic factors over stock returns changed over time and tended to vary with the volatility of returns. The degree to which stock returns were predictable seemed quite low during the relatively calm markets in the 1960s, but increased to a level where net of transaction costs could have been exploited by investors in the volatile markets of the 1970s.

In another study, Andersen et al. (2003) provided a general framework for forecasting intraday and daily data using a simple long-memory Gaussian vector autoregression model which was found to perform better in comparison to the ARCH or related models. For this purpose, they used daily data of the Deutsche mark/dollar and yen/dollar spot exchange rates covering a decade. In an older study, Andersen et al. (1999) estimated the integrated volatility which links volatility to the return variance as it is approximated by a cumulative sum of the squared intraday returns. They also estimated forecasts of one month period or short intraday providing good forecasts of volatility measures. In addition, the use of high-frequency returns had improved the inter-daily volatility forecasts. Accurate modelling of volatility is important as it related to the forecasting of Value-at-Risk (VaR) thresholds. In particular, the forecasting performance of the VARMA-GARCH model of Ling and McAleer (2002), which includes spillover effects of all assets, the CCC model of Bollerslev (1990), which includes no spillovers, and the new PS-GARCH model, which accounts for aggregate spillovers parsimoniously, are compared using a VaR example. According to McAleer and Da Veiga (2004), the inclusion of spillover effects is not important in forecasting VaR thresholds, even when these spillovers are statistically significant.

Andersen et al. (2005) provided important theoretical developments and empirical findings in volatility forecasting. In particular, they discussed a series of economic situations in which volatility played a crucial role. They also employed GARCH models in order to present a variety of different procedures for univariate and multivariate volatility modelling.

More recently, Diebold and Yilmaz (2007) provided a simple method for measuring the interdependence of asset returns and volatilities, namely, return spillovers and volatility spillovers. They found that both trends and bursts in spillovers are important empirically. In particular, in their analysis they used 16 global equity markets and examined both crisis and non-crisis events. They found that return spillovers display trends, while volatility spillovers display bursts.

While the pertinent literature is based on a number of different approaches to be used for the predictability of stock price returns in cash and option markets, Dimson and Marsh concluded that

> "with the increasing interest in using complicated econometric techniques for volatility forecasting, our research strikes a warning bell. For those who are interested in forecasts with reasonable predictive accuracy, the best forecasting models may well be the simplest ones." (Dimson and Marsh, 1990, p.420)

Our current study is based on the findings of Dimson and Marsh (1990) in order to re-examine the accuracy of the three aforementioned forecasting models and their power of predictability, acknowledging the fact that not only simplistic models, but also more sophisticated models, may prove useful for forecasting purposes.

3 Data and methodology

3.1 Data

The data set in this study consist of time series of stock market indices. The examined stock market indices are those of Australia, Canada, France, Italy, Japan, the UK, the USA, and Germany. The examined period spans from January 1982 to October 2007. We leave out the period from November to December 2007 for forecasting purposes. The data are weekly and were obtained from Datastream. The indices are based on Wednesday's closing prices expressed in local currencies and do not include dividends. Table 1 refers to the examined stock market indices.

Table 1 Stock exchanges and indices of the countries

Countries	*Exchange*	*Stock index*
Australia	Sydney	AUSTALL
Canada	Toronto	TTOCOMP
France	Paris	TOTMKFR
Italy	Milan	MILANBC
Japan	Tokyo	JAPDOWA
UK	London	FTSE100
USA	New York	S&P COMP
Germany	Frankfurt	DAXINDX

The returns for each market (R_t) are computed as the first difference of the natural logarithm of stock market indices. That is:

$$R_t = \ln(P_t / P_{t-1}) \quad (1)$$

where

P_t: Level of price index at time t

P_{t-1}: Level of stock price at time $t-1$

R_t: Natural logarithm of stock price return at time t.

3.2 Random walk model

This method uses as a forecast the most recent information available concerning the actual value of the stock price. Thus, if a forecast is being prepared for a time horizon of one period, the most recent actual value would be used as the forecast for the next period. This is the method used to obtain the forecasts for weekly stock price returns of the selected stock market indices. The forecast that is based is as follows:

$$F_{t+i} = R_t \tag{2}$$

where

F_{t+1}: Forecast for period $t + i$

t: Present period

i: Number of periods ahead being forecast

R_t: Latest actual return (for period t).

For example, some studies (e.g., Makridakis and Wheelwright, 1989) have shown that stock markets, certain commodity futures markets and currency exchange markets often behave like RWMs, which would make the above equation the most appropriate for forecasting purposes. This implies that there are fluctuations in the data, but that the turning points can not be predicted.

3.3 Single exponential smoothing model

A strong argument has to do with the most recent observations which might contain the most current information about what will happen in the future and, thus, they should be given relatively more weight to this than the older observations. What we would like to do is to use a weighting scheme that would apply the most weight to the most recent observed values and decreasing weights to the older values. The SESM satisfies this requirement and eliminates the need for storing the historical values of the variable.

In principle, the SESM operates in a manner analogous to that of moving averages by 'smoothing' historical observations to eliminate randomness.

The general form for exponential smoothing is given by the following equation:

$$F_{t+1} = F_t + \alpha(R_t - F_t) \text{ or } F_{t+1} = F_t + \alpha e_t \tag{4}$$

where

F_{t+1}: Forecast for period $t + 1$

F_t: Forecast for period t

R_t: Actual value of stock price return at period t

e_t: Error term

$0.5 < \alpha > 0.1$.

In this model, the new forecast prepared by SESM is simply the old forecast plus 'α' times the error in the old forecast, that is, the term $R_t - F_t$ is simply the error in the earlier forecast. In this model it is evident that when 'α' has a value close to one, the new forecast will include a substantial adjustment for any error that occurred in the preceding forecast. Conversely, when 'α' is close to zero, the new forecast will not show much adjustment for the error from the previous forecast. Thus, the effect of a large or small 'α' is analogous to the effect of including a small or large number of observations in computing a moving average.

A small value of 'α' such as 0.1 tends to produce forecasts that are more smooth (that is, with less fluctuation) than larger values of 'α', such as 0.5. However, to find the value of 'α' that produces the best forecast for the past data we need to compute the MAPE of the stock prices distribution.

3.4 Conditionally heteroskedastic models

There are two components in a GARCH-M model that require forecasting, the conditional mean and the conditional variance. The forecasting model applied here is defined in four steps as follows:

Step 1:

$$r_{t+j} = \beta R_{t+j} + \gamma h_{t+j}^2, \quad j = 1, 2, \ldots, p \tag{5}$$

and

$$h_{t+1}^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t+1-i}^2 + \sum_{i=1}^{q} \varphi_i h_{t+1-i}^2 \tag{6}$$

where

r_{t+j}: Actual stock price return at period $t + j$

R_{t+j}: Forecast stock price return at period $t + j$

h_{t+j}^2 : Conditional variance at period $t + j$

u_{t+j}^2 : Squared error term at period $t + j - i$.

β and γ are ML estimators of the regression coefficients; R_{t+j} is the j-step ahead forecast of r_t; h_{t+j}^2 is the j-step ahead forecast of the conditional variance, namely, $E\,(u_{t+j}^2 / \Omega_t)$, $j = 1, 2, \ldots, p$.

Similarly, two and three-step ahead forecasts are given by:

Step 2:

$$h_{t+2}^2 = \alpha_0 + (\alpha_1 + j_1)\, h_{t+1}^2 + \sum_{t=2}^{p} \alpha_i u_{t+2-i}^2 + \sum_{i=2}^{q} \varphi_i s h_{t+2-i}^2 . \tag{7}$$

Step 3:

$$h_{t+3}^2 = \alpha_0 + (\alpha_1 + \varphi_1) + h_{t+2}^2 + (\alpha_2 + \varphi_2)h_{t+1}^2 + \sum_{i=3}^{p} \alpha_i u_{t+3-i}^2 + \sum_{i=3}^{q} \varphi_i h_{t+3-i}^2. \tag{8}$$

Step 4:

$$h_{t+4}^2 = \alpha_0 + (\alpha_1 + \varphi_1) + h_{t+3}^2 + (\alpha_2 + \varphi_2)h_{t+2}^2 + (\alpha_3 + \varphi_3)h_{t+1}^2 + \sum_{i=4}^{p} \alpha_i u_{t+4-i}^2 + \sum_{i=4}^{q} \varphi_i h_{t+4-i}^2. \tag{9}$$

3.5 *Forecasting accuracy*

As a forecasting accuracy measure, we use the MAPE and the benchmark Naïve forecast 1's MAPE. More specifically, we compare the value of the MAPE for the three models, namely, RWM, SESM and CHM with the MAPE of the benchmark Naïve forecast 1 case (NF1).

In particular, the MAPE for the three models has the following formula:

$$\text{Mean Absolute Percentage Error:} \quad \text{MAPE} = \sum_{i=1}^{n} | PE_t | / n \tag{10}$$

The MAPE of the benchmark NF1 case has the following general form:

$$\text{NF1}_{\text{MAPE}} = \left(\sum_{i=2}^{n} | R_i - R_{i-1} / R_i | / n - 1 \right) \times 100 \tag{11}$$

where

R_i: Actual return at time i

R_{i-1}: Actual return at time $i - 1$

n: The number of observations.

Only $n - 1$ terms are included in computing the MAPE of this Naive forecast 1 approach, since forecasting begins with period 2 rather than period 1. The difference between the MAPE obtained from a more formal method of forecasting and that obtained using NF1 provides a measure of the improvement attainable through the use of that formal forecasting method. This type of comparison is much more useful than simply computing the MAPE of the formal method, since it provides a basis for evaluating the relative accuracy of those results.

4 Empirical findings

Table 2 reports the results of our analysis concerning the forecasting accuracy of the Random Walk, the Single Exponential Smoothing and the CHM. The third column of Table 2 shows the values of the MAPE of the RWM. When the coefficients are significant at the 5% significance level this means that the value of the MAPE in the

RWM is lower than the value of the MAPE in the NF1 case. Otherwise, if the coefficients are not statistically significant at the 5% significance level the value of the MAPE in the RWM is higher than the value of the MAPE in the NF1 case. In the same way, we interpret the significance of the results for the SESM and the CHM.

Table 2 Short term forecasting accuracy results return series for the period November–December 2007

Stock market exchanges	*Benchmark*	*Random walk*	*GARRCH-M*	*Single exponential smoothing*	*Conditional heteroscedastic*
	MF1MAPE	*MAPE*	*MAPE*	*MAPE*	*MAPE*
Australia	278.17	360.99	587.95	263.17*	550.89
Canada	143.43	193.88	363.76	174.97	347.37
France	139.76	157.96	188.99	163.82	260.41
Japan	176.79	206.34	141.95*	161.13*	234.64
USA	117.71	136.68	743.93	157.32	278.33
UK	172.57	211.77	511.93	211.04	397.29
Germany	142.55	159.74	971.47	280.77	500.45
Italy	187.04	180.51*	144.40*	225.93	536.57

*denotes significant value for MAPE in relation to MF1 MAPE.

Even though simple in its nature our approach provides a benchmark for evaluating the significance of forecasting for each of the three examined models. While there are a number of ways to evaluate the forecasting accuracy of models, we opt to use the MAPE in order to see which of the three models could provide a good forecast by simply referring to the MAPE. We could also refer to other similar evaluating forecasting measures such as the mean squared error; however, it is commonly known that the importance of the MAPE is as a good gauge for measuring the forecasting validity of models.

Comparing the results of the MAPE between the three models and the NF1 case, we could say that the results indicate that in most of the industrialised stock, the value of the MAPE of the RWM is higher than that of the NF1 case. This happens for all the stock markets, except for Italy. For this stock market as well, the MAPE of the CHM is also lower compared to the NF1 case. Thus, the CHM provides good forecasts for the stock market of Japan. While these are the findings with respect to the forecasting accuracy of the two models, the SESM seems to be superior compared to the other two models for the forecasting accuracy of the Japanese and Australian stock markets. Overall, the results show that the forecasting accuracy over the period November–December 2007 is not superior for any of the examined models. This means that no a single model is found to be better than any other and, therefore, we can conclude that each model is better than another only under some circumstances, depending on the nature of the stock market on which we are referring to.

As the GARCH model is supposed to be the most sophisticated, we present in Table 3 the forecasting results for the period November–December 2007. It is worth mentioning that the forecasting results for the Japanese stock exchange are stable and equal to 0.032557 for the entire forecasting period (November–December 2007). However, we observe that the forecasting values of the CHM seem to be different. In particular, for the case of the Australian stock market the trend is downwards for the whole forecasting period. There is a similar result for the case of the Canadian stock market. Looking now at the French and the US stock markets, we can say that the trends are upwards for the forecasting period. For the rest of the stock exchanges (e.g., the UK, Germany and Italy), the trend is downwards, which under special circumstances could be a global event that led the stock exchanges to move together. If this is the case, this could be observed by employing more sophisticated techniques, such as the co-integration technique, in order to see whether the markets move together for a specific period of time.

Table 3 GARCH-M (1, 1) volatility forecasting results from one to eight steps ahead forecasts

Stock exchanges	*November 2007*				*December 2007*			
	Week 1	*Week 2*	*Week 3*	*Week 4*	*Week 1*	*Week 2*	*Week 3*	*Week 4*
Australia	0.043965	0.036803	0.032011	0.028926	0.027011	0.025856	0.025174	0.024777
Canada	0.024611	0.024056	0.023571	0.023147	0.022779	0.022459	0.022182	0.021942
France	0.022727	0.022858	0.022982	0.023099	0.023208	0.023311	0.023408	0.0235
Japan	0.032557	0.032557	0.032557	0.032557	0.032557	0.032557	0.032557	0.032557
USA	0.023034	0.023056	0.023078	0.023099	0.02312	0.023141	0.023161	0.023181
UK	0.027501	0.026302	0.025431	0.024803	0.024355	0.024037	0.023812	0.023653
Germany	0.032856	0.032693	0.032534	0.032376	0.032222	0.03207	0.031921	0.031774
Italy	0.033952	0.033819	0.033694	0.033577	0.033467	0.033363	0.033265	0.033174

Looking at the forecasting graphs (Figures 1–8) for the forecasting period we attempt to interpret the trend for the two models, that is, the RWM and the CHM. The trend of the graphs shows that the GARCH model does not account for the cyclical patterns that exist in the actual data series. This might be due to the fact that the GARCH model has been initially made in order to identify the clustering effects in the data set. On the other hand, the RWM, while it is simpler than the other two models, identifies well the cyclical patterns of the data set. The forecasting results of the GARCH model show a persistence on the data set which is not captured by the RWM that does not account for this characteristic. However, the actual data set of Figures 1–8 is going in parallel with the RWM rather than the CHM, showing a more realistic forecasting for the case of RWM.

Figure 1 Forecasting returns for Australia (see online version for colours)

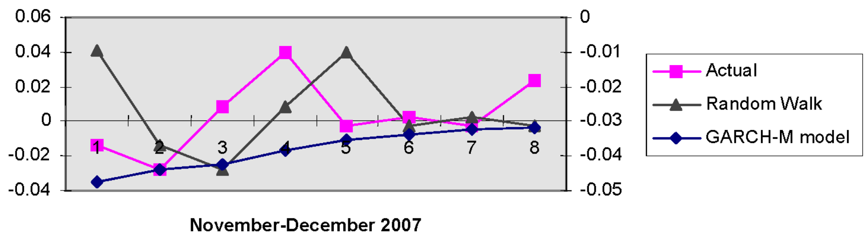


Figure 2 Forecasting returns for Canada (see online version for colours)

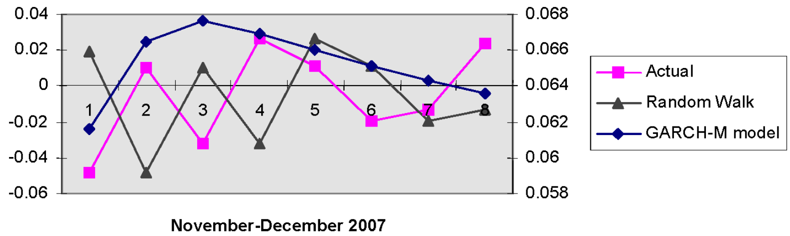


Figure 3 Forecasting returns for France (see online version for colours)

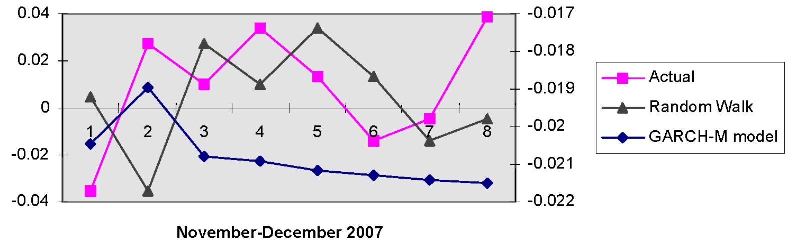


Figure 4 Forecasting returns for Japan (see online version for colours)

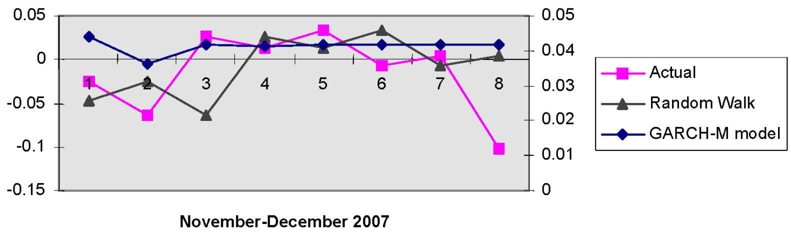


Figure 5 Forecasting returns for the UK (see online version for colours)

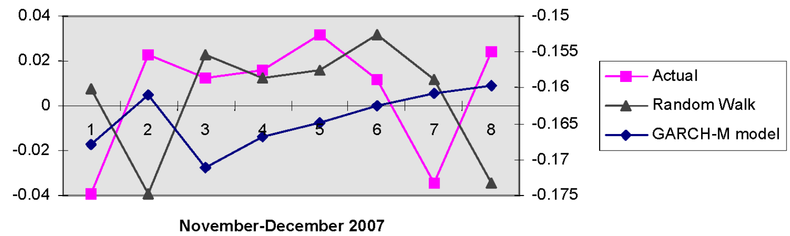


Figure 6 Forecasting returns for the USA (see online version for colours)

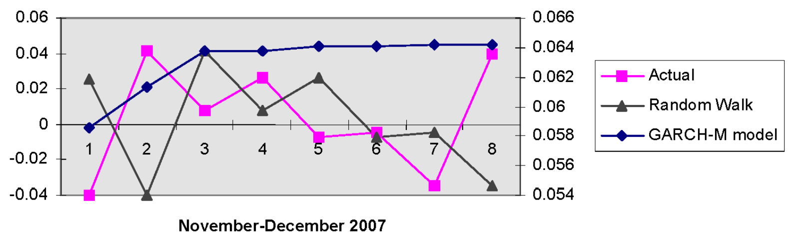


Figure 7 Forecasting returns for Germany (see online version for colours)

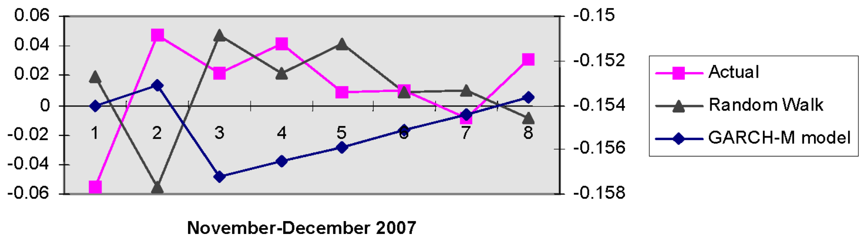
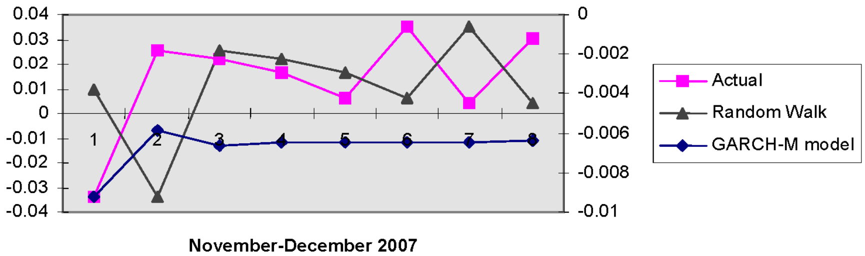


Figure 8 Forecasting returns for Italy (see online version for colours)



5 Conclusions

The empirical results reveal that no a single model provides better forecasting accuracy results than the other ones. We found that the RWM is the best forecasting model for the Italian stock market. As we can see from the Figure 8 of the Italian stock market, the trend of the actual data is quite cyclical with upwards and downwards which can be identified very well from the RWM. We also find that the GARCH model is the best forecasting model for the case of the Japanese and the Italian stock markets. Figure 4 shows that for Japan the CHM provides a stable forecasting result without following the actual values of the return series for the period of November-December 2007. The same result is obvious for the Italian stock market, namely the CHM does not follow up the trend of the actual return series. Finally, the results reveal that the best forecasting model is the SESM for the stock markets of Australia (Figure 1) and Japan.

While the results of the forecasting accuracy of the MAPE reveal that no single model is better than any other, the plots produce the RWM as the one with the best forecasting accuracy, at least in comparison to the CHM. This might be due to the fact that the GARCH model is based on the second moment of return series and suffers from serial correlation which might make it less valid for short-term predictions in comparison to the RWM, which does not account for autocorrelation. In other words, investors could use the RWM than the CHM quite often and especially for the stock markets where there is a small memory of repeat for the distribution of return series.

This means that the cyclical pattern is somehow stable for a small period of 2–3 weeks and then it vanishes. However, this is not the case for smaller stock exchanges where the market mimics past behaviour for longer periods and, for example, ARFIMA models[1] might be the best model for forecasting its accuracy. The fact that the GARCH model is not superior to the RWM might be due to the fact that the CHM has a conditional memory of volatility which means that it behaves in clusters for a short period of time (e.g., 2 or 3 weeks) and then changes again, resulting in a stable behaviour for some time. Thus, investors should know that picks (such as crises) which characterise stock markets could be identified easily from the GARCH model, while trends (such as public announcements) could be identified by less sophisticated models such as the RWM and the SESM.

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Note

[1]ARFIMA models also belong to ARCH family models.