FORECASTING β: AN EVALUATION OF THE BLOOMBERG HEURISTIC[1]

Edward. J. Lusk[*], Henrieta Koulayan[**]

Abstract

We investigated the performance of the Bloomberg forecasting heuristic: 1/3 + 2/3 × β, as a one-period-ahead forecast of the one-factor CAPM β. We tested this Bloomberg heuristic using data from 131 companies that were on the S&P 500 continuously for more than 15 years. We found that the Bloomberg forecasts of β were more than five times higher in absolute percentage error [APE] than the APEs produced by Collopy and Armstrong using Rule Based Forecasts of general time series of economic data. Regarding the relative absolute error [RAE] which uses the Random Walk [RW] model as the forecasting benchmark, we found that overall the Bloomberg heuristic did not outperform the RW benchmark. We included the Holt two-parameter forecasts of β to provide a context for the Bloomberg results. Overall, the Holt model in both the APE and RAE error measure terms did no better than did the Bloomberg heuristic. These results call into question the use the Bloomberg heuristic as a useful model to forecast β. They further suggest that forecasting β is a challenging task neither given to simple heuristics based solely on historical βs such as that of Bloomberg nor even simple, but time tested, two-parameter models such as the Holt time series model. Our results suggest that perhaps to do an acceptable job of forecasting β, one needs to incorporate information about the domain as a way of updating the estimates developed using historical information.

Key words: One-Period-Ahead-Forecasts, Holt, Random Walk Model.
JEL Classification: G12 G14.

I. Introduction

The equity beta [β], since its initial introduction by Sharpe (1964), has gained wide acceptance as a relevant measure of systematic risk in portfolio analysis and in evaluation of the firm's market relative performance. See Brealey, Myers and Allen (2006, Chs. 3, 5 and 13) for some of the ways that information on β may be used in decision-making. The importance of β in planning strategic resource allocation decisions places a premium on developing useful forecasts of β as they are inputs into various decision models.

One of the first questions to be addressed in forecasting β is its time series characterization. This was first investigated and reported on by Blume (1971, 1975 and 1979) who found, conforming to one's intuition given the dynamic nature of trading markets, that β was both a firm and time-related variable. This result then rationalizes a modelling context for forecasting β. Let us now consider the results of Blume's investigation that form the basis of the Bloomberg heuristic that according to Ibbotson Associates (2004) is the most widely used β forecasting model.

The Blume procedure consists of regressing βs from one historical period onto βs from a prior period and then using these regression results to adjust the βs for the forecast period. By performing this analysis over various time periods, Blume identified the following convergent *tendency,* emphasis here given to the word tendency: EQ [1]

[*] State University of New York, USA.
[**] Otto-von-Guericke University, Germany.

[1] The authors wish to thank Marshall E. Blume, Howard Butcher III Professor of Finance, and Director of the Rodney L. White Center for Financial Research, The Wharton School, the University of Pennsylvania, Philadelphia PA. USA and Mr. Nikolay Avramov, Financial Modelling Research Associate, FinAnalytica Inc., Sofia, Bulgaria for their careful reading and helpful suggestions. A note of thanks also to Ms. Ellen Slack, of the Lippincott Library of The Wharton School for her editorial assistance.

$$\hat{\beta}_{t+1} = 0.371 + 0.635 \times \beta_t .$$

The Blume result, which has the "appearance" of a convex combination, was then re-formed into what we know it as today: the Bloomberg heuristic EQ [2]:

$$\hat{\beta}_{t+1} = 1/3 + 2/3 \times \beta_t .$$

The Bloomberg heuristic simply says: *The one-period-ahead forecast of β is 1/3 plus 2/3 of the current β*. We want to underscore that the Bloomberg heuristic [BH] is not a simplification of the statistical procedure by which Blume arrived at the summary result reported as EQ [1]. It is essentially an isolated out-of-context simple heuristic that Bloomberg recommends using as their one-step-ahead forecast of β.

The aim of this paper is to evaluate this widely used one-period-ahead β forecasting heuristic; to provide an evaluation context for the examination of the BH, forecasts produced by the Holt two-parameter exponential smoothing time series model are provided. Consider now the study design.

II. Testing the Bloomberg Model: The Study Design

Over the years, the Holt model has proven to be very useful in many forecasting situations essentially due to its ability to react to current information while maintaining a memory of trend (See Hanke et al. (2001)). Due to its impressive performance in a time series forecasting competition that examined the forecasting accuracy of 24 forecasting models for 1001 time series (See Makridakis et al. (1982)), the Holt model was selected as one of the basic models in the Rule Based Forecasting modelling system which is now the current state of the art of time series forecasting procedures (See Collopy and Armstrong (1992)).

In evaluating the forecasting performance of both the BH and the Holt model, we will use the Random Walk [RW] model, the simplest forecasting model, as a benchmark (See Armstrong and Collopy (1992)). The RW model uses the last observation as a prediction for the next period EQ [3]:

$$\hat{\beta}_t = \beta_{t-1}.$$

This is the most naïve forecast of β. It says the forecast of the next period β is the actual β from the previous period – i.e., predict the β for next year as the value of β measured for the current year. The RW model is an excellent benchmark for evaluating the performance of a forecasting model in that if one cannot significantly improve of this most naïve forecast then this calls into question the effectiveness of the forecast model. We will use this benchmark to evaluate both the Bloomberg heuristic and the Holt model. It will be the "acid" test of these models. This deceptively simple naïve model of using as the forecast the last observed value also performed very well in the Makridakis competition (1982) outperforming many of the more sophisticated time series modelling approaches including the ARIMA method of Box and Jenkins (See Box, Jenkins and Reinsel (1994)).

We do not intend to investigate what is the best way to forecast β, that is, of course, an important study but beyond the scope of this study which is focused on the evaluation of the forecast effectiveness of the Bloomberg heuristic.

2.1. The Sample

The sample of firms consists of 131 companies for the period from 1985 to 2003 which were continually on the S&P 500 value-weighted-index. For this set of firms, one would expect that the BH and the Holt model would be able to render reasonably useful one-period-ahead forecasts assuming of course that it is the case that the historical β contains information as to β's future tendency. For our sample of firms, overall the β was 0.67; also, in no year did the 95 percent confidence interval of β for the sampled firms contain 1.0.

Using daily return data, we computed βs for each of the 19 study years. Therefore, for each of the 131 firms there were 19 β estimates one for each of the study years. The firm and matched market data were downloaded from the Center for Research in Security Prices (CRSP™) through WRDS™.

2.2. Forming the forecasts

The Random Walk and Bloomberg forecasts were formed by using equations [2] and [3]. We used the Holt procedure as it is programmed in JMP; this software optimises the level and trend parameters in producing the forecasts (See Sall et al. (2005)). For the Holt procedure, we used the first five years (1985 to 1989) of data to produce the forecasts. Thereafter, we used a rolling accrual – i.e., for each year the one-period-ahead-forecasts were formed with all of the preceding historical information. For example, the Holt forecast for 1994 used the nine years from 1985 to and including 1993.

2.3. Error measures

Following Armstrong and Collopy (1992), to report on forecast accuracy we will use the following two error measures: The Absolute Percentage Error (APE):

$$APE = abs\,[\hat{\beta}_t - \beta_t] / \beta_t,$$

and the Relative Absolute Error (RAE):

$$RAE = abs([\hat{\beta}_t - \beta_t] / [\hat{\beta}_{rw(t)} - \beta_t]),$$

where: $\hat{\beta}_t$ represents the forecast of β at time t, for the Bloomberg or the Holt models,

β_t represents the one factor model measured β at time t, and

$\hat{\beta}_{rw(t)}$ represents the naïve benchmark forecast of β at time t – i.e., the actual β_{t-1}.

We, as recommended by Armstrong and Collopy (1992), winsorized the data. Due to the large number of Box-Plot outliers in the APE and RAE data, even after Winsorizing, we will report medians and use the Wilcoxon two-sample non-parametric test for purposes of inference. Further, we will report two-tailed p-values for the test between the BH and the Holt model. Finally, we have eliminated 2001 from the study due to the relative market chaos created by both the Enron as well as the WTC event that followed in the next month.

III. The Results

3.1. APE measures

The Winsorized absolute percentage errors [WAPE], in percentage terms for the two models, are presented in Table 1. The p-value is reported for the test that there is a difference between the Bloomberg heuristic and the Holt model.

Table 1

APE Medians for the Bloomberg and the Holt one-period-ahead β Forecasts in percentage terms

Year	Bloomberg	Holt	P-value
1990	14	18	0.62
1991	18	16	0.57
1992	17	18	0.81
1993	19	20	0.33
1994	17	20	0.50
1995	27	22	0.16
1996	22	20	0.30

Table 1 (continuous)

Year	Bloomberg	Holt	P-value
1997	26	17	0.01
1998	32	22	0.01
1999	69	34	<0.001
2000	109	58	<0.001
2003	13	24	<0.001
Overall	**20.5**	**20**	**0.98**

Overall we see that the APE is on the order of 20% for both models. For example, the Bloomberg Heuristic, in absolute value terms, recorded predications that were in median terms only within 20.5% of the value of the actual β. Given that most of the βs for firms on the major exchanges range from 0.25 to 1. 30, Ibbotson Associates (2004, p. 98), a 20% error probably blurs β's membership in one of the three decision relevant zones: [less than 1], [equal to 1] or [greater to 1]. To further give a context to the magnitudes of the APE reported in Table 1, consider that Collopy and Armstrong (1992, p. 1405) report for their Rule Based Forecasting [RBF] procedure, a median APE of 3.2%. The two models tested in our study had APEs that were more than five times the RBF benchmark; this result is statistically significant at $p < 0.0001$.

We see that the Holt model seems to outperform the Bloomberg heuristic [BH] starting in 1997 at point when the market was well into its bubble formation phase. We offer as a conjecture that perhaps the two-parameter Holt model could better sense the loss of covariance that our sample of firms had with the dot.com driven market than did the BH. However, it is important to note that starting in 1997 both the BH and Holt models begin doing poorly with respect to the WAPE; the BH just does far worse.

As a final evaluation context for these APE results, both the Bloomberg heuristic and the Holt model perform badly raising the question of the usefulness of these predictions.

3.2. RAE measure

The Winsorized relative absolute errors for the two models over the forecasting years are presented in Table 2.

Table 2

RAE Medians for the Bloomberg and the Holt one-period-ahead β Forecasts in percentage terms

Year	Bloomberg	Holt	P-value
1990	117	114	0.89
1991	113	113	0.59
1992	98	102	0.84
1993	104	107	0.26
1994	81	98	0.44
1995	114	99	0.02
1996	96	100	0.69
1997	163	107	<0.001
1998	150	99	<0.001
1999	153	95	<0.001
2000	227	99	<0.001
2003	57	106	<0.001
Overall	**114**	**101**	**0.27**

Overall and for most of the individual years, the RAEs of the BH are such that they do not test to be statistically significant less than 100%. Recall that 100% in RAE terms means that the absolute percentage error of the model – e.g., the Bloomberg heuristic – was the same as the absolute percentage error of the naïve model. Therefore this suggests that they both fail the "acid test" in that neither the Bloomberg heuristic nor the Holt model do better than the naïve forecast of β. Finally, as an absolute comparison, Collopy and Armstrong report a median RAE of 63% which tested as statistically lower from the Bloomberg result, $p < 0.0001$.

We also re-analyzed the data for the BH as a moving five-year window starting in 1985 where we formed for each organisation an estimate of β based upon five years of activity under the assumption that perhaps there was undue measurement error in the β estimated using a data-window of only one year. We selected five years based upon the recommendations of Ibbotson Associates, Compustat™ and Value Line™ all of whom suggest a period of five years for measuring β. For the ten yearly estimates from 1990 to 1999, using the five-year moving window, the results for the BH are no different – i.e., the APE and RAE results for this re-analysis do not change the summary results reported above.

IV. Conclusion

In this paper we investigated the forecasting performance of the Bloomberg forecasting heuristic by using data of 131 companies that were on the S&P 500 continuously for more than 15 years. The results are clear:

1. We find that for the APE measure the Bloomberg heuristic [BH] is relatively high compared to the RBF procedure where the APE for the Bloomberg heuristic was more than five times as high as the APE reported by Collopy and Armstrong (1992).
2. The same is true for the RAE measure where it is clear that the BH is not statistically significantly better than the naïve model that was used as a benchmark.

These results call into question the value of the Bloomberg heuristic as a one period ahead forecast of β. This suggests that forecasting β is a challenging task neither given to simple heuristics based solely on historical βs such as that of Bloomberg nor even to simple, but time tested, two parameter models such as the Holt time series model. This may be interpreted that to do an acceptable job of forecasting β, one needs to incorporate information about the forecasting domain as a way of updating the estimates developed using historical information.

References

1. Armstrong J.S., F. Collopy. Error Measures for Generalizing about Forecasting Methods: Empirical Comparisons//International Journal of Forecasting, 1992. – № 8. – pp. 69-80.
2. Blume, M.E. On the Assessment of Risk//Journal of Finance, 1971. – № 26. – pp. 1-10.
3. Blume, M.E. Betas and Their Regression Tendencies//Journal of Finance, 1975. – № 30. – pp. 785-795.
4. Blume, M.E. Betas and Their Regression Tendencies: Some Further Evidence//Journal of Finance, 1979. – № 43. – pp. 265-267.
5. Brealey, R., S. Myers, F. Allen. Corporate Finance:8th Ed. – New York: McGraw Hill. 2006. – 515 pp.
6. Box, G.E.P., G. Jenkins, G. Reinsel. Time Series Analysis: Forecasting and Control:3rd Ed. – New Jersey: Prentice Hall, 1994. – 391 pp.
7. Collopy, F., J.S. Armstrong. Rule-based Forecasting: Development and Validation of an Expert Systems Approach to Combining Time Series Extrapolations// Management Science, 1992. – № 38. – pp. 1394-1414.
8. Hanke, J., D. Wichern, A. Reitsch. Business Forecasting:2nd Ed. - New Jersey: Prentice Hall. 2001. – 338 pp.
9. Makridakis, S., A. Andersen, R. Carbone, R. Fildes, M. Hibon, R. Lewandowski, J. Newton, E. Parzen, R. Winkler. The Accuracy of Extrapolation (Time Series) Methods: Results of a Forecasting Competition//Journal of Forecasting, 1982 – № 1. – pp. 111-153.
10. Sall, J., A. Lehman, L. Creighton. (2005). JMP™ Start Statistic-Version 5:2nd Ed. – California: Duxbury Press, 2005. – 434 pp.
11. Sharpe, W. Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk//The Journal of Finance, 1964 – № 16. – pp. 425-442.