Stock Index Return Forecast: Information of the Constituents

Charlie X. CAI [a*]
University of Leeds

Khine KYAW [b]
Plymouth University

Qi ZHANG [c]
University of Leeds

Economics Letters, Forthcoming 2012

Abstract

We investigate whether the use of component forecasts improve the accuracy of a portfolio forecast which uses only aggregate data. The results show that the use of component data improves the accuracy of aggregate forecasts. Furthermore, the long-short trading strategy based on the component forecasts always generates substantially higher returns than the buy-and-hold strategy.

JEL classification: G11, G12, G17

Keywords: Index forecasting, Portfolio strategy, Stock returns.

a Senior Lecturer in Accounting and Finance and Deputy Director of the International Institute of Banking and Financial Services (IIBFS) Leeds University Business School, Leeds, UK

b Lecturer in Finance, Plymouth Business School, Plymouth University, Hampton Street, Plymouth PL4 8AA, UK

c Lecturer in Accounting and Finance, Leeds University Business School, Leeds, UK.

* Corresponding Author: Charlie Cai, busxc@leeds.ac.uk; Tel: +44 113 3434 505; Fax: +44 113 3434 459.

1 INTRODUCTION

Forecasting equity returns has always been a challenging task for both practitioners and researchers. The existing forecasting practices usually treat a composite index as a single time series: see Breen, Glosten and Jagannathan (1989), Altay and Satman (2005), and Kanas (2001). One major drawback of such practices is that it ignores the potentially valuable information provided by the constituents' dynamics. Indeed, Fok, Dijk and Franses (2005) and Hernandez-Murillo and Owyang (2006) show that the use of disaggregate data can improve the accuracy of aggregate economic data forecasts. Castle and Hendry (2010) echo the usefulness of disaggregate information on the timely estimation (referred as nowcast) of aggregate economic variables with potential location shift. Furthermore, Hendry and Hubrich (2010) demonstrate in their Monte Carlo simulations that the use of disaggregate information improve aggregate forecast if the disaggregates follow different stochastic structures and the components are interdependent. Like aggregate economic series, aggregate financial series consists of a range of individual series each with its own unique information set. Therefore, the use of individual component data can potentially enhance the accuracy of aggregate stock index return forecasts.

On the other hand, noise and estimation error can undermine the benefits of using disaggregate series for forecasting. Disaggregate data are noisier than the aggregates constructed from them, and are more difficult to forecast (Allen and Fildes, 2001). Furthermore, the use of disaggregate series increases the number of estimations needed to forecast an aggregate series, which consequently increases the estimation error in the aggregated forecasts. Indeed, Hendry and Hubrich (2006) conclude that theoretically disaggregate information might improve forecast accuracy of the aggregate forecast, but the scope of such an improvement needs to be assessed on a case-by-case basis because it depends on the particular forecasting situation.

Given the trade-off between the potential for information efficiency, and the potential for estimation error and noise in using disaggregate data for forecasting, we examine whether the use of constituents' information can improve the index forecasting performance.

2 FORECASTING APPROACH AND DATA

We employ the AR(i)-GARCH(p,q) model which has been widely used in finance research and practice, and daily return series of FTSE100 index and its constituents for the period from 01/01/1999 to 31/12/2010.

We denote the index return forecasts obtained from the constituents data as 'composite-of-components forecasts', $\hat{r}_{comp,t}$, and the forecasts from univariate index data as 'conventional forecasts', $\hat{r}_{conv,t}$.

The composite-of-components forecasts are obtained as follows. We fit an AR(i)-GARCH(p,q) model on the returns of each constituent stock in the index portfolio using an estimation window (e.g., 250 days). Then we construct the next day out-of-sample forecasts, and calculate the $\hat{r}_{comp,t}$ as the weighted average of individual stock return forecasts[1]. We then roll over the estimation window by one day to generate another set of forecasts, and repeat the procedure until ten years of return forecasts are generated. We then obtain the corresponding conventional forecasts, $\hat{r}_{conv,t}$, by applying the rolling estimation of AR(i)-GARCH(p,q) model to the index returns.

As sensitivity checks, we vary the width of estimation window, lag lengths of the model and size of the portfolio. Specifically, we vary the width of estimation window from 60-, 120-, 250-, to 500 days; estimate AR(i)-GARCH(p,q) models with 1-, 3- or 5- lags; and apply the models to a variety of portfolio sizes ranging from 10-, 30-, 60-, to 100-stocks[2].

We use statistical tests to evaluate the out-of-sample forecasting performance. We compute the squared error (*SE*) between the forecasts and the actual returns.

$$SE_{comp,t} = (\hat{r}_{comp,t} - r_t)^2 \text{ and}$$
$$SE_{conv,t} = (\hat{r}_{conv,t} - r_t)^2,$$

where r_t is the realized return. We further compute the difference between the two as follow:

$$diff\_SE_t = SE_{comp,t} - SE_{conv,t}$$

We use t-test and Signed rank test respectively to check the statistical significance of the difference in mean and median of the squared errors (see Diebold and Mariano (1995) for a discussion on comparing forecasting accuracy).

A model that appears to have performed well according to the statistical evaluation criteria does not necessarily generate economic benefits (Brooks, Rew and Ritson (2001)). An increase in the overall noise from the estimations of component data may swamp the information efficiency a more detailed forecast brings forth. To assess the economic significance of the approaches, we apply a long-short trading strategy whereby a long (short) position is held when a positive (negative) return is forecasted. As a benchmark, we implement a buy-and-hold strategy whereby the portfolio is bought and held throughout the forecast evaluation period. We

[1] We use market capitalization at the beginning of the month as the weight.

[2] The corresponding index portfolio return is constructed as the weighted average of constituent returns.

calculate the portfolio returns and variance for each strategy. We compare the utility value of the portfolios by calculating the Certainty-equivalent return (CER) as follow:

$$CER_{S,\gamma} = \overline{\mu}_S - \frac{\gamma}{2}\sigma_S^2 ,$$

where $\overline{\mu}_S$ and σ_S^2 are the mean and variance of the returns from each strategy, S . γ is the risk aversion coefficient that takes on a value of 1, 3 or 5.

3 EMPIRICAL RESULTS

Table 1 shows that portfolio forecasts obtained from the component data yield better forecasts (lower squared-errors) than those obtained from the conventional approach. It is consistently so for all the AR(i)-GARCH(p,q) models we have tested. Moreover, the differences in the mean and median squared-errors from the two approaches are statistically significant in all cases except in the first case. Thus, the composite-of-components approach provides better return forecasts than the conventional approach in forecasting the index portfolio returns.

Table 2 reports the CERs generated from applying the long-short strategy against the CERs generated from the benchmark buy-and-hold trading strategy. The composite-of-components forecasts tend to generate higher CERs than those the conventional portfolio forecasts, or those from the buy-and-hold strategy. The exception is for the AR(3)-GARCH(3,3) model with which the composite-of-components and conventional forecast approaches perform similarly and yield the highest level of CERs among the models tested. Overall, the results suggest that active investment management based on the two forecasts are better than passive indexing. Furthermore, the long-short strategy based on the composite-of-components forecasts produces a robust and better performance than the conventional forecasts.

4 CONCLUSIONS

We examine whether the use of forecasts from component data enhances the accuracy of portfolio return forecasts. Statistically, portfolio return forecasts from the composite-of-components approach tend to provide a more accurate forecast than the forecasts from the conventional approach (i.e., applying forecasting models directly on the returns of the portfolio). Furthermore, the statistical improvements can be translated into economic benefits when a long-short trading strategy is implemented in accordance with the forecasts.

Overall, our analysis demonstrates the statistical and economic benefits of using component data in forecasting aggregate series in the context of stock index forecasting. We show that the conventional approach to forecasting can perform well only if an appropriate model specification is chosen (i.e., AR(3)-GARCH(3,3) in Table 2). However, if an appropriate model specification is hard to come by, the use of information embedded in the components can improve the statistical accuracy of the forecasts and consequently the economic benefits.

Examining the effects of model specification, especially models with nonlinear dynamics, could be a potentially fruitful research area.

REFERENCES

Allen, P.G., Fildes, R., 2001. Econometric Forecasting. *Principles of Forecasting: A Handbook for Researchers and Practitioners*, J. Scott Armstrong (ed.): Norwell, MA: Kluwer Academic Publishers.

Altay, E., Satman, M.H., 2005. Stock market forecasting: Artificial neural network and linear regression comparison in emerging market. Journal of Financial Management and Analysis 18, 18-33.

Breen, W., Glosten, L.R., Jagannathan, R., 1989. Economic significance of predictable variations in stock index returns. Journal of Finance XLIV, 1177-1189.

Brooks, C., Rew, A.G., Ritson, S., 2001. A trading strategy based on the lead-lag relationship between the spot index and futures contract for the FTSE100. International Journal of Forecasting 17, 31-44.

Castle, J. L. and Hendry, D. F. (2010), Nowcasting from disaggregates in the face of location shifts. Journal of Forecasting, 29, 200–214.

Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. Journal of Business & Economic Statistics 13, 253-263.

Fok, D., Dijk, D., Franses, P.H., 2005. Forecasting aggregates using panels of nonlinear time series. International Journal of Forecasting 21, 785-794.

Hendry, D.F., Hubrich, K., 2006. Forecasting economic aggregates by disaggregates (February 2006). ECB Working Paper No. 589.

Hendry, D.F., Hubrich, K., 2010. Combining disaggregate forecasts or combining disaggregate information to forecast an aggregate (February 2006). ECB Working Paper No. 1155.

Hernandez-Murillo, R., Owyang, M., 2006. The information content of regional employment data for forecasting aggregate conditions. Economics Letters 90, 335-339.

Kanas, A., 2001. Neural network linear forecasts of stock returns. International Journal of Finance and Economics 6, 245-254.

Table 1 Squared Error (SE)

This table report the SEs and the difference in corresponding SEs for the two approaches to forecasting returns. SEs are measured in basis points; t-test and signed rank test are used for testing the difference in mean and median respectively. The identifications of each estimation are as follows: the number after the letter F indicates the number of stocks included in the estimation (e.g., F10 indicates only the top 10 stocks by market capitalization are considered in the estimation.); the number after the letters AR, P, and Q indicates the orders corresponding to the letters *i*, *p*, and *q* used in the AR(i)-GARCH(p,q) model; and the number after the letter W indicates the length of the rolling estimation window in days. The sample is FTSE100 stocks from FTSE index during the period 1999 to 2010. The composite-of-components forecast is calculated as the weighted average of component forecasts where the market capitalisation at the beginning of the calendar month is used as the weight for the stock. SE_comp and SE_conv reports the statistics from using composite-of-components and conventional portfolio forecast, respectively. ***, ** and * indicates statistical significance at 1%, 5% and 10% respectively.

	SE_comp		SE_conv		diff_SE				
	mean	median	mean	median	mean		median		N
F100_AR1_P1_Q1_W250	92.51	62.30	92.76	62.10	-0.26		0.07		2530
F100_AR3_P3_Q3_W250	92.55	61.83	93.21	62.27	-0.66	**	-0.27	*	2530
F100_AR5_P5_Q5_W250	92.59	61.86	93.77	62.63	-1.18	***	-0.68	***	2530
F10_AR5_P5_Q5_W250	96.74	67.66	98.04	69.84	-1.29	***	-0.52	***	2530
F30_AR5_P5_Q5_W250	95.46	64.30	96.64	65.57	-1.18	***	-0.60	**	2530
F60_AR5_P5_Q5_W250	93.08	62.27	94.20	63.43	-1.12	***	-0.66	***	2530
F100_AR5_P5_Q5_W60	93.94	64.00	96.10	66.58	-2.16	***	-1.35	***	2713
F100_AR5_P5_Q5_W120	92.20	63.20	94.23	63.62	-2.02	***	-1.39	***	2657

Table 2 CERs of the Portfolio Strategies

This table reports the certainty equivalent return (annualized) of portfolio strategy utilizing the forecasted return. The long-short strategy returns and the benchmark buy and hold returns are reported.

Gamma	1			3			5		
	B&H	COMP	CONV	B&H	COMP	CONV	B&H	COMP	CONV
F100_AR1_P1_Q1_W250	-1.61%	2.55%	10.41%	-3.93%	0.20%	8.01%	-8.57%	-4.44%	3.37%
F100_AR3_P3_Q3_W250	-1.59%	13.74%	13.83%	-3.90%	11.31%	11.41%	-8.55%	6.68%	6.77%
F100_AR5_P5_Q5_W250	-1.66%	12.89%	0.93%	-3.98%	10.47%	-1.40%	-8.62%	5.84%	-6.05%
F10_AR5_P5_Q5_W250	-4.97%	12.28%	5.28%	-7.39%	9.72%	2.78%	-12.31%	4.82%	-2.13%
F30_AR5_P5_Q5_W250	-2.60%	8.54%	4.48%	-5.04%	6.01%	1.99%	-9.96%	1.10%	-2.93%
F60_AR5_P5_Q5_W250	-1.93%	9.99%	0.38%	-4.26%	7.57%	-1.97%	-8.96%	2.88%	-6.67%
F100_AR5_P5_Q5_W60	-1.78%	3.71%	-1.44%	-4.04%	1.40%	-3.71%	-8.60%	-3.15%	-8.26%
F100_AR5_P5_Q5_W120	-1.51%	3.12%	4.04%	-3.77%	0.82%	1.74%	-8.32%	-3.72%	-2.81%