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FORECASTING THE FUTURE: DECOMPOSITION APPROACHES TO STOCK EXCHANGE INDEX PREDICTION

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Abstract: *Forecasting stock exchange index values is a fundamental pursuit in financial analysis, traditionally achieved by modeling past index values. However, an alternative approach involves separately forecasting prices for each individual stock comprising the index and then aggregating these forecasts to predict the index value, considering corresponding weights. This study explores the efficacy and utility of such separate forecasting methods in comparison to conventional approaches. Drawing upon the concept of market efficiency posited by Fama (1970), which suggests that direct forecasting may be futile, let alone the indirect method of separate forecasting, there arises a critical inquiry into the rationale and practicality of adopting such techniques. This paper delves into the implications of both methods, considering their theoretical underpinnings and empirical performance.*

Keywords: *Stock Exchange Index, Forecasting Methods, Market Efficiency, Financial Analysis, Fama (1970)*

1 Introduction

Stock exchange index values can be forecasted in the usual way, i. e. such that we model the past values of the index. Or, we can try to do it differently by separately forecasting prices for each single stock that composes the index and after that combining those individual forecasts back into the index forecast taking corresponding weights into account.

There is in place an immediate questioning about sense and usefulness of such separate forecasting.

If we are to believe the market efficiency (Fama, 1970), also a direct way of forecasting is supposed to be unsuccessful, let alone the indirect separate forecasting that lacks even the inertness of the forecasted time series. We assume that, especially in more turbulent periods, decomposing the index can bring to the surface certain movement that would otherwise remain hidden among the other components, and therefore undetected. The comparison between the two approaches was made on the basis of AR (1) model and AR (1) model with ARCH(1) upgrade. Besides, we were also interested in differences between the results during the recession period compared to the period before. As it turns out, forecasting the direction of index value change during the recession period is more successful using the suggested alternative approach.

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2 Data and Methods

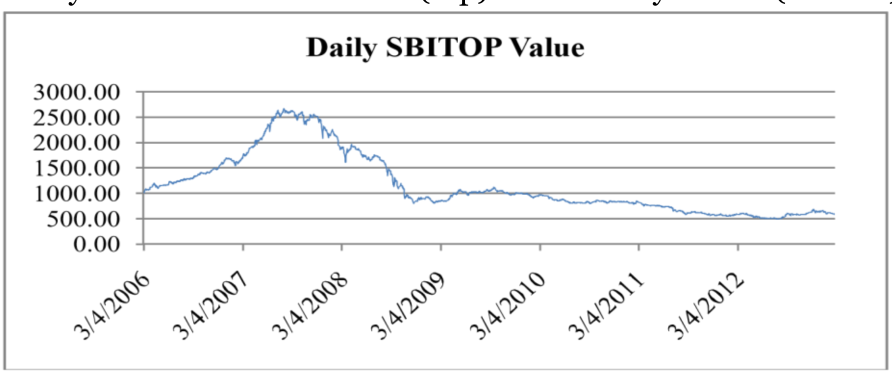
The idea of forecasting stock index values through decomposition, separate forecasting of individual stocks and final re-composition was tested on the SBI TOP (Slovenian stock exchange index) case. SBI TOP consists of the most liquid stocks that are traded with at Ljubljana Stock Exchange. The data on SBI TOP index and its composing stocks are available from the data archives of Ljubljana Stock Exchange (http://www.ljse.si/, April 2013), and the information on the index composition changes is available from the Ljubljana Stock Exchange information systemSEOnet (http://seonet.ljse.si/, April 2013).

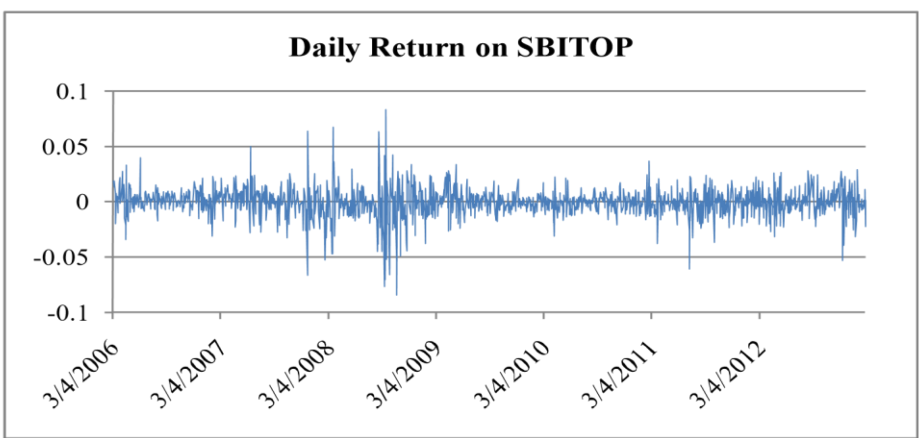
The period analyzed is from the first quote of the SBI TOP index value, which was on April 3, 2006, untilMarch 28, 2013, which makes 1739 daily observations.For some stocks that entered the market later, the time series is appropriately shorter. Index consists of 5 to 10 most liquid stocks, on the last day of observation there were 7 stocks included in the index.

To meet the model assumptions as thoroughly as possible, the time series is usually modeled in its stationary form, which means that the values should oscillate around some constant (mean) value.

Figure 1 shows the original SBITOP index daily value that represents a nonstationary time series (top), and daily return on SBITOP index that is stationary (bottom).Daily return for the period is calculated as = ln (___), where represents the daily index value.

Figure 1:Daily value of SBITOP index (top) and its daily return (bottom)





Often used methods for time series modeling and forecasting are various variants of linear ARMA(AutoRegressive Moving Average)model combinations (Box, Jenkins, Reinsel, 1994). We will use the basicAR(1) form, i. e. autoregressive process of the first order.

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As it is characteristic for stock exchange rates to be volatile, we will also check the version that includes volatility (or variable variance) modeling as well, i. e. AR(1) model with ARCH(1)(AutoRegressiveConditional Heteroscedastic) extension(Engle, 1982).

For every single period we estimate the daily return time series model up to the period (− 1) and then make a 1-day-ahead forecast for the period on the basis of this estimate (i. e. we produce rolling estimates).

At the end, the forecasted daily returns are transformed into the forecasts of index values that are finally compared to the true values.

The index values are estimated by both versions of model – first directly, and then also via the decomposition procedure. In the latter case we forecast separately stock prices for every single stock, and after that combine these separate forecasts back into the index taking the corresponding index structure and correction factors into account.

The analysis was done for different time spans: firstly for the whole observed period, then only for the subperiod before recession (up to September 30th, 2008), and finally for the recession subperiod (from October 1st, 2008 on).

3 Results

Comparison of forecasted values of SBI TOP index to its true values is shown in Table 1. There are many different criteria to evaluate the forecasting errors (Brooks, 2005) – in Table 1 we present RMSE (Root Mean Square Error) and BIC (Bayesian Information Criterion), also known as SC (Schwarz Criterion), that is calculated as $\text{BIC}(K) = -\frac{2l}{T} + \frac{K \log T}{T}$, where K represents the number of estimated parameters, T the size of the sample, and $l$the logarithm of the likelihood function.Both measures take on lower values for better forecasting models.

It can be noticed that all four ways of forecasting were similarly successful. However, both error measures were slightly lower for direct modeling which means that the usual method is better when forecasting the exact values of the index.

Table 1:Comparison of forecasting success of the four different types of SBI TOP index forecasting for the three different time spans (for each period the lowest values of RMSE and BIC are bolded and indicate the best modelfor that period)

RMSE **BIC**	**AR – Directly**	**AR – De/Re-Composition**	**AR + ARCH – Directly**	**AR + ARCH – De/Re-Composit**
Whole Period	17.17 14521.16	17.44 14573.91	**17.14** **14515.44**	17.44 14573.83
Period Before Recession	**24.59** **5371.34**	24.63 5373.07	24.59 5371.44	24.69 5376.28
Recession Period	**11.49** **8673.91**	12.14 8797.57	11.59 8694.99	12.05 8780.66

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When forecasting the exact values of the index, the simplest approach, which is direct modeling of SBI TOP index daily return time series by AR(1) model, was the most successful. This method was somewhat worse (compared to AR + ARCH direct modeling) when analyzing the whole period, but when splitting the time series into two parts (before and during the recession) it was the most successful method in both subperiods.

However, it is pretty much utopian to expect to correctly forecast the value of the index, especially in the recession time when index values are very volatile. Therefore, we checked the forecasting quality of the four mentioned procedures also regarding the direction of the index valuechange. Table 2 shows percentages of successfully forecasted directions of index value changes. Again, the four different approaches were applied on the three different time spans.

Table 2: Comparison of successfully forecasted directions of SBI TOP index value changesfor the four different types of SBI TOP index forecasting for the three different time spans(for each period the highest percentage share is boldedand indicates the best modelfor that period)

Percentage Of Correc Direction Forecasts	**t AR – Directly**	**AR – De/Re-Composition**	**Ar + Arch – Directly**	**Ar + Arch – De/Re-Composition**
Whole Period	58.17	**58.87**	56.82	58.52
Period Before Recession	**63.28**	62.93	61.55	61.55
Recession Period	55.53	56.77	54.37	**56.95**

Also from this point of view the AR(1) model was the most successful for the time before recession, but for forecasting the direction of value change through whole period, and especially during the recession, it turned out that decomposition of index, separate forecasting of individual stocks, and re-composition back into the index was a better choice.

Apart from that, it can also be noticed that percentages of successfully forecasted directions of index value changes were higher than 50 % in all cases, implying that forecasting on the basis of time series modeling is better than guessing by chance, which means that Slovenian stock market is still at least partially inefficient. **4 Conclusion**

The value of a stock index can be forecasted on the basis of the analysis of its past values, or separate forecasts of prices of those stocks that are included in the index can be made and then composed back into an index forecast.

The comparison of both approaches was done on the case of Slovenian stock index SBI TOP, that consists of 5 up to 10 most liquid stocks traded at Ljubljana Stock Exchange. For two models (AR(1) and AR(1) with ARCH(1) extension) we estimated the index (and individual stocks) daily return for three different time spans (whole period, time before recession, and recession subperiod).Using rolling estimates we produced 1-day-ahead forecasts and compared them with the true values.

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On the basis of comparing forecasted values to the true values of SBI TOP index by RMSE and BIC measures, the most successful model was the simplest direct forecasting with AR(1) model.
However, in turbulent periods, as is the current recession period, it doesn't make sense to expect to be able to correctly forecast the value of the index. Therefore, we were interested also in successfulness of the four approaches when forecasting the direction of the index value change. For the subperiod before the recession the direct forecasting with AR(1) model was still the most successful. But when forecasting the direction of value change through the whole period, and especially during the recession, we got higher percentage of correct forecast matching using the decomposition approach. This means that in the period of higher volatility tracking the partial movement of individual components was more important than inertness of the time series of the index itself.
Of course, it is impossible to generalize the findings about suitability of direct or indirect stock index value forecasting without some further analysis using different models, different stock indices, different subperiods…But anyway, the idea of decomposing a stock index and forecasting its components separately is at least worth considering, as shows the Slovenian example.

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