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Using Neural Networks to Forecast Volatility for an Asset Allocation Strategy Based on the Target Volatility

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Abstract

The objective of this study is to use artificial neural networks for volatility forecasting to enhance the ability of an asset allocation strategy based on the target volatility. The target volatility level is achieved by dynamically allocating between a risky asset and a risk-free cash position. However, a challenge to data-driven approaches is the limited availability of data since periods of high volatility, such as during financial crises, are relatively rare. To resolve this issue, we apply a stability-oriented approach to compare data for the current period to a past set of data for a period of low volatility, providing a much more abundant source of data for comparison. In order to explore the impact of the proposed model, the results of this approach will be compared to different volatility forecast methodologies, such as the volatility index, the historical volatility, the exponentially weighted moving average (EWMA), and the generalized autoregressive conditional heteroskedasticity (GARCH) model. Trading measures are used to evaluate the performance of the models for forecasting volatility. An empirical study of the proposed model is conducted using the Korea Composite Stock Price Index 200 (KOSPI 200) and certificate of deposit interest rates from January, 2006 to February, 2016.

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Keywords: Artificial neural networks; Forecasting volatility; Asset allocation strategy; Target volatility.

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1. Introduction

Recently, many institutional investors and fund managers have used an investment strategy known as target volatility (or risk control), aimed at maintaining a target level of volatility (i.e., risk) for a portfolio [3, 11]. In particular, insurance companies have sold variable annuity (VA) funds to their customers, applying the target volatility asset allocation strategy [3]. Generally, the target volatility strategy consists of a risky asset and a risk-free cash position. Compared to a traditional fixed-allocation strategy that consists of 60% equity and 40% bonds (60/40), a target volatility strategy adjusts the investment proportion between risky (i.e., equities) and risk-free assets (i.e., bonds) in order to maintain the predetermined level of volatility for the portfolio. The investment proportion between the risky and the risk-free assets is calculated by estimating the volatility of the risky assets returns. In other words, if estimated volatility is higher than the target volatility, the investment proportion of the risky assets will decrease. On the other hand, if the predicted volatility is lower than the target volatility, the risky asset allocation will increase. Thus, forecasting the volatility is an important process for implementing a target volatility strategy.

However, volatility models (i.e., statistical or model-driven approaches) such as Autoregressive Conditional Heteroscedasticity (ARCH) [2] and Generalized ARCH (GARCH) [1] require strict assumptions about distributions of data. Due to the limitations of the statistical models, data mining or machine learning techniques have been applied to various domains. In particular, the Artificial Neural Network (ANN) model is a nonparametric model and has the ability to learn the pattern of data without any assumptions [5, 10]. The usefulness of the ANN has also been demonstrated for forecasting volatility in the financial markets. For example, Amornwattana and Enke [12, 13] developed a hybrid ANN model for forecasting volatility for options trading. Hajizadeh et al. [4] proposed a hybrid model based on EGARCH and an ANN to forecast the volatility of the S&P 500 index. Monfared and Enke [8, 9] also proposed a hybrid GJR-GARCH Neural Network model to enhance the performance of volatility forecasting using an adaptive neural network filter for cancelling noise in the data.

Nonetheless, a challenge to data-driven approaches is the limited availability of data since periods of high volatility, such as during financial crises, are rare. To resolve this issue, we apply a stability-oriented approach [5, 6, 10] to compare data for the current period to a past set of data for a period of low volatility, providing a much more abundant source of data to use for comparison. Furthermore, we simulate predicted volatility into the target volatility strategy composed of the Korea Composite Stock Price Index 200 (KOSPI 200) and certificate of deposit interest rates from January, 2006 to February, 2016. The proposed model is compared to different volatility forecast methodologies, including the volatility index (VIX, also known as fear index), the historical volatility (i.e., a moving average, MA), the exponentially weighted moving average (EWMA), and the GARCH model.

2. Target volatility strategy

The underlying principle of the target volatility asset allocation strategy is to consistently adjust the exposure to a given asset in order to maintain a target volatility level for the portfolio [3, 11]. In this study, we consider a daily rebalancing strategy. The weight of equity in the portfolio is calculated by Eq. (1), where $\hat{\sigma}_t^{equity}$ is an estimate of the volatility of equity returns, and σ^{target} is the target volatility, applied between time t and the next rebalancing time, $t+1$.

$$w_t^{equity} = \min\left(\frac{\sigma^{target}}{\hat{\sigma}_t^{equity}}, 100\%\right) \tag{1}$$

Some parameters are needed to implement the target volatility strategy. These include the volatility target, the computation of current volatility, the maximum amount of leverage, and the frequency of rebalancing. However, we consider that the maximum weight of equity (=100%) is restricted to be a constraint (i.e. no leverage) and applies to the 10% of the target volatility with the daily rebalancing strategy since the objective of this study is to use ANNs for volatility forecasting to enhance the ability of an asset allocation strategy based on the target volatility.

3. Model specification

The main idea in the proposed model is to find a stable period of volatility from the past and to measure the gap (i.e., distance) between the current and stable periods. This process is accomplished by fitting an ANN model to the data of the selected stable period of volatility. The fitted ANN model is then applied to the data of the current period to measure the gap based on the residuals from the fitted model. The statistical testing problem in this study is presupposed as follows:

H_0: Volatility in the given period is stable.
H_1: Volatility in the given period is not stable.

Note that from a statistical point of view, one significant advantage of this approach is to improve statistical reliability since the test statistics and their null distributions may be derived with abundant data [6].

3.1. Phase 1: Identify the stable period

The stable period of volatility is defined as a stationary process without changes in parameters, such as the mean and the variance, over time. Thus, it is necessary to identify the stable period of volatility using an Augmented Dickey-Fuller (ADF) test, i.e., the null hypothesis that the underlying data is a pure random walk. We use the VKOSPI (Korea's representative implied volatility index) as a volatility proxy instead to the squared return since the KOSPI200 Risk Control Index is based on the VKOSPI and is published every day. We perform a unit root test to search stable periods of the VKOSPI with the ADF test. The stable period is explored every day using 252 trading days per year. The null hypothesis of the ADF test can be rejected since the statistic is -3.44106, with a p-value of 0.049 at a significance level of 0.10. The selected stable period is from April 06, 2010 to April 07, 2011 (see. Fig. 1).

3.2. Phase 2: Fitting the neural networks model

As given in Eq. (2), a set of data for a stable period of length (n) and model of order (p) can be expressed as

$$S_{t,n} = f_n(S_{t-1,n}, S_{t-2,n}, \cdots, S_{t-p,n}) + \varepsilon_{t,n} . \tag{2}$$

We employ a back-propagation neural network (BPN) architecture, which is one of the most widely used ANNs in financial applications. In this study, the BPN architecture consists of three-layers, including the input layer (10 nodes), hidden layer (10 nodes), and the output layer (1 node). In general, no robust theoretical foundation exists that can be used to select the appropriate BPN architecture [7]. Thus, the architecture for the BPN in this study is determined by trial-and-error. Also, a logistic (or sigmoid) function is used as an activation function with a learning rate, momentum rate, and initial weight of 0.1, 0.1, and 0.3, respectively, for the BPN training. Figure 1 shows the actual and predicted values of the VKOSPI index during a stable period of volatility.

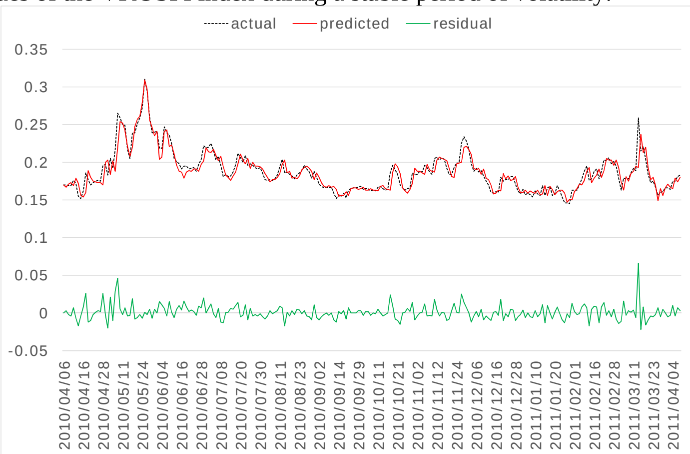

Fig. 1. Actual and predicted values for the VKOSPI Index during a stable period of volatility, along with residuals

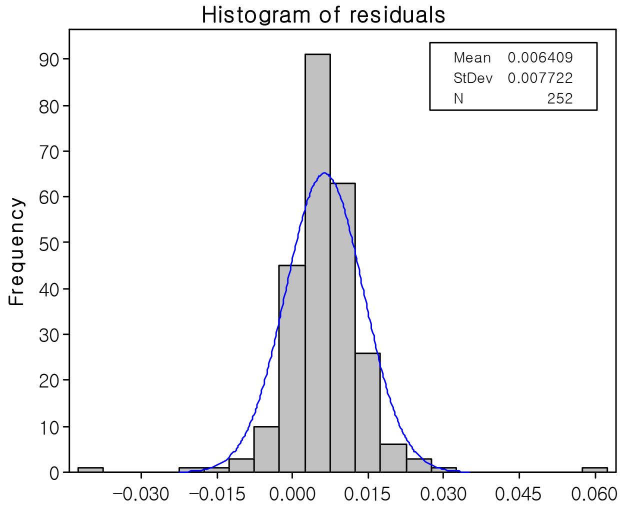

Fig. 2. Histogram of residuals

In addition, the histogram of residuals in Fig. 2 is a graphical technique for assessing whether or not the residuals are approximately normally distributed. Fig. 2 shows that utilizing an ANN to fit the stable period produces residuals with a normal distribution. Therefore, the ANN model fitted for the stable period of volatility is well constructed.

3.3. Phase 3: p-value calculation and forecasting volatility

The p-value provides the probability of assuming the null hypothesis is true (i.e., volatility in the given period is stable). This can be interpreted that if the p-value is less than α, then it is unlikely that volatility in the given period is stable; if the p-value is more than α, then the null hypothesis is not rejected. In this study, the null distributions can be constructed by using an empirical distribution that is selected from the stable period of volatility. Thus, the ability to calculate the p-value is a major technical strength in this study.

$$\hat{F}_n(x) = \frac{\text{the number of elements in the sample} \leq x}{n} \tag{3}$$

The p-value calculated from Eq. (3) is applied into the target volatility strategy to prevent a financial crisis (or down market risk) because it provides a probability that the volatility is in a stable period. Therefore, if p-value is less than 0.2, the volatility of risky assets assumes 90% because the maximum value of the VKOSPI was about 90% during the U.S. subprime mortgage crisis. On the other hand, if p-value is more than 0.2, the predicted value of volatility based on the ANN model is applied into the target volatility strategy as the estimated volatility.

4. Experimental results

An empirical study of the proposed model is conducted using the Korea Composite Stock Price Index 200 (KOSPI 200) and certificate of deposit interest rates from January, 2006 to February, 2016. The data used in this study is downloaded from the Korea exchange (http://www.krx.co.kr/). The trading results are compared against the different volatility forecasting methodologies such as the VKOSPI (Volatility Index of KOSPI 200), GARCH (1,1), EWMA, MA (10), MA (30), and the fixed-allocation strategy (i.e., equity: 60%, bond: 40%), as shown in Table 1. As the default settings for the trading, the initial cash position is set to ten billion won (i.e., ten million dollar) and the fund management fee is set to 1%. It can be seen that asset allocation strategies based on target volatility performs better than the fixed-allocation strategy since it generates less maximum drawdown and daily loss. In addition, the proposed model generates the highest Sharpe ratio (0.32). The Sharpe ratio measures the excess return per unit of risk for the trading strategy. Thus, a portfolio with a higher Sharper ratio provides a better return for the same unit of risk. Annualized volatility of each strategy is less, or close to the target volatility (10%), except for the fixed-allocation strategy. These results indicate that the target volatility strategy is an efficient tool of handling the portfolio volatility.

Table 1. Trading results of target volatility strategy with different volatility forecasting methodologies (target volatility = 10%)

	ANN	VKOSPI	GARCH (1,1)	EWMA	MA (10)	MA (30)	FIX
Cumulative Profit (%)	24.86	22.20	27.91	26.92	23.68	25.66	37.41
Annualized Return (%)	2.49	2.22	2.79	2.69	2.37	2.57	3.74
Annualized Volatility (%)	7.89	8.88	9.97	10.10	11.43	10.69	13.22
Sharpe Ratio	0.32	0.25	0.28	0.26	0.21	0.24	0.28
Maximum Daily Profit (%)	2.11	2.00	2.42	2.36	2.69	2.62	7.34
Maximum Daily Loss (%)	-2.37	-2.37	-4.11	-2.74	-3.78	-2.67	-6.22
Maximum Drawdown (%)	-18.33	-20.92	-22.72	-23.83	-26.88	-23.96	-41.64

As an example, the VKOSPI had reached levels of about 90% during the financial crisis (i.e., the U.S. subprime mortgage crisis) in October 2008. By targeting volatility of 10%, the target volatility strategies help to mitigate exposure to the risky asset during the financial crisis. In fact, the target volatility with the ANN had been exposed to only 11% of the risky asset towards the end of 2008. A comparison of the trading performance results is also shown in Figs. 3 and 4. These results indicate that the target volatility is useful for downside risk during the financial crisis.

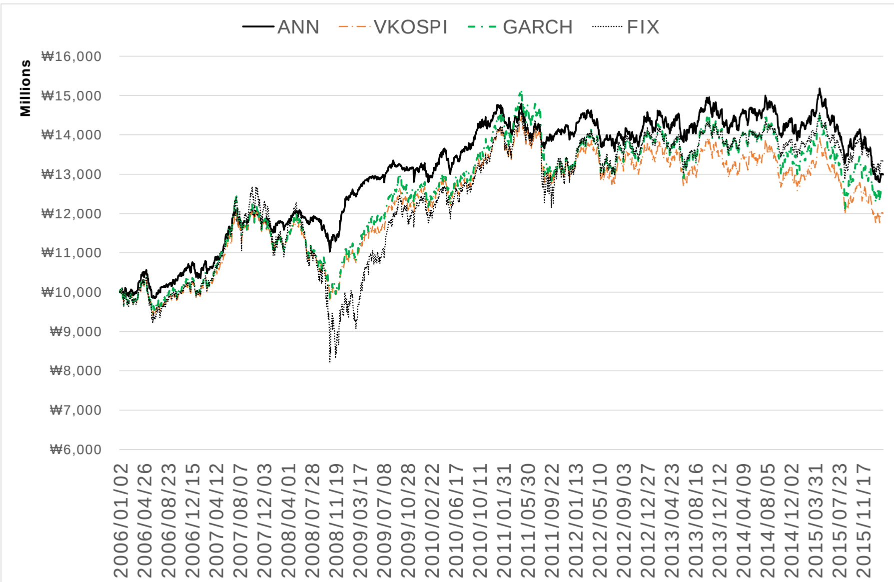

Fig. 3. Cumulative profits for the ANN, VKOSPI, GARCH and FIX strategies

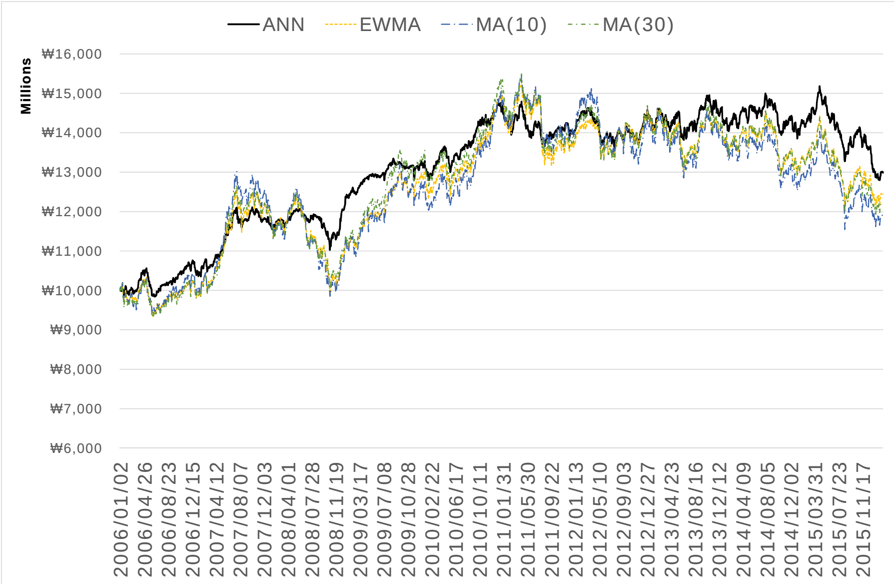

Fig. 4. Cumulative profits for the ANN, EWMA, MA(10), and MA(30) strategies

5. Conclusions and future work

This study proposed to enhance the performance of an asset allocation strategy based on the target volatility using artificial neural networks for volatility forecasting. Compared to different volatility forecast methodologies, the proposed model based on the stability-oriented approach provided a successful trading performance. For further study, other intelligent techniques, such as support vector regression (SVR) and fuzzy logic, can be considered to fit the stable period. We expect that this approach can also be extended to other markets, such as the currency exchange and interest rate markets.

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