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中 華 民 國 98 年 5 月 31 日

摘要

以家庭及人生生涯規劃為基礎之理財規劃顧問服務，是近年來逐漸興起之新興金融服務。然而在實務上，家庭及人生的理財規劃需同時考量各種不同的外在因素，如法律、節稅等限制，並且也需配合不同之投資行為與風險偏好選擇不同的投資策略與資產配置。因此一個完美的理財規劃模型，是一個非常複雜的多目標決策問題。傳統上這類問題大多採用線性規劃的方式，來求得最佳解，然而這類的傳統方法學，並無法即時因應外界多變的環境來進行動態的調適，而原本根據某個時間點所做的規劃，也無法在長期時間的考驗下仍然保持最佳化，因此本計畫將利用人工智慧的方法學，建構一個能隨著環境的變動進行動態調適的理財規劃模型。本計畫第一年度之成果，是發展出以自組織類神經網路為基礎之最佳化動態避險比例估算模型，我們利用技術指標分析來描述動態變化之理財環境，並使用自組織類神經網路將財務資產之價格時間序列進行分群，之後利用時間序列模式之比對，來估算最適避險比例。我們設計了五種不同資料取樣方式的模型，並比較短、中、長不同時間區間之避險績效，最後與傳統方法進行比較。研究實證利用台灣期貨市場交易資料，研究結果顯示本研究所提出之模型，將能有效估計動態避險比例，未來應用在理財規劃上，配合避險資產組合之配置，將有助於達成長期理財規劃之目標。

關鍵詞：最佳避險比例、自組織類神經網路、期貨避險

Abstract

The family or life financial planning is a emerging financial service in recent years. However, it is not easy to make plan that many factors must be considered, such as tax, law and various risk preference. In practice, the financial planning is a complex multi-objective decision problem with many restricted condition. Traditionally, linear program and numerical optimization skill were used to solve these problems. But the investment environment is dynamic and change rapid, that the financial planning should be dynamic adaptive with time. We propose a model which is capable with dynamic adaptive and suitable for long time financial planning.The result of this project in the first year is to develop a optimal dynamic hedge ratio estimation model using self-organizing map (SOM). Technique analysis indicators, which are widely used in investment, were adapted as the dynamic environment descriptive parameters for financial planning. A novel approach is then proposed using SOM for these time series data clustering and similar pattern recognition to improve the optimal hedge ratio estimation. Five SOM-based models, considering the weight for averaging and the interval for data sampling, and two traditional models, ordinary least square method and naïve hedge, were compared in Taiwan stock market hedging. The experimental processing demonstrated the feasibility of applying SOM and the empirical results shown that SOM approach provides a useful alternative approach to the optimal hedge ratio estimation. Furthermore, when applying this model for financial planning and simultaneously dynamic adjusting the hedging portfolio, it is helpful to achieve the long-term objective of financial planning.

Keywords: Optimal Hedge Ratio、Self-Organizing Map、Futures Hedging

1. Introduction

The futures market is one of the most important aspects of the financial market. In 2007, the total trading volume of global futures and options reached 15 billion US dollars; this growth rate has accelerated since then [1]. Many investors consider the futures market as a powerful risk management tool because it can provide hedging, speculation, arbitrage, and price discovery functions. On the other hand, it is helpful in increasing market efficiency and integrity.

As a risk management tool, hedging has become an important issue. Many conditions should be determined when hedging: hedge target, hedge horizon, hedge ratio, and other like conditions. In general, the hedge target is chosen according to the correlation between the spot and futures, and the hedge horizon is determined by the hedger's subjective identity. Traditionally, the appropriate hedge ratio can be estimated by the ordinary least square (OLS) method or the mean-variance model. The OHR is commonly defined as the hedge ratio under the minimal risk with specific risk aversion. But these models are time invariant and cannot reflect the dynamic behaviour of the time series. Recently, studies have applied econometrics models (e.g., GARCH family models) to estimate the OHR in empirical studies which suggest that the OHR has the time variant and the hedged portfolio needs to be adjusted frequently during the hedge horizon [3] [4].

Nevertheless, these financial models, which are based on the assumption that the investors' behaviour is completely rational and the financial markets are efficient and have been challenged since the emergence of such financial behaviour in the last three decades. In other words, the return series of the financial asset does not fit the normal distribution [5]; on the contrary, most of them are fat-tailed or leptokurtic. Therefore, the hedge ratio estimation based on the OLS and mean-variance (MV) models have poor accuracy, theoretically. Moreover, additional conditions such as risk aversion and utility function are hard to be estimated. The expected payoff is assumed marginable, and the return series of different trading day is independent, hence causing the inaccuracy of the OHR estimation.

The GARCH family models are capable of catching the dynamic behaviour of the financial time series and have been widely used for forecasting volatility and for estimating portfolio risk. However, these models have several drawbacks when dealing with time series forecasting. One of the drawbacks shows that the models require the time series to be stationary; thus, the price series of a financial asset is usually transformed to the return series by differential. It will, nonetheless, eliminate much information and ignore the property such as the co-integrated. Consequently, studies have tried to improve the GARCH family models by adding the error term or other variables to the models. Such improvement can increase accuracy, but the models, together with other variables, becomes more and more complicated. Another drawback is shown in the data sampling frequency. Most empirical studies adopt the same sampling frequency for estimation and forecasting periods. For example, the hedge ratio in the next five days is determined according to data with five-day sampling frequency; the hedge ratio in the next three weeks is determined according to the data with three-week sampling frequency. These models cannot work when dealing with different sampling frequencies; the information and property of the original time series may be eliminated after data sampling [6]. Nonetheless, while certain studies are devoted to the improvement of the GARCH models [7] [11], others propose to simply alternate approaches based on the moving average [8].

Another issue is the hedge strategy, which can be classified as static and dynamic hedge. In order to avoid transaction cost, the static hedge strategy suggests that the hedge portfolio should not be changed frequently during the hedge horizon. The natural property of the financial time series, however, is dynamically changing. Studies suggest that the hedger should consider time-variant hedge ratio in order to obtain better hedge effeteness. As a result, the dynamic hedge strategy stands that the hedge portfolio should be adjusted more frequently according to the latest estimated hedge ratio until the hedge horizon is due.

In this study, we propose the new hedge ratio estimating approach using SOM which serves as an unsupervised two-layered network that can organize a topological map. The resulting map shows the natural relationships among the patterns that are given to the network. SOM is suitable for clustering analysis and has been applied to time series forecasting [9] [10]. However, the feasibility of using SOM to deal with the variance and covariance of time series forecasting has not been studied.

The research process is described as follows. First, the time series are clustered with SOM. Second, the hedge ratio is calculated based on the cluster of the similarity time series pattern. We assume that the similar time series pattern will have the same behaviour and will be suitable for hedge ratio estimation. Finally, several SOM-based models we propose are investigated and compared with the traditional models using the rolling window approach in out-sample testing. The experiment results can provide a valuable reference for adopting the SOM approach without considering too many assumptions and restrictions in previous models.

The rest of the paper is organized as follows: Section 2 illustrates the basic model for the OHR estimation; Section 3 details the research method; Section 4 analyzes the experiment results; and lastly, Section 5 draws conclusions from the study.

2. Estimation of the Optimal Hedge Ratio

2.1 Minimum Variance Hedging

Minimum variance hedging is the most important concept of portfolio risk management. Investors hold the spot position and futures position at the same time to compose the portfolio. The risk of the portfolio is usually measured by the variance. Consequently, hedging with the minimum risk hedge ratio is also called minimum variance hedging. For a long position in the spot market, the return hedged portfolio is given by

$$\Delta HP = \Delta S - h\,\Delta F \tag{1}$$

where h is the hedge ratio. ΔS and ΔF are the changes in the spot and futures prices, respectively. The price change can also be represented as the return, which is continuously compounded and defined as $ln(P_t / P_{t-1})$ multiplied by 100.

The OHR is the value of h that maximizes the investor's expected utility. When the futures price follows a martingale, the expected futures return is zero; therefore, the futures position will not affect the expected return of the portfolio. The OHR is simply the value of h that minimizes the variance of equation (1) which is given by

$$\frac{\partial\, \mathrm{var}(\Delta HP)}{\partial h} = 2h\sigma_{\Delta F}^2 - 2\sigma_{\Delta S,\Delta F} = 0 \tag{2}$$

where $\sigma_{\Delta F}^2$ is the variance of the futures return and $\sigma_{\Delta S,\,\Delta F}$ is the covariance between the spot return and the futures return. The OHR is determined by solving equation (2):

$$h^* = \frac{\sigma_{\Delta S,\,\Delta F}}{\sigma_{\Delta F}^2} \tag{3}$$

The OHR given by equation (3) can be estimated by regressing the spot return on the futures return using OLS. This approach is also viewed as the conventional OHR. Equation (3) also considers the conditioning on recent information for more efficient estimate of the OHR. The most commonly used practice is the rolling window approach, where the variance and covariance of the spot and futures are estimated at time *t* according to the conditioning on the time *t-1* information set.

The degree of hedging effeteness is measured by the percentage reduction in the variance of portfolio after hedging. Therefore, the hedge effectiveness (HE) can be noted as

$$HE = \frac{\sigma_{un-hedged}^2 - \sigma_{hedged}^2}{\sigma_{unhedged}^2} = 1 - \frac{\mathrm{var}(\Delta HP)}{\mathrm{var}(\Delta S)} \tag{4}$$

2.2. The SOM Approach

Traditional OLS hedge ratio is estimated on the regressing spot return on the futures return under the assumption that the probability distribution of the spot and futures return series come from normal distribution. However, most financial asset returns do not follow the assumption; hence, the variance and covariance estimated by OLS is inaccurate. Consequently, we propose that the variance and covariance should be estimated using similar time series data. SOM clustered historical time series data with similar patterns. The perfect hedge ratio, such that the HE equation (4) equals to 1, can be calculated in advance. Therefore, when the hedge ratio for next hedge horizon is estimated, we can refer to the known hedge ratio in the past with similar time series pattern. A corresponding flow chart of the proposed scheme is shown in Figure 1.

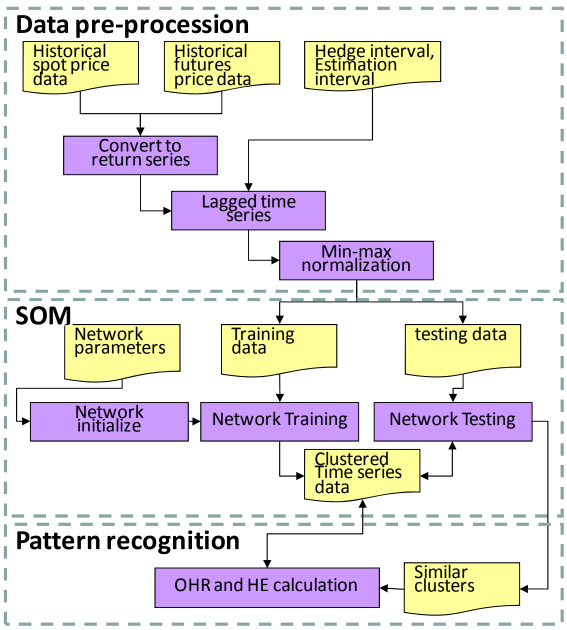

Figure 1. The SOM approach for OHR estimation

The OHR estimating procedure involves five steps:

(a) SOM initialization. The appropriate parameters of the SOM are determined: network topology, number of the neuron in the input layer, radius of the near area, learning rate, among others.

(b) Data pre-procession. The input variables for time series pattern recognition and similarity search are verified; the lagged time series is calculated; and the input value between -1 and 1 is normalized.
(c) Network training. A vector composed of the historical time series is entered into the SOM. The output of a neuron is established by calculating a similar measure between the weight of that neuron and the external input using the competitive learning, which is widely used in machine learning.
(d) Similar pattern recognition. In testing period, the trained SOM can select the similar days in the historical time series for OHR estimation.
(e) OHR calculation. The OHR is estimated using the OLS hedge ratio of the similar clustered time series data.

3. Research Method

3.1 Constructing the SOM Model

The feasibility of using SOM to estimate the OHR is examined through the five SOM-based models that we propose. Generally, the hedge ratio implies the relationship of the spot and futures price change degree. Many empirical studies indicate the existence of the co-integration relations between spot and futures prices; the co-integration relations would be eliminated when mapping the price series to the return series. Furthermore, the basis between the spot and futures prices is helpful for estimating the hedge ratio [2]. Therefore, we adopt the two series, the spot price series and the basis series, as the input variables of SOM model. The SOM model can be expressed as follows:

$$P_t^S = [p_{t-e}^S, .., p_{t-1}^S, p_t^S] \quad (5)$$

$$P_t^F = [p_{t-e}^F, .., p_{t-1}^F, p_t^F] \quad (6)$$

$$B_t^{S,F} = P_t^S - P_t^F \quad (7)$$

$$N^k = F(P_t^S, B_t^{S,F}) \quad (8)$$

where P_t^S , P_t^F are the spots and futures price series with *e* days lag before current day, respectively. $B_t^{S,F}$ is the basis series derived from the spot and futures prices. F is the function representing the SOM. N^k is the output of the SOM, representing the numbers of the clustered time series data.

The SOM model for OHR estimation is designed on two basic concepts: one, to calculate the average OHR of the clustered data; and two, to calculate the OHR using the data in different intervals.

Let E_t and $\hat{E}_t$ denote the clustered data sets. $\hat{P}_t^S$ and $\hat{P}_t^F$ are the price series in the *f* days ahead hedge intervals

$$E_t = \{P_t^S, P_t^F\} \quad (9)$$

$$\hat{P}_t^S = [p_{t+1}^S, p_{t+2}^S .., p_{t+f}^S] \quad (10)$$

$$\hat{P}_t^F = [p_{t+1}^F, p_{t+2}^F .., p_{t+f}^F] \quad (11)$$

$$\hat{E}_t = \{\hat{P}_t^S, \hat{P}_t^F\} \quad (12)$$

Five different SOM-based OHRs are estimated by equations (13) to (18):

1. Time-weighted average

$$OHR_{SOM\_TWA} = \frac{\sum_{i=1}^{m} \frac{1}{d_i} h_i}{\sum_{i=1}^{m} \frac{1}{d_i}} \quad (13)$$

where $$h_i = \frac{\sigma_{\Delta S_t \Delta F_t}}{\sigma^2_{\Delta F_t}} \bigg| \hat{E}_t \quad (14)$$

2. Equal-weighted average

$$OHR_{SOM\_EWA} = OHR_{SOM\_EWA} \Big|_{d=1} \quad (15)$$

3. Estimation interval

$$OHR_{SOM\_EI} = \frac{\sigma_{\Delta S_t \Delta F_t}}{\sigma^2_{\Delta F_t}} \bigg| E_t \quad (16)$$

4. Hedge interval

$$OHR_{SOM\_HI} = \frac{\sigma_{\Delta S_t \Delta F_t}}{\sigma^2_{\Delta F_t}} \bigg| \hat{E}_t \quad (17)$$

5. Estimation and hedging intervals

$$OHR_{SOM\_EH} = \frac{\sigma_{\Delta S_t \Delta F_t}}{\sigma^2_{\Delta F_t}} \bigg| \{E_t, \hat{E}_t\} \quad (18)$$

3.2 Data and Experiment Design

This study obtains the empirical trading data of the daily closing price of the Taiwan weighted index (Taiwan Stock Exchange and the Taiwan Index Futures traded on the Taiwan Futures Exchange, AREMOS database). The futures prices series was gathered from the nearest month contracts and rolled over to the next nearest contracts on the maturity day due to the consideration of liquidity and price spread risk. The data were selected from 2 January 2003 to 14 July 2008. After clearing the irregular data, a total of 1,300 observations are used for experiments.

After operating for *e* days lag and *f* days ahead in equations (5) ~ (12), the data are divided into two parts. The first 1,000 records are used for SOM in-sample training, and the last 200 records are used for out-sample testing. A rolling window scheme is designed for dynamic hedge ratio estimation, as illustrated in

Figure 2. The rolling windows are expected to roll 200 times to test the 200 out-sample data for each experiment.

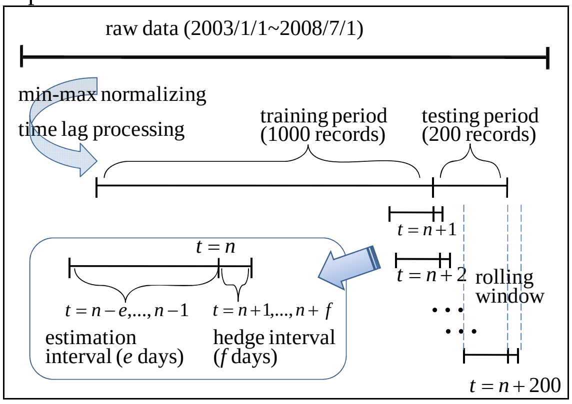

Figure 2. Rolling window

We assume that the hedged portfolio is adjusted every f days; this is the hedged interval. The hedge effectiveness is calculated at the end of the hedge interval on the $(t+f)$ -th day using equation (4). In order to reflect the real hedge effectiveness during the hedge interval, we use equation (10) and (11) to obtain the hedge effectiveness.

The experiments are designed to investigate the feasibility of SOM for OHR estimation. Therefore, the value of the main parameters and variables used in the SOM model are tested, including the numbers of nodes in the SOM topology, the numbers of days in the estimation interval, and the number of days of the hedge interval. A total of 72 experiments are performed in this study according to the different parameters listed in Table 1. In addition, for each experiment performed 200 times for dynamic hedge using rolling window, we use the average of the OHR and HE for evaluating.

The SOM models we proposed are also compared with two traditional methods: the OLS hedge and the naïve hedge. The OLS hedge ratio is calculated with the sampled data from the 1,000 records in the SOM training period. For example, if the hedge interval is one week, we use the weekly data gathered in the training period to estimate the OLS hedge ratio. Moreover, the OLS hedge effectiveness is calculated according to the SOM models using the daily data of the following week.

Table 1. Parameters setting of the experiments

Parameter	Unit	Value
Number of SOM nodes	Nodes	2^2, 3^2, 4^2
Estimation interval (e)	Days	7, 14, 21, 28
Hedge interval (f)	Days	3, 5, 7, 14, 21, 28

4. Experiment Results

The appropriate parameter setting of the SOM models we proposed is one of the key interests in this study. Figure 3 illustrates the hedge effectiveness under different parameter settings for estimating the time-weighted average OHR. Figure 3 clearly shows that the estimation interval and the number of SOM nodes are not sensitive to the HE under the same hedge interval, except when the hedge interval is three days. In addition, the HE increases when the hedge interval increases.

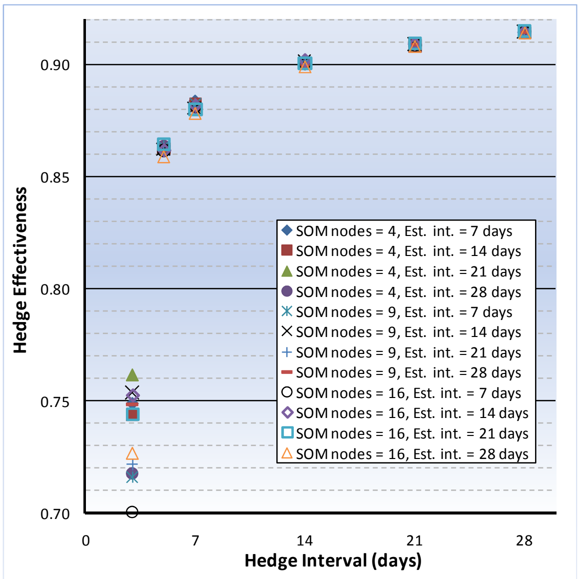

Figure 3. HE distribution in various conditions

To understand the differences among the modes in testing period, we pick one of the experiments and detail the results in Figures 4, 5, and 6. The experiment we picked is performed when the number of SOM nodes, the estimation interval, and the hedge interval are set to 4 days, 7 days, and 7 days, respectively.

In Figure 4, the spot and futures prices are very close. However, a market downturn occurs from 23 July 2007 to 3 September 2007; the basis becomes more positive. Meanwhile, the OHR and HE in Figures 5 and 6 are not particular with other periods. When the market upturn occurs as shown in Figure 5 between 14 June 2007 and 19 September 2007, the HE in Figure 6 becomes worst. Figure 5 also shows the OHR of the time-weighted average SOM model is the smallest most of the time. Moreover, the OHR of OLS model seems to vibrate periodically.

For the next step, we compare the five proposed SOM models with the two traditional models. The HE value represents the degree of the risk reduction; the value of OHR refers to the hedge cost. Consequently, the model with high HE and low OHR value is excellent. The different parameter settings of SOM models lead to approximate experiment results in the same hedge interval. Only the six best outcomes are selected according to the SOM-TWA-HE of the 72 experiments and are listed in Table 2 for comparison.

When the hedge interval is three days, the traditional OLS model has the best HE and OHR. In the five days hedge interval, the OLS model's HE can also beat the SOM models, besides the SOM_TWA. The HE and OHR of the five SOM models are very close, with the SOM_TWA model as the best among them. The naïve model is the worst in all hedge intervals within our expectation.

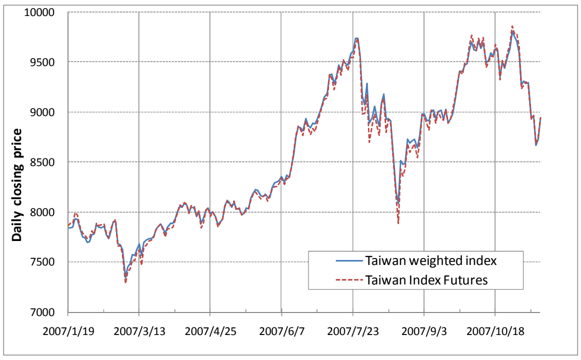

Figure 4. Out-sample testing data

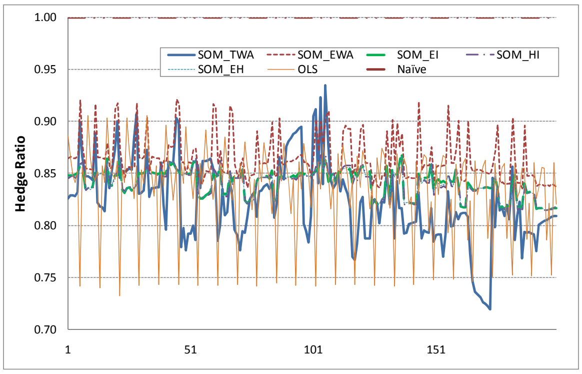

Figure 5. OHR in the testing period

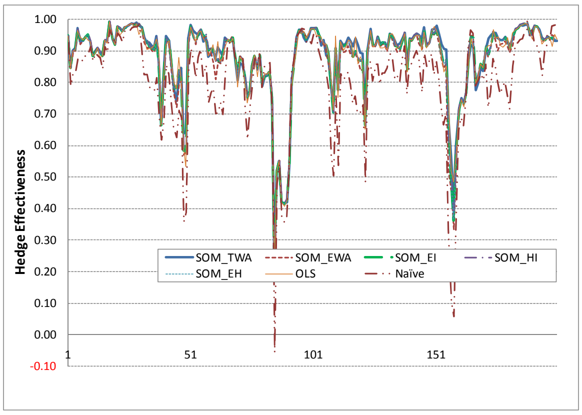

Figure 6. Hedge Effectiveness in the testing period

Table 2. Model comparison

Hedge Int. (*f*)	**3 days**		**5 days**		**7 days**		**14 days**		**21 days**		**28 days**	
SOM Models												
	H.E.	**O.H.R.**	**H.E.**	**O.H.R.**	**H.E.**	**O.H.R.**	**H.E.**	**O.H.R.**	**H.E.**	**O.H.R.**	**H.E.**	**O.H.R.**
SOM_TWA	0.7619	0.8509	**0.8642**	**0.8143**	**0.8835**	**0.8233**	**0.9020**	**0.8303**	**0.9094**	0.8368	**0.9151**	0.8371
SOM_EWA	0.7457	0.8839	0.8552	0.8529	0.8731	0.8638	0.8984	0.8587	0.9075	0.8574	0.9130	0.8577
SOM_EI	0.7692	0.8432	0.8556	0.8489	0.8795	0.8410	0.8997	0.8436	0.9087	0.8430	0.9146	0.8406
SOM_HI	0.7691	0.8421	0.8595	0.8420	0.8797	0.8402	0.9002	0.8419	0.9091	0.8415	0.9142	0.8423
SOM_EH	0.7691	0.8423	0.8590	0.8430	0.8796	0.8406	0.9000	0.8427	0.9090	0.8422	0.9144	0.8413
Model param.	SOM nodes: 4 Est. int. (*e*): 21		SOM nodes: 16 Est. int. (*e*): 21		SOM nodes: 4 Est. int. (*e*): 7		SOM nodes: 16 Est. int. (*e*): 14		SOM nodes: 9 Est. int. (*e*): 21		SOM nodes: 9 Est. int. (*e*): 21	
Traditional Models												
	H.E.	**O.H.R.**	**H.E.**	**O.H.R.**	**H.E.**	**O.H.R.**	**H.E.**	**O.H.R.**	**H.E.**	**O.H.R.**	**H.E.**	**O.H.R.**
OLS	**0.7700**	**0.8340**	**0.8632**	**0.8349**	0.8789	0.8354	0.8983	0.8383	0.9002	**0.8345**	0.9091	0.8436
Naïve	0.6484	1.000	0.7754	1.000	0.8036	1.000	0.8383	1.000	0.8518	1.000	0.8597	1.000

5. Conclusion and Future Work

This study uses SOM to cluster the time series data and also uses the similarity clustered data for the OHR estimation. The empirical results briefly show the outcomes of the proposed models, as compared with the traditional models. The SOM approaches can have a little improvement to hedge effectiveness, with the smaller hedge ratio being helpful in decreasing hedge cost. Furthermore, when the hedge horizon is increased, the hedge effectiveness is also increased. These results indicate that the setting of the parameters in SOM models is not sensitive to hedge effectiveness. Consequently, the model parameters estimation procedure can be avoided. In the future, the SOM model may be used to verify the strength of other markets. Finally, we suggest that other information derived from the time series (e.g., the technique indicators or the filter banks) be used for data clustering to improve the SOM model.

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計畫成果自評

本計畫原規劃三年研究期間，後經核定為兩年，因此我們將計畫執行之期程縮短並提前完成計畫目標。在實際執行計畫的第一年，我們完成了理財規劃所需之各項短期、中期、長期之時間序列趨勢預測模型，我們利用了 SOM 建構出不同避險區間之最佳化動態避險比例評估模型，這些成果將有助於第二年計畫中，建構出完整之「智慧型動態調適之理財規劃模型及決策輔助系統」。

目前我們正準備在第二年度展開理財規劃模型之投資模擬驗證部分，預計將整合第一年之成果，建構出一套完整的決策輔助系統。

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