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A clustering time series model for the optimal hedge ratio decision making

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ABSTRACT

In this study, a novel procedure combining computational intelligence and statistical methodologies is proposed to improve the accuracy of minimum-variance optimal hedge ratio (OHR) estimation over various hedging horizons. The time series of financial asset returns are clustered hierarchically using a growing hierarchical self-organizing map (GHSOM) based on the dynamic behaviors of market fluctuation extracted by measurement of variances, covariance, price spread, and their first and second differences. Instead of using original observations, observations with similar patterns in the same cluster and weighted by a resample process are collected to estimate the OHR. Four stock market indexes and related futures contracts, including Taiwan Weighted Index (TWI), Standard & Poor's 500 Index (S&P 500), Financial Times Stock Exchange 100 Index (FTSE 100), and NIKKEI 255 Index, are adopted in empirical experiments to investigate the correlation between hedging horizon and performance. Results of the experiments demonstrate that the proposed approach can significantly improve OHR decisions for mid-term and long-term hedging compared with traditional ordinary least squares and naïve models.

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1. Introduction

Hedging has been of interest to both academicians and practitioners with the emergence of financial derivatives markets, which is carried out by establishing the position of a derivative instrument to offset exposure to price fluctuations opposite to that of underlying assets to minimize exposure to unwanted risk. To achieve this, the hedger determines a hedge ratio, i.e. the amount of futures contracts to buy or sell for each unit of the underlying asset on which he bears price risk. Therefore, an investor's hedging decisions heavily depend on the models which are capable with the dynamic evolution of the pairwise correlations between futures and spot markets and give appropriate estimates of these hedge ratios.

In the existing literature, the most widely used hedging strategy is to adopt the minimum-variance hedge ratio [1]. The optimal hedge ratio (OHR) is suggested to be obtained by simply regressing the spot market return on the futures market return using ordinary least squares (OLS) under the criterion of minimum variance [2]. However, these approaches obtained the classical time-invariant OHR which

appears inappropriate with the time-varying nature of many financial markets. Improvements were made to capture time-varying features, such as by adopting dynamic hedging strategies based on the bivariate generalized autoregressive conditional heteroskedasticity (GARCH) framework [45–49] or the stochastic volatility (SV) model [5,50]. Although these studies were successful in capturing time-varying features, some concerns are raised when considering the long hedging horizon [3,4], and the distribution of data [6,7].

More recently, other approaches based on non-parametric models have been proposed to avoid undue restrictions. Apart from the classical statistics methodology, Markov regime switching (MRS) [8], Kalman Filter [9], wavelet analysis [10–12], and particle swarm optimization (PSO) [13] were adopted as analysis tools or as a new approach to hedge ratio research. Although some of these models are more burdensome in computing, the accuracy of results have been improved and better hedging performance is obtained. However, rather limited research efforts have been devoted to improve the classic OLS-based method as written in the textbook using interdisciplinary skill and knowledge across classic statistics and computational time series cluster technique [59–61].

In this paper, we address the issue of bivariate time series from the OHR estimation perspective, and investigate the feasibility of OHR estimating using pattern recognition technique to collect similar data samples for variance and covariance estimation. In contrast to

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classical OHR estimation under the minimum-variance framework, a two-phase model, which conserves the classic minimum-variance theoretical framework but avoids the complex restrictions and assumption of the OLS-based approach, is proposed based on growing hierarchical self-organizing map (GHSOM). The goal of the first phase is to recognize the data samples which have similar pattern. We suggest some features which represent the dynamic behaviors of bivariate variance-covariance structure for similarity measurement using GHSOM. In the second phase, we suggest replacing the raw data samples of the bivariate time series with the similar ones via the proposed data resampling and weight process in order to modify the distribution of the raw data.

This paper is organized in five main sections. Literature review of the recent development on the relevant methods of estimating the hedge ratio and time series clustering technique is described in Section 2. The proposed model for OHR decision making is described in Section 3. Section 4 presents the experiments, and discusses the empirical test results. The concluding remarks and suggestion for future works are provided in Section 5.

2. Literature review of related work

2.1. Minimum variance hedge

The basic concept of hedging involves the elimination of fluctuations in the value of a spot position by tracking futures contracts that are opposite to the position held by the spot market. For a long position in the spot market, the return of a hedged portfolio is given by

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

where ΔHP is the change in the value of the hedge portfolio; ΔS and ΔF are the changes in the spot and futures prices, i.e. the returns, respectively; and r is the hedge ratio. OHR is the value of r that maximizes the expected utility of the investor; it is defined as the expected return and risk of the hedged portfolio. The expected return of futures is 0 when the futures price follows a martingale; hence, the futures position will not affect the expected return of the portfolio.

The risk of the hedge portfolio is defined by its variance in the mean-variance framework. Therefore, OHR is simply the value of r that minimizes the variance of Eq. (1), which is given by

$$\frac{\partial Var(\Delta HP)}{\partial r} = 2r \times Var(\Delta F) - 2Cov(\Delta S, \Delta F) = 0 \tag{2}$$

where $Var(\Delta F)$ is the variance of the futures return and $Cov(\Delta S, \Delta F)$ is the covariance between the spot return and the futures return. OHR is determined by solving Eq. (2):

$$r^* = \frac{Cov(\Delta S, \Delta F)}{Var(\Delta F)} \tag{3}$$

The OHR given by Eq. (3) can be estimated by regressing the spot return on the futures return using OLS, which corresponds to conventional or classical OHR.

Hedging performance is typically evaluated by hedging effectiveness (HE). The degree of hedging effectiveness is measured by the percentage reduction in the variance of portfolio after hedging [3]. The variance of hedge portfolio with estimated OHR can be expressed as

$$Var_{hedged} = Var(\Delta HP) = Var(\Delta S_t - r\Delta F_t) \tag{4}$$

where r is the OHR. Therefore, HE can be expressed as

$$HE = \frac{Var_{un-hedged} - Var_{hedged}}{Var_{unhedged}} \times 100\% = \frac{Var(\Delta S) - Var(\Delta HP)}{Var(\Delta S)} \times 100\% = \left(1 - \frac{Var(\Delta HP)}{Var(\Delta S)}\right) \times 100\% \tag{5}$$

The value of HE can be used to evaluate the model of OHR estimation. A higher HE represents better OHR estimation, and vice versa.

2.2. Models for estimating the OHR

The simplest approach suggested to minimize portfolio risk is naïve hedge, which sets the hedge ratio equal to 1 over the whole hedging horizon. The correlation between spot and futures prices is assumed to be perfect, but it challenges the fact that the spot and futures prices are naturally stochastic and time variant. In order to accurately recognize the correlation between futures and spot prices, the static OLS hedge which uses the OLS coefficient of a regression of spot return on futures return is proposed [1]. However, it considers the joint distribution of spot and futures return as constant, and hence leads to suboptimal hedging decisions in periods of high basis volatility.

Recently, numerous works have focused on improving hedging performance using the dynamics in the joint distribution of returns and the time-varying nature of OHRs. Optimal hedge ratios are estimated using the family of GARCH models proposed by Engle [63], Engle and Kroner [64], and Bollerslev [65,66]. Various GARCH models are studied in literature to investigate hedge ratio and hedging performance, including bivariate GARCH model with diagonal vech parameterization for commodity futures contracts [69], bivariate constant-correlation GARCH (CC-GARCH) model for foreign currency futures [45] and stock index futures [67], GARCH model with Baba-Engle-Kraft-Kroner (BEKK) parameterization for interest-rate futures [70], augmented GARCH model for the freight futures market [71], and orthogonal GARCH and CC-GARCH for the electricity futures market [68]. Although, these improvement models can capture the dynamic behavior of a time series for OHR estimation, these approaches do not work robustly when dealing with the OHR decisions over different hedging horizons. Only a few studies consider different hedging horizons for hedge ratio estimation [3–6,12,47,51,52], but the relationship between hedging horizons and hedge ratio still needed to be investigated using other methods.

Hedge horizons are often crucially important for making hedge ratio decision, because investors, such as regulators and speculative investors, as well as individuals and institutions participating in the financial markets have different behaviors with various hedging horizon length. However, three problems occurred in incorporating the hedging horizon in OHR estimation. First, the long-horizon OHR estimator based on a handful independent observations generated from long-horizon return series is unreliable [3]. This is because the frequency of data must match the hedging horizon (e.g., weekly or monthly data must be used to estimate the hedge ratio where the hedging horizon is one week or one month, respectively). Low data frequency would result in a substantial reduction in sample size [4]. Second, the assumption for the error term of the GARCH/SV model would lead to inaccurate results when estimating the multiperiod hedge ratio [5]. Third, the assumption for the underlying data-generating process, such as a unit root process, is unsuitable when the assumed condition does not hold true, as evidenced in many commodities markets [6].

The weight of observations in OHR estimating is another issue. Due to the conditional distribution of most financial asset returns tend to vary over time, most OLS-based approaches adopt a rolling window scheme to obtain recent information for estimating the variance and covariance of spot and futures returns. However,

rolling window estimators use an equally weighted moving average of past squared returns and their cross products. Observations have equal weight in the variance–covariance matrix estimator of the arbitrarily defined estimation period, but they have zero weight beyond the estimation period. GARCH class models are successful in capturing time-varying features for estimating conditional variance–covariance matrices, but they place too much weight on extreme observations when the distribution of data is leptokurtic and fat-tailed [7].

2.3. Cluster analysis for time series

Clustering financial time series is a new approach to analyze the dynamic behavior of time series, and to forecast any future tendency of the time series for purposes of decision making. Many financial problems have been studied based on cluster analysis via computational intelligence approach instead of the conventional approach. Dose and Cincotti [62] use a stochastic-optimization technique based on time series cluster analysis for index tracking and enhanced index tracking problems. Pattarin et al. [15] propose a classification algorithm for mutual funds style analysis, which combines different statistical techniques and exploits information readily available at low cost. In their analysis, time series of past returns is used to retrieve synthetic and informative description of contexts characterized by high degrees of complexity, which is useful in identifying the styles of mutual funds. Gafiychuk et al. [16] use the self-organizing methods to investigate the time series data of the Dow Jones index. Basalto et al. [17] use a novel clustering procedure, which is applied to the financial time series of the Dow Jones industrial average (DJIA) index to find companies that share similar behaviors. The techniques proposed could extract relevant information from raw market data and yield meaningful hints as to the mutual time evolution of stocks. Karandikar et al. [18] develop a volatility clustering model to forecast value at risk (VaR). The feasibility and benefits of the model are demonstrated in an electricity price return series. Zhu [19] proposed a new model based on cluster analysis for oil futures price forecasting. This model is demonstrated using the historical data from NYMEX market, and shows that the proposed model can effectively and stably improve the precision of oil futures price forecasting. Focardi and Fabozzi [20] adopt a clustering-based methodology to determine optimal tracking portfolio to track indexes. Papanastassiou [21] discuss classification and clustering of financial time series data based on a parametric GARCH (1,1) representation to assess their riskiness.

In spite of the prevalence of numerous clustering algorithms, including their success in a number of different application domains, clustering remains challengeable. The methods of data processing, feature extraction, similarity measurement, and topology of cluster construction are different when dealing with different data. For time series data, features extraction methods are organized by past research into three groups [53] working directly with the data either in the time or frequency domain; working indirectly with features extracted from the raw data; and working indirectly with models built from raw data. Defining an appropriate similarity measure and objective function is also an issue of choosing clustering algorithm. Nevertheless, Jain [54] emphasizes that “there is no best clustering algorithm” when comparing the results of different clustering algorithms.

Clustering time series offers two benefits, one is that clustering can avoid the improper assumption and restriction of data, and the other is that data objects with similar dynamic behavior in their evolution over time are pooled and can thus help in data modeling. Gershenfeld et al. [22] propose a cluster-weighted model for time series analysis, which is a simple special case of the general theory of probabilistic networks but one that can handle most of the limitations of practical data sets without unduly constraining either data or user. They show that nonlinear, non-stationary, non-Gaussian, and discontinuous signals can be described by expanding the

probabilistic dependence of the future depending on past relationships of local models. Fruhwirth-Schnatter and Kaufmann [23] propose to pool multiple time series into several groups using finite-mixture models. Within a panel of time series, only those that display “similar” dynamic properties are pooled to estimate the parameters of the generating process. They estimate the groups of time series simultaneously with group-specific model parameters using Bayesian Markov chain Monte Carlo simulation methods. They document the efficiency gains in estimation, and forecasting is realized relative to the overall pooling of the time series. D’Urso and Maharaj [24] suggest that time series often display dynamic behavior in their evolution over time, which should be taken into account when attempting to cluster the time series. They proposed a fuzzy clustering approach based on autocorrelation functions to determine and represent the underlying structure in the given time series.

2.4. Growing hierarchical self-organizing map

Recently, growing hierarchical self-organizing map (GHSOM) is used for cluster analysis and is presently the best available analysis tool in many research fields [31–33]. Extended from the Kohonen’s self-organizing feature map (SOM) [30], which is an unsupervised neural network that organizes a topological map, GHSOM has a hierarchical architecture of multiple layers. Each layer comprises several independent clusters representing the growing SOM [14]. SOM has shown the ability of pattern discovery [25,26] and prediction [27–29] for time series data. The resulting map shows the natural relationships among patterns given in the network. However, the number of clusters, which describes the topology of the SOM, needs to be determined in advance. Moreover, the topology of the SOM lacks the ability to represent hierarchical relations of the data. Unlike traditional cluster analysis techniques, a GHSOM need not determine the number of clusters in advance. When applying GHSOM algorithm, time series data with similar patterns are clustered together. If the similarity of data in the same cluster is below a certain threshold, data are clustered once again by breadth or depth, thus expanding the SOM clusters. The topology of the clusters is automatically determined by the characteristics of the input data during the unsupervised training process, and related with the threshold setting for width and depth expansion. In this study, GHSOM is used for the time series analysis to estimate the clustered-based variance and covariance, which have not been studied in detail.

3. Methodology

3.1. Procedure of the proposed model

The conventional approach to OHR estimation is simply to regress the spot and futures series. The basic operating steps are shown in Fig. 1. The first step is to collect the market price of spots and futures as original data. Next, the original price series is sampled so it coincides with the hedging horizon and then transformed into a return series by differencing. Finally, these data are used to estimate variance and covariance using OLS to obtain the OHR.

In this study, two modifications of the conventional approach are proposed based on the philosophy that data with similar dynamic behaviors may appear in the future with higher probability than dissimilar ones, as shown in the top part of Fig. 1. The original composition of data for OHR estimation is modified by the selected data with a similar pattern, which is performed in two phases. Phase I is clustering time series and Phase II is modifying the probability distribution. The objective of Phase I is to identify higher probability data, which would occur in the next hedging horizon based on the whole data set, and ignore lower probability data. In Phase II, the

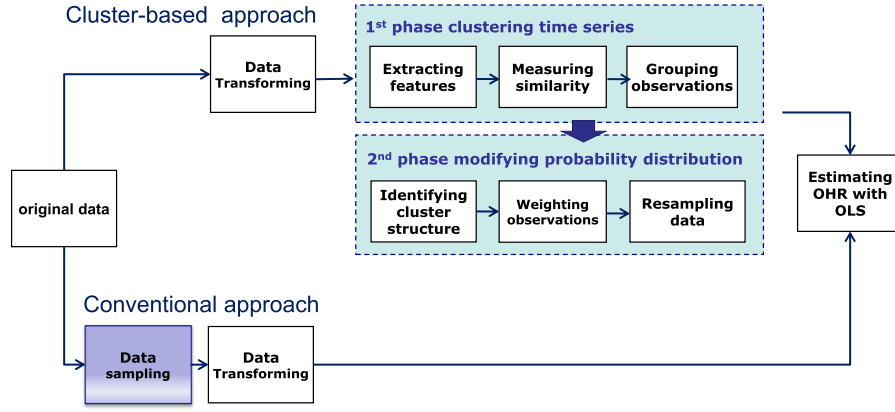


Fig. 1. The cluster-based approach.

data composed by the higher probability data are expected to be more approximate to the normal distribution than the original data, suggesting decreased inaccuracy caused by leptokurtic and fat-tailed distributions.

3.2. Data transformation

The original data for OHR estimation gathered from the financial market are the daily closing (or settlement) prices of spot and futures. The price series are then be transformed to return series by differencing the price series. We consider continuously compounded data and magnify the scale by multiplying by 100 to avoid a small scale. The return series is expressed as the price change:

$$\Delta S_t, \Delta F_t = \ln(P_t/P_{t-1})100 \quad (6)$$

where ΔS and ΔF are price changes of spot and futures, respectively; P is the price series; and t refers to the present time.

These return series are then divided into two parts, in-sample estimating period and out-of-sampling testing period. The hedge portfolio in this study is adjusts every hedging horizon according to the latest estimated OHR until the out-of-sample testing period is due. A rolling window scheme is applied to achieve the dynamic hedging strategy. The rolling windows scheme estimates the OHR at time t according to the conditioning on the time $t-1$ data set, which is exhibited in Fig. 2. Herein, h denotes the hedging horizon while e is the in-sample estimating period. The length of the rolling window is $e+h$. OHR is estimated based on the observations in the in-sample estimating period, from $t-e$ to t , then used for hedging from t to $t+h$. Next, the window is rolled one hedging horizon ahead in order to reestimate the OHR based on the observations from $t+h-e$ to $t+h$. Then, we use the new OHR for the next hedging horizon, from $t+h$ to $t+2h$. OHR is reestimated every h day, and then used to adjust the hedging portfolio until the out-of-sample testing period is due.

3.3. Extracting the feature of dynamic behaviors

The dynamic behaviors exist in financial time series, and these dynamic behaviors are helpful for time series forecasting [23,24]. In this study, variance, covariance, price spread, and their first and second differencing are adopted as the features representing the dynamic behavior of time series for clustering. Although, most research adopted the original price or return series and their derivative technique indices, that exists certain dependency, are adopted as the features for financial market prediction and can obtain well performance [55]. These features extracted from single variable time series are hardly to present the behavior patterns of bivariate time series. Consequently, we adopt variance and covariance for

consideration of the volatility cluster behavior [56] and the joint distribution of bivariate time series. Price spread that critically influences the OHR [57] is also adopted. Furthermore, the independence variables represent the first and second moment which, similar to the physical concepts of potential energy (price spread), momentum (first-order differencing), and activation force (second-order differencing) [23] [58], are adopted. These features are calculated using the data one in the most recent hedging horizons, denoted by h , as follows:

$$Var(\Delta S_t) = Var[\Delta S_{t-h}, \dots, \Delta S_t] \quad (7)$$

$$Var(\Delta F_t) = Var[\Delta F_{t-h}, \dots, \Delta F_t] \quad (8)$$

$$Cov(\Delta S_t, \Delta F_t) = Cov \begin{bmatrix} \Delta S_{t-h}, \dots, \Delta S_t \\ \Delta F_{t-h}, \dots, \Delta F_t \end{bmatrix} \quad (9)$$

$$Spread(S_t, F_t) = [F_{t-h} - S_{t-h}, \dots, F_t - S_t] \quad (10)$$

The first and second order difference of these features are shown as

$$X'_t = \frac{X_t - X_{t-1}}{X_{t-1}} \quad (11)$$

$$X''_t = \frac{X'_t - X'_{t-1}}{X'_{t-1}} \quad (12)$$

where X represents the functions of Var , Cov , and $Spread$. Twelve vectors of variable are eligible to represent the dynamic behavior of an observation and are used as the input matrix of variables for GHSOM (Table 1).

3.4. Clustering by GHSOM

Each observation can extract a feature vector from the data from the previous hedging horizon. The feature vectors of the observations in the estimation interval include input matrix of GHSOM for OHR estimation. The GHSOM algorithm in this study is implemented in MATLAB [35]. When using the GHSOM, the result network topology is adjusted by the presetting parameters, including breadth of map, depth of GHSOM and threshold of cluster capacity, to fit the requirement of analyzer. If the group size of cluster exceeds the threshold, the data will be clustered once again by breadth or depth, hence expanding the SOM clusters. To emphasize the hierarchical relationship of the clusters and to avoid data from being too concentrated on some clusters, the parameters of bread, depth, and threshold are respectively set as 0.001, 0.8, and 100, after several trials based on our experiment data.

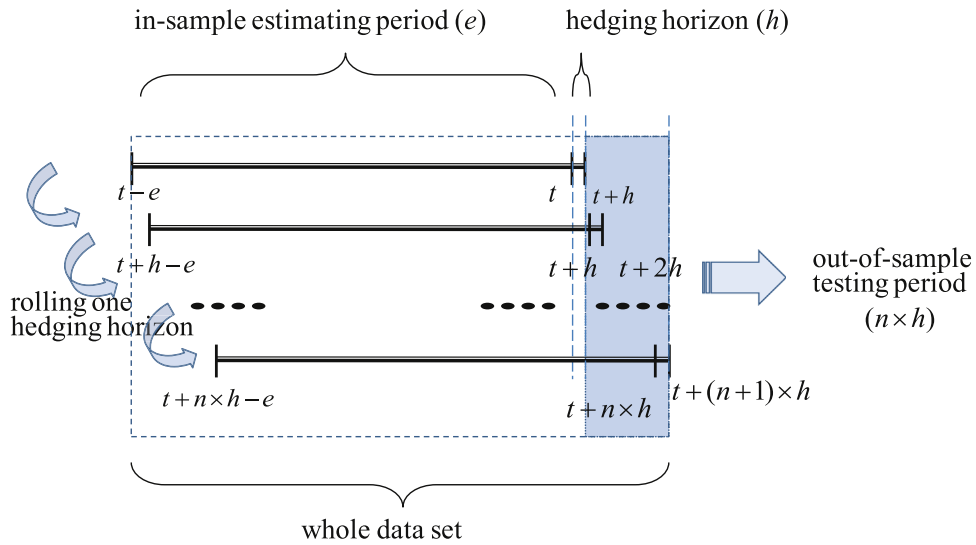


Fig. 2. The rolling windows scheme.

Table 1
Features of the observation.

Dynamic behaviors	Eligible input variables	Notations
<ul style="list-style-type: none"> ● Volatility clustering property. ● Momentum of volatility change. ● activation force that cause volatility change. 	Variance Variance of spot/futures return series First order differential of variance Second order differential of variance	$Var(\Delta S), Var(\Delta F)$ $Var'(\Delta S), Var'(\Delta F)$ $Var''(\Delta S), Var''(\Delta F)$
<ul style="list-style-type: none"> ● Joint distribution of spot and future return series. ● Momentum of joint distribution change. ● activation force that cause joint distribution change. 	Covariance Covariance of spot and futures return series First order differential of covariance Second order differential of covariance	$Cov(\Delta S, \Delta F)$ $Cov'(\Delta S, \Delta F)$ $Cov''(\Delta S, \Delta F)$
<ul style="list-style-type: none"> ● Potential energy. ● Momentum of Potential energy. ● activation force that cause Potential energy change. 	Price spread Spread of spot and futures price series First order differential of $Spread(S, F)$ Second order differential of $Spread(S, F)$	$Spread(S, F)$ $Spread'(S, F)$ $Spread''(S, F)$

The features vector extracted from the historical time series, which are processed by min-max normalization between -1 and 1 , are feed into to the GHSOM, and the hierarchically clustered data are given. Fig. 3 illustrates two important relations of these hierarchical clusters. First, the number of data samples in each cluster is different. Clusters in the upper layers of the hierarchical architecture contain more data samples than those in the lower layers. Secondly, the hierarchical architecture also represents the degree of similarity. Any sample can be identified on the cluster based on the layer it belongs to. The host cluster in the lowest layer contains the least data but has the highest similarity with the forecasting data. In addition, similarity with data is decreased in the upper layer clusters.

To estimate the OHR for the next hedging horizon, the features of dynamic behaviors are extracted from the data in one hedge horizon ahead for each sample data in estimating period. After being hierarchically clustered, a group of similar data samples are collected by the cluster they belongs to in each layer.

3.5. Data resampling and weighting

Data samples with similar behavior may occur more frequently in the future and should be more emphasized than the dissimilar ones. However, when data are grouped by cluster analysis, the original data are divided into several groups, with each group only containing partial data. The number of similar data samples is far

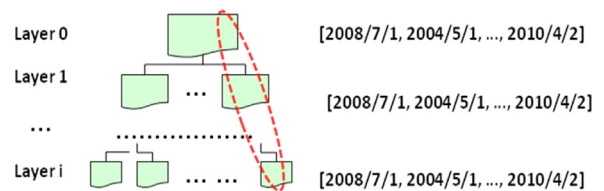


Fig. 3. An example of the hierarchical clustered data.

less than the original data. Reducing sample size causes inaccuracy when OLS for OHR estimation is employed [4]. To overcome this problem, we propose to adopt in-cluster resampling, which has been used for solving sample-reduced problems [36,37]. Moreover, the architecture of hierarchical cluster is very similar to the hierarchical stratified resampling scheme, in which the observations are divided into several groups according to their properties. Consequently, we expand the sample size by randomly replicating the similar data samples in the cluster for each layer until the sample size reaches the same population size of the estimation period. The more similar data will be replicated more frequently, thus increasing the occurrence probability in the whole population. As the results, the sample size is expanded to the original sample size of estimating period by multiplying the layer of the hierarchical architecture. The pseudo code for data resampling and

```

Function modifying distribution {
  For (each layer in the GHSOM cluster results)
    Identify the cluster number  $clus_{l,c}$  where the latest observation  $obs_{latest}$  belongs to
    For (each observation  $obs_i$  in the cluster  $clus_{l,c}$ )
      Insert the observations  $obs_{i+h}$  into the collection  $col_l$ 
    End for
    Resample the collection  $col_l$  randomly with repetition until the size of  $col_l$  equals the
      estimation interval
    End for
  }

Notations:
   $clus_{l,c}$ : the cluster number, where  $l$  is the number of layers, and  $c$  is the number of the
    cluster in layer  $l$ 
   $obs_{latest}$ : the latest observation in a rolling window
   $obs_i, obs_{i+h}$ : the observations of a cluster, where  $i$  is the number of observations, and  $h$ 
    is the hedging horizon
   $col_l$ : the collection of observations for layer  $l$ 
    
```

Fig. 4. The pseudo code of data resampling and weighting.

weighting is described in Fig. 4. The probability distribution of the original time series is modified by combining the original population data in estimating period and the resampling the similar data samples. When the conditional distribution of spot and futures returns is predictable, a more efficient estimate of the OHR can be obtained by conditioning on recent information [34].

3.6. OHR estimating

In this study, OHR estimation is improved by replacing the original data samples in the estimation period with the collection of unequal weighted similar data samples. The traditional OLS method for OHR estimation, expressed by Eq. (3), and is modified to Eq. (13), in which $\Delta\tilde{S}$ and $\Delta\tilde{F}$ refer to the collection of observations derived from spot and futures return series, respectively.

$$r^* = \frac{Cov(\Delta\tilde{S}, \Delta\tilde{F})}{Var(\Delta\tilde{F})} \tag{13}$$

3.7. Model evaluation

The value of hedging effectiveness (HE) and the variance of hedge portfolio, expressed by Eqs. (5) and (4), are used to evaluate the model of OHR estimation in this study. Furthermore, White's Reality Check is adopted to compare the different OHR estimation models and to test the statistical significance of variance deduction [38,39]. The reality check consists of a non-parametric test that checks if any of the numbers in the concurrent methods yield forecasts that are significantly better than a given benchmark method; then, it corrects the data snooping bias. Data snooping bias may occur when a given dataset is reused by one or more researchers for model selection. The null hypothesis that the performance of the proposed hedging model has no predictive

superiority over the conventional model is not rejected. The hypotheses are as follows:

- H0.** No method is better than the benchmark.
- H1.** At least one method is better than the benchmark.

4. Experimental design and results analysis

4.1. Experimental design

The experiments in this study are designed with two objectives: feasibility of the proposed GHSOM model and hedging performance over various hedging horizons for OHR decision making based on different models. Two factors are considered in the experiments. One is the features selection for dynamic behaviors, the other is the days of hedging horizon.

The feasibility of the proposed GHSOM model is examined using dynamic behaviors extracted as the feature of the time series. The feature-extracting process of the proposed model is tested in different settings to achieve the best parameters. The feature vectors that represent the dynamic behaviors of time series for GHSOM similarity measurement are composed of variance, covariance, price spread, and their first and second order differences. We design six combinations of these parameters, which are adopted in the experimental models to verify the performance over various hedging horizons. Table 2 presents the parameter settings of these models.

The optimal hedge ratio is estimated by the proposed model concerned with the hedging horizon, and the hedging decision is evaluated by hedging effectiveness. For each hedging horizon in the testing period, the hedged portfolio is adjusted once according to the latest OHR at the beginning of a hedge horizon and lasts until the beginning of the next hedging horizon. At the end of the testing

period, hedging effectiveness is calculated based on the variance of the hedging portfolio in each hedging horizon. Hedge horizons in the experiments are set at 1, 7, 14, 21, and 28 days, which cover the intervals from short-term to long-term. To compare hedging performance, the superiority of the proposed model is verified using two conventional models, the OLS and naïve models, both of which are widely used in OHR research on different hedging horizons [6,12].

4.2. Experiment data and basic statistics

This study obtained empirical trading data of the daily closing price from various stock and futures markets, including Taiwan Weighted

Table 2
Parameter settings for testing dynamic behavior.

Code of testing model	Input parameters (selected features)		
	Variance	Covariance	Price spread
GHSOM_V0	$Var(\Delta S), Var(\Delta F)$		
GHSOM_V2	$Var(\Delta S), Var(\Delta F)$ $Var'(\Delta S), Var'(\Delta F)$ $Var''(\Delta S), Var''(\Delta F)$		
GHSOM_V0C0S0	$Var(\Delta S), Var(\Delta F)$	$Cov(\Delta S, \Delta F)$	$Spread(S, F)$
GHSOM_V2C0S0	$Var(\Delta S), Var(\Delta F)$ $Var'(\Delta S), Var'(\Delta F)$ $Var''(\Delta S), Var''(\Delta F)$	$Cov(\Delta S, \Delta F)$	$Spread(S, F)$
GHSOM_V0C2S2	$Var(\Delta S), Var(\Delta F)$	$Cov(\Delta S, \Delta F)$ $Cov'(\Delta S, \Delta F)$ $Cov''(\Delta S, \Delta F)$	$Spread(S, F)$ $Spread'(S, F)$ $Spread''(S, F)$
GHSOM_V2C2S2	$Var(\Delta S), Var(\Delta F)$ $Var'(\Delta S), Var'(\Delta F)$ $Var''(\Delta S), Var''(\Delta F)$	$Cov(\Delta S, \Delta F)$ $Cov'(\Delta S, \Delta F)$ $Cov''(\Delta S, \Delta F)$	$Spread(S, F)$ $Spread'(S, F)$ $Spread''(S, F)$

Table 3
Experiment data.

Index (Spot)	Exchange (Futures)	Observations
Taiwan Weighted Index (TWI)	Taiwan Futures Exchange (TAIFEX)	2217
Standard & Poor's 500 index (S&P 500)	Chicago Mercantile Exchange (CME)	2263
Financial Times Stock Exchange 100 Index (FTSE 100)	London International Financial Futures and Options Exchange (LIFFE)	2215
NIKKEI 255 Index	Osaka Securities Exchange (OSE)	2275

Note: Data period is from July 21, 1999 to July 18, 2008.

Table 4
Basic distributional statistics of return series.

	TWI		S&P 500		FTSE 100		NIKKEI 255	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Mean	-0.0060	-0.0068	-0.0040	-0.0042	-0.0072	-0.0073	-0.0160	-0.0158
Maximum	6.1721	6.7659	5.5744	5.7549	5.9026	5.9506	7.2217	8.0043
Minimum	-9.9360	-11.0795	-6.0045	-6.2709	-5.8853	-6.0625	-7.2340	-7.5986
Std. Dev.	1.5931	1.8262	1.1287	1.1404	1.1657	1.1663	1.4058	1.4346
Kurtosis	5.2942	5.8891	5.2732	5.4067	5.7929	5.7588	4.6042	4.6496
Skewness	-0.1883	-0.1867	0.0600	0.0274	-0.2096	-0.1658	-0.2075	-0.2122
Jarque-Bera (JB)	499.0886***	783.5957***	488.3711***	546.2142***	755.7494***	731.5745***	253.2913***	267.633***
F-test for equal variances (p value)	0.0000***		0.6247		0.9790		0.3396	

Note: (1) The skewness of normal distribution is zero. (2) The kurtosis of normal distribution is 3. (3) The hypothesis of F-test is that two independent samples, spot and futures return, come from normal distributions with the same variance.

*** Represents significance at the 1% level.

Index (TWI), Standard & Poor's 500 Index (S&P 500), Financial Times Stock Exchange 100 Index (FTSE 100), NIKKEI 255 Index, and their correlated futures contracts. Table 3 lists the stock market index and exchange of their correlative futures contracts trade. All data were obtained from the Thomson Datastream database in the same period from July 21, 1999 to July 18, 2008. 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 return series are defined as the logarithmic first difference of price series multiplied by 100 using Eq. (1). The numbers of observation for each market are listed in Table 3. Among the total observations, the first 90% is considered the estimation period, and the remaining 10% is considered the testing period.

Table 4 shows some basic distributional characteristics of the spot and futures return series. All eight series show significant skewness, kurtosis, and Jarque-Bera (JB) statistics, implying non-normal distributions with fatter tails. Comparisons of the standard deviation of return, kurtosis, and JB statistics indicate that the largest and smallest discrepancy between the spot and futures data are in TWI and FTSE 100, respectively. In other words, the correlation between spot and futures is highest in FTSE 100 and lowest in TWI. The large discrepancy between the spot and futures data displays more extreme movements than would be predicted by a normal distribution. The F-test for equal variance between spot and futures also indicates different characteristics in each market. The result shows that the null hypothesis of equal variance is rejected in TWI, but cannot be rejected in S&P 500, FTSE 100, and NIKKEI 255 Index. Consequently, the data of the same period gathered from different markets may exhibit different behaviors and cause inconsistencies in the results.

4.3. Comparisons of dynamic behaviors prediction

The variance, covariance, price spread, and first and second differences of the observations in previous hedging horizons are suggested to capture the dynamic behavior for predicting fluctuations in the next hedging horizon. Table 5 presents the hedging effectiveness for all models. Results indicate that based on the same experiment data, the GHSOM model can obtain the best performance compared with the traditional OLS and naïve models, except for short-term hedging in FTSE 100 and one day hedging in S&P 500. A comparison of the six experiment models in all market data indicates that the best GHSOM model is different over different hedging horizons. For seven days hedging, the GHSOM_V0 model is the best model in all market data. However, for the 1 day and 28 days hedging, the GHSOM_V2 and GHSOM_V2C0S0 models are the best models in three of four market data.

Table 5
Comparisons of dynamic behaviors.

Market/model	Hedging effectiveness Hedging horizon (days)				
	1	7	14	21	28
<i>TWI</i>					
GHSOM_V0	93.3309%*	97.1661%**	99.2656%	99.3811%	99.3131%
GHSOM_V2	93.3905%**	97.1534%*	99.2480%	99.3942%	99.3556%*
GHSOM_V0C0S0	93.2715%	96.9289%	99.2751%	99.3947%	99.3160%
GHSOM_V2C0S0	93.0998%	96.8809%	99.2879%*	99.4342%*	99.3802%**
GHSOM_V0C2S2	93.1081%	97.0102%	99.3111%**	99.4327%	99.3431%
GHSOM_V2C2S2	93.1798%	96.9169%	99.2047%	99.4666%**	99.3470%
OLS	93.3055%	97.0244%	99.1612%	99.3860%	99.3089%
Naïve	90.6982%	96.0278%	98.5331%	99.0888%	98.8415%
<i>S&P 500</i>					
GHSOM_V0	96.6140%	99.1678%**	99.3126%	99.6413%	99.6493%
GHSOM_V2	96.6662%*	99.1206%	99.3777%	99.6010%	99.6513%
GHSOM_V0C0S0	96.6401%	99.1236%	99.3860%**	99.6888%**	99.7094%
GHSOM_V2C0S0	96.6447%	99.0880%	99.3856%*	99.6806%*	99.7310%**
GHSOM_V0C2S2	96.6069%	99.0630%	99.3837%	99.6774%	99.6793%
GHSOM_V2C2S2	96.6221%	99.0656%	99.3667%	99.6661%	99.7263%*
OLS	96.6510%	99.1287%*	99.3705%	99.5911%	99.6131%
Naïve	96.7974%**	99.0029%	99.3045%	99.4826%	99.5752%
<i>FTSE 100</i>					
GHSOM_V0	96.9688%	98.5911%	98.5323%	99.0140%	99.4868%**
GHSOM_V2	97.0511%*	98.5522%	98.5596%	99.1438%	99.4483%
GHSOM_V0C0S0	96.9842%	98.5673%	98.5690%	99.1743%	99.4857%*
GHSOM_V2C0S0	96.9828%	98.6141%*	98.5572%	99.2197%*	99.4751%
GHSOM_V0C2S2	96.9945%	98.5904%	98.5883%	99.1774%	99.4475%
GHSOM_V2C2S2	97.0278%	98.5823%	98.6069%	99.2263%**	99.4764%
OLS	97.0130%	98.5552%	98.6306%*	99.0979%	99.4767%
Naïve	97.1492%**	98.6258%**	98.8094%**	99.1005%	99.3223%
<i>NIKKEI 255</i>					
GHSOM_V0	96.4072%	99.4409%**	99.5007%	99.5261%	99.8709%
GHSOM_V2	96.4909%	99.3939%	99.4533%	99.5560%**	99.9036%*
GHSOM_V0C0S0	96.5677%**	99.4311%*	99.5075%*	99.5499%*	99.8948%
GHSOM_V2C0S0	96.5026%	99.4310%	99.4954%	99.5245%	99.9051%**
GHSOM_V0C2S2	96.5099%	99.4037%	99.5107%**	99.5274%	99.8899%
GHSOM_V2C2S2	96.4615%	99.3797%	99.4698%	99.5431%	99.8893%
OLS	96.5501%*	99.4271%	99.5002%	99.5072%	99.9023%
Naïve	96.2222%	99.3305%	99.4317%	99.4585%	99.8711%

* Represents the second best HE among eight models at the same hedging horizon.

** Represents the best HE among eight models at the same hedging horizon.

The results imply that the ability to capture fluctuation under various timescales is different for GHSOM models. Short-term dynamic behavior may be captured by variance and its first and second differences. Long-term tendency may need more variables for its description than short-term tendency by adding covariance and price spread.

4.4. Comparison of hedging performance

For a comparison of hedging performance, we list the best GHSOM model from the six experiments models, and the two conventional models (naïve and OLS) in Table 6. Table 6 shows that increasing the hedging horizon will increase the variance of unhedged portfolio but will be effectively reduced by the hedging model. The percentage of variance reduction, shown as hedging effectiveness in Table 5, is higher in a long hedging horizon than in a short one.

A comparison of the model using the variance of hedged portfolio in Table 6 shows that the GHSOM model is superior to the OLS model; for TWI and NIKKEI 255, the GHSOM model obtains the minimum variance in all hedging horizons. However, the conventional OLS model cannot obtain minimum variance for all markets. Notably, for FTSE 100 and S&P 500 in short-term hedging, the static naïve model obtains the minimum variance. A possible reason for this may be the high correlation of the fluctuations of spot and futures for FTSE 100.

This can be observed from the closing statistics value of the spot and futures market in Table 3.

The value of hedging effectiveness is slightly different in these models. To test the significance of these models' performance improvements, we perform White's reality check. When OLS is treated as the benchmark, the null hypothesis of no improvement of GHSOM model over benchmark is rejected for 28 days hedging in TWI, 21 and 28 days hedging in S&P 500, 21 days hedging in FTSE 100 and NIKKEI 255 at the significance level of 1%. Results of the reality check provide evidence that the proposed CI-model can improve the OLS model, especially in long-term hedging.

4.5. Comparison of OHR

Table 7, which includes OLS and the best GHSOM model for comparison, presents the average OHR and standard deviation for the underlying models. For all market data, the average OHR estimated using GHSOM and OLS models is very close though a large discrepancy that exists in the standard deviation. Maximum standard deviation of the OLS model is 0.0069 for the one day hedging for FTSE 100. However, minimum standard deviation of the GHSOM model is 0.0070 for 28 days hedging for S&P 500. Results suggest that the OHR estimated using the GHSOM model is more variant than that of the OLS model.

Table 6
Variance of the portfolio.

Market/models	Variance Hedging horizon				
	1	7	14	21	28
TWI					
Unhedged	2.7527	20.5443	41.8060	35.5709	39.9629
Naïve	0.2561	0.8161	0.6132	0.1840	0.1698
OLS	0.1843	0.6113	0.3507	0.1454	0.1546
GHSOM	0.1819 ^a	0.5822 ^a	0.2880 ^a	0.1148 ^a	0.1056 ^a
Reality check p value	0.134	0.026 [*]	0.015 [*]	0.085	0.000 ^{**}
S&P 500					
Unhedged	1.6688	7.7995	14.9320	35.5709	39.9629
Naïve	0.0534 ^a	0.0778	0.1039	0.1840	0.1698
OLS	0.0559	0.0680	0.0940	0.1454	0.1546
GHSOM	0.0556	0.0649 ^a	0.0917 ^a	0.1107 ^a	0.1075 ^a
Reality check p value	0.354	0.072	0.257	0.000 ^{**}	0.000 ^{**}
FTSE 100					
Unhedged	2.0479	8.3512	23.6463	35.0068	57.8882
Naïve	0.0584 ^a	0.1148 ^a	0.2815 ^a	0.3149	0.3923
OLS	0.0612	0.1207	0.3238	0.3158	0.3029
GHSOM	0.0604	0.1157	0.3294	0.2709 ^a	0.2971 ^a
Reality check p value	0.039 [*]	0.022 [*]	1.000	0.002 ^{**}	0.050 [*]
NIKKEI 255					
Unhedged	2.8548	17.2076	46.2477	38.9337	87.7568
Naïve	0.1078	0.1152	0.2628	0.2108	0.1131
OLS	0.0985	0.0986	0.2312	0.1919	0.0857
GHSOM	0.0980 ^a	0.0962 ^a	0.2263 ^a	0.1729 ^a	0.0833 ^a
Reality check p value	0.318	0.078	0.151	0.004 ^{**}	0.136

Note: The benchmark model for White's reality check is the OLS model.

* Represents significance at the 5% level.

** Represents significance at the 1% level.

^a Represents the minimum variance among the naïve, OLS, and GHSOM hedged portfolios.

Table 7
Comparison of OHR.

Hedging horizon/ Model	OHR							
	TWI		S&P 500		FTSE 100		NIKKEI 255	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
1								
OLS	0.8189	0.0012	0.9636	0.0037	0.9819	0.0069	0.9429	0.0015
GHSOM	0.8263	0.0268	0.9649	0.0163	0.9833	0.0145	0.9474	0.0175
7								
OLS	0.9423	0.0019	0.9746	0.0021	0.9738	0.0040	0.9799	0.0010
GHSOM	0.9288	0.0150	0.9751	0.0088	0.9821	0.0100	0.9826	0.0058
14								
OLS	0.9570	0.0019	0.9818	0.0024	0.9746	0.0057	0.9737	0.0015
GHSOM	0.9493	0.0134	0.9821	0.0143	0.9851	0.0159	0.9832	0.0078
21								
OLS	0.9625	0.0021	0.9872	0.0039	0.9647	0.0045	0.9851	0.0019
GHSOM	0.9598	0.0145	0.9847	0.0099	0.9701	0.0149	0.9867	0.0078
28								
OLS	0.9647	0.0012	0.9960	0.0023	0.9589	0.0045	0.9764	0.0010
GHSOM	0.9624	0.0066	0.9882	0.0070	0.9676	0.0118	0.9858	0.0083

Figs. 5–8 present the plot of OHR estimated by the best GHSOM and OLS models over 1 and 28 days hedging horizons for all market data, correspondingly. In both figures, the OHR estimated using the traditional OLS model approximates a straight line, and the values are almost the same during the hedge period. However, the OHR

estimated using the GHSOM model is time-varying, which can reflect the dynamic behavior of the financial time series.

Fig. 7 also indicates the difference of FTSE 100 among all markets. The OHRs given by OLS model become smaller when the hedging horizons are longer. But it is contrary as observed in Figs. 5, 6, and 8. Simultaneously, for FTSE 100, Table 4 shows the highest p-value of F-test for equal variances, and Tables 5 and 6 show the best model is naïve. Consequently, the market behavior of FTSE 100 is a special case which is hardly suitable to make hedge decision.

4.6. Discussion

The experimental results show that the model comparisons may differ in different markets. Some studies indicate GARCH family models to be superior to the OLS model in a specific market [40]. However, other studies indicate opposing opinions, stating that the OLS hedge ratio performs better than other popular multivariate GARCH models [41,42]. The naïve hedge ratio of 1 is suggested as the optimal hedge ratio when the hedging horizon is long [6]. The superiority of the hedging model can be evaluated using White's reality check. However, this evaluation is not significant for model comparisons in one day hedging [39,43]. This phenomenon may be due to the dissimilar behavior of markets: the behavior of an emerging market differs from a mature market. For example, hedging effectiveness can be enhanced by a certain model in emerging markets such as the Hungarian BSI market, but not for developed markets such as the US S&P 500 market [44]. A similar result can be observed in this study, that is, the hedging effectiveness in TWI is different from that of UK FTSE 100.

Another issue that arises in this study is that the improvement of HE is very slight when comparing different models, e.g. from 93.30% to 93.39% (0.09% improvement) on 1 day TWI dataset. The explanation of minor improvement is due to the small scale of variance and covariance computing, which is commonly reported in OHR literature. For example, Lee and Yoder's RS-BEKK models [39] compared with OLS model improve the variance reduction from 77.4732% to 78.8891% for corn, and from 99.2068% to 99.2087% for nickel. Li's threshold VECM model [44] compared with OLS model improve the variance reduction from 96.22848% to 96.2646% for S&P 500. Moon et al. [42] report that principal component GARCH model compared with rolling OLS model improve the variance reduction from 95.45% to 95.52%. Although, the improvement is minor in this study, the proposed GHSOM model is capable of discovering similar behavior in the same market and can adapt to the characteristics of a particular market. Therefore, the long-term tendency of markets can be captured easily and the statistical significance when compared with OLS model in this study can be obtained.

5. Conclusions and future works

The empirical findings in this study are consistent with the following notations. First, hedging horizon will increase hedging effectiveness. When hedge horizon is increased, hedging effectiveness is also increased. Second, the proposed GHSOM model can improve the typical OLS model, especially in long-term hedging. Third, the present findings lend support to the superiority of the GHSOM model in enhancing hedging effectiveness for emerging markets, but not for developed markets such as the US S&P 500 and UK FTSE 100 markets. Finally, the OHR estimated using the GHSOM model is more volatile than the OHR estimated using the OLS model, which implies that the GHSOM model can rapidly

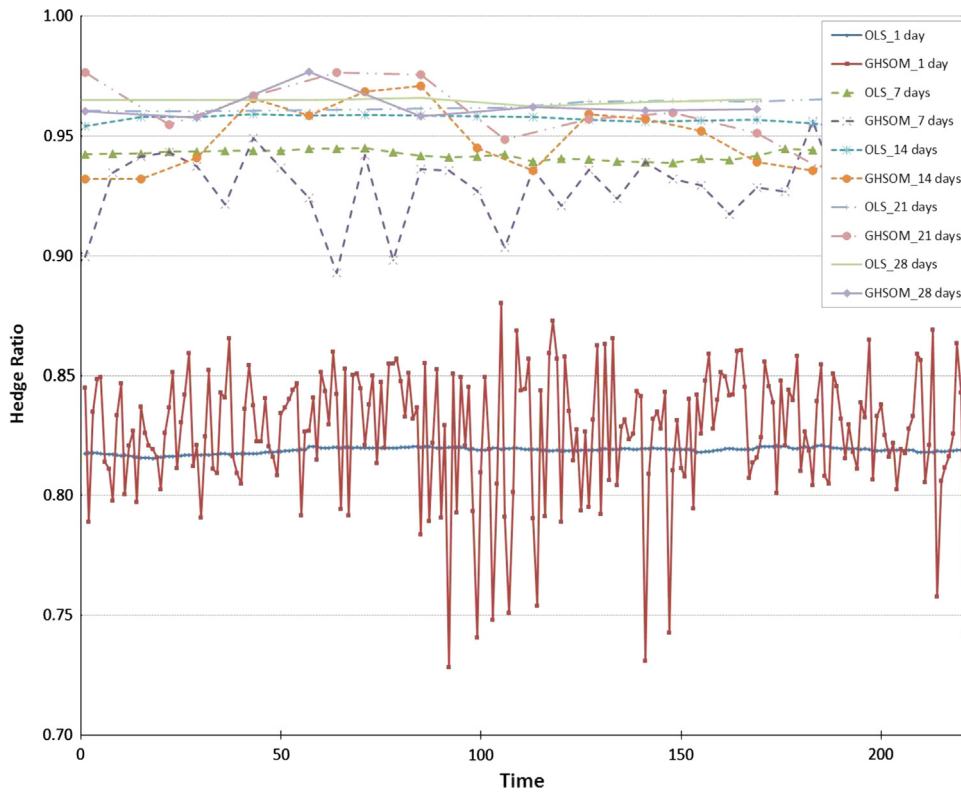


Fig. 5. Comparison of OHR in different hedging horizons for TWI.

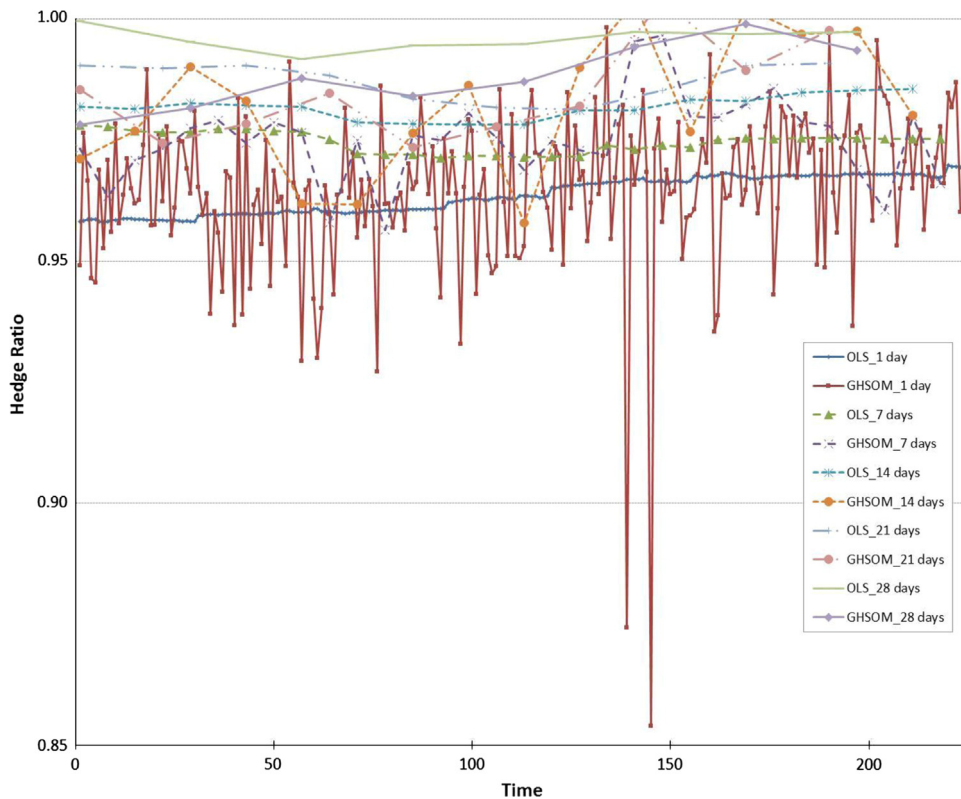


Fig. 6. Comparison of OHR in different hedging horizons for S&P 500.

reflect the time-variant property of financial time series and provide accurate estimation for dynamic hedging decision.

Although this research still has some restriction of model parameters selection, this novel approach based on GHSOM can

improve the performance of traditional approach without too many inappropriate assumptions and restrictions. Consequently, the proposed model can also be considered as a powerful tool to investigate any financial market, in which the probability

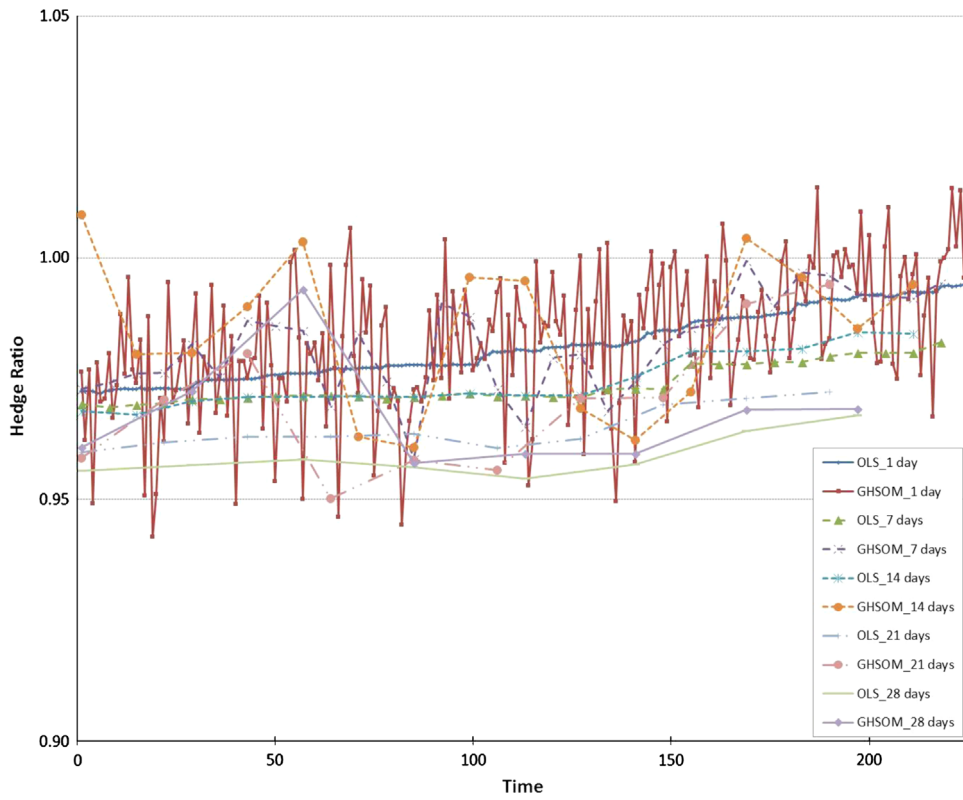


Fig. 7. Comparison of OHR in different hedging horizons for FTSE 100.

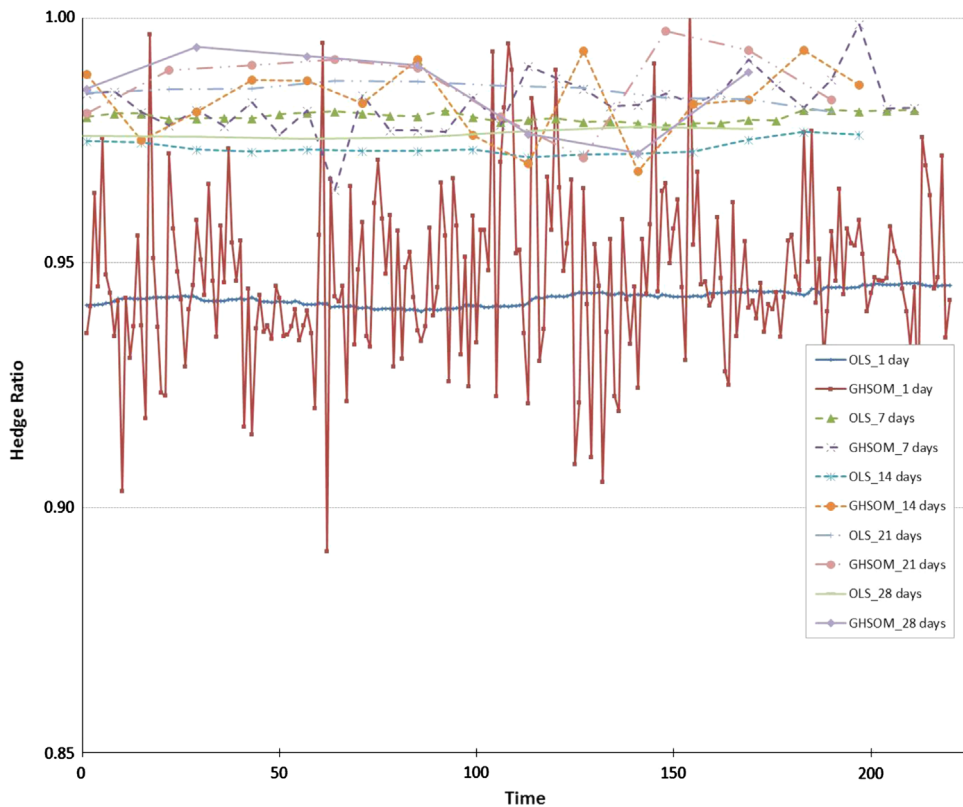


Fig. 8. Comparison of OHR in different hedging horizons for NIKKEI 255.

distribution of data is unrestricted and not necessary to fit any type of probability distribution.

The findings, although significant, have some limitations and are expected to be investigated further. The recommendations for future

works are summarized as follows. This research only conducts model and OHR estimations on stock index futures. However, the model has the potential to be applied to other futures markets, such as foreign exchange futures or commodity futures.

The proposed GHSOM model is expected to be used as a tool for investigating the relevant issue of volatility in financial engineering, such as volatility forecasting, modifying beta coefficient in capital asset pricing model (CAPM), and estimating value of risk (VaR).

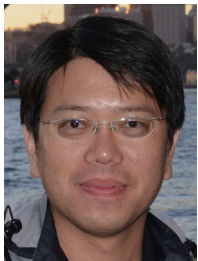
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