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Cross-correlation and the predictability of financial return series

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ABSTRACT

This paper examines whether we can improve the predictability of financial return series by exploiting the effect of cross-correlations among different financial markets. We forecast financial return series based on the support vector machines (SVM) method, which can surpass the random-walk model consistently. By comparing the mean absolute errors and the root mean squared errors, we show that it is hard to improve the predictability of financial return series by incorporating correlated return series into SVM-based forecasting models, even though there are Granger causal relationships among them.

1. Introduction

Forecasting financial returns has been regarded as one of the greatest challenging applications of modern economic forecasts. It is quite difficult to predict financial returns because financial datasets are characterized by being non-stationary, having an unstructured nature, and having hidden relationships. However, both individuals and organizations are always devoted to accurately predicting various kinds of financial returns so as to develop profitable trading strategies and avoid the risk of potentially large losses. A large number of models has been proposed to provide investors with more accurate forecasts. Based on conventionally statistical methods, time-series models have been very popular in constructing various kinds of financial market forecasting models in the past [1]. Considering financial bubbles and crashes plays an important role in risk management; several econophysicists have conducted much effort to forecast stock prices when the market is in a bubble or anti-bubble phase [2], such as the S&P 500 index [3,4], US treasury bond [5], and the Chinese stock markets [6,7]. The authors have proposed detailed mathematical models of speculative bubbles and crashes, which have attracted many researchers and practitioners [2–7].

In recent years, artificial neural networks (ANN) have been demonstrated to be successful research models to forecast financial markets [8]. ANN models were developed to forecast, detect, and summarize the structure of financial variables without relying too much on specific assumptions and error distributions. For example, Rodriguez et al. [9] found that an ANN consistently surpasses the random-walk model and provides better forecasts than the linear autoregression model and the smooth transition autoregression model. Other researchers attempted to hybridize several artificial intelligence techniques to improve the predictive performance of ANNs. Kim and Han [10] proposed a genetic algorithm approach to determine the connection weights of neural networks so as to reduce the dimensionality of the feature space and enhance the predictive performance. Tsaih et al. [11] integrated the rule-based technique and ANNs to predict the directions of the S&P 500 stock index future on a daily basis. However, the ANN had some limitations in learning high-dimensional data and selecting a large number of control parameters. The support vector machine (SVM) is another promising method for forecasting financial time series [12]. It uses a risk function consisting of the empirical error and a regularized term; the latter

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is derived from the structural risk minimization principle. Kim [13] showed that the SVM provided a better alternative to stock market forecasting by comparing it with back-propagation neural networks and case-based reasoning. Huang et al. [14] investigated the predictability of financial movement directions with a SVM by forecasting the weekly movement directions of the NIKKEI 225 index. Their experimental results indicate that the SVM outperformed other classification methods, including linear discriminant analysis, quadratic discriminant analysis and Elman back-propagation neural networks. Pai and Lin [15] showed that the combination of a SVM model and the autoregressive integrated moving average (ARIMA) model outperformed individual forecasting models.

Different from most of the forecasting literature which emphasize better forecasting methods, this paper explores the relationship between the predictability and statistical properties of financial return series. Cross-correlation is observed not only in financial indices but also in individual stocks [16,17]. Intuitively, cross-correlation might be related to the predictability of financial returns. One recent study showed that it was useful for improving the directional prediction correctness in forecasting the Australian stock index [18]. However, this preliminary result has not been confirmed or extensively examined by other researchers. This paper employs the most promising SVM method to examine whether we can improve forecasting performances by exploiting the typical property of cross-correlation observed in financial time series. Our results indicate that it is hard to improve the predictability of financial returns by incorporating correlated return series into a SVM-based forecasting model, even though there are Granger causal relationships among them. Therefore, it is not necessary to take the cross-correlation into consideration when we forecast financial return series based on the SVM method.

2. The data and general ideas

This paper analyzed four financial return series, which are across the bond market, the commodity market, and two stock markets. Each return series was calculated by the logarithmic change of the corresponding price series, $r(t) = \ln P(t) - \ln P(t-1)$, in which $P(t)$ denotes the price on day t. Specifically, these datasets are calculated from the closing prices of the trading 10-yr Treasury bond rate, Reuters Jefferies CRB index, Nasdaq Composite index, and S&P 500 index. They are obtained from the Board of Governors of the Federal Reserve System, www.jefferies.com, and the finance section of Yahoo, respectively. The whole datasets cover the period from January 3, 1994 to April 24, 2009, and each return series includes a total of 3856 observations. It is worth noting that the USA financial market and economy had endured the prosperous, stable, catastrophic periods and suffered from extreme fluctuations, which makes our results more convincing.

Serial data and their hidden relationships are often used to develop inequality constraints on the parameters of the model when we develop a parametric model for complex systems. Data collaboration means to integrate diverse, heterogeneous data through the combination of constraints that describes each piece of data [19]. Analogously, cross-correlations of a financial return series can be viewed as one kind of temporal constraint among different financial markets when we develop a financial return series forecasting model. In our forecasting framework, we choose lagged historical return data and correlated financial return series as the input variables to predict financial market behaviors. This work is empirical and we do not plan to provide theoretical grounds for the observed results.

As there is no formal theory supporting one financial index return as a function of other financial variables, choosing correlated financial return series is somewhat arbitrary. However, from the viewpoint of investors, it is reasonable to conjecture that there are intermarket influences among the commodity markets, stock markets, and bond markets [20]. In periods of economic contraction, bonds tend to perform well against falling stocks and commodities. During early economic expansion, interest rates are low and bond prices perform well. Stocks turn up after bonds, so for a period of time the two have a positive correlation. Performance in the stock market is a function of profit expectations, which themselves are affected by factors such as commodity prices and the business cycle. When interest rates are low and bonds have been on the rise, profit expectations rise as the economy improves which results in increasing stock prices. Stocks are affected by the price of commodities, which can be viewed as input prices. If commodity prices make a sharp increase, this will cause a negative supply shock which sends the stock market tumbling. If commodity prices are rising moderately, stocks tend to rise as higher profits are generated. Decreasing commodity prices cause the aggregate price level to decrease, which lowers revenue, and lowers stock prices. Therefore, we conjecture that there might be strong cross-correlation relationships among the trading 10-yr Treasury bond rate, the Reuters Jefferies CRB index, the Nasdaq Composite index and the S&P 500 index.

Several traditional methods were used to study cross-correlations between paired time series, such as the correlation coefficient matrix [21,22], random matrix theory [23] and the cross-correlation function method [24]. In this paper, we examine the cross-correlated relationships among the four financial markets by performing the detrended cross-correlation analysis on each paired index return series (see Fig. 1(a)) and absolute return series (see Fig. 1(b)). Similar to Refs. [17,25], for two given time series x_i^1 and x_i^2, let $X_k^1 = \sum_{i=1}^{k} x_i^1$ and $X_k^2 = \sum_{i=1}^{k} x_i^2$, where $i, k = 1, \ldots, N$. We divide X_k^1 and X_k^2 into $N - n$ boxes, each box contains $n + 1$ pieces of data, which are $X_i^1, X_{i+1}^1, \ldots, X_{i+n}^1$ and $X_i^2, X_{i+1}^2, \ldots, X_{i+n}^2$, $i = 1, \ldots, N$, their one order polynomial fittings are $Y_{k,i}^1$ and $Y_{k,i}^2$ $(i \le k \le i + n)$. Let $f_{DCCA}^2(n, i) = 1/(n-1) \sum_{k=i}^{i+n} (X_k^1 - Y_{k,i}^1)(X_k^2 - Y_{k,i}^2)$ and $F^2(n) = (N - n)^{-1} \sum_{i=1}^{N-n} f_{DCCA}^2(n, i)$. We approximate the square root of the detrended covariance with the function relationship $F(n) \sim n^{\lambda}$. For the S&P 500 return series, the exponents fitted in Fig. 1(a) indicate that there are power-law cross-correlations between S&P 500 and other indices return series. Furthermore, we can find long-range cross-correlations by analyzing the paired absolute return series. As shown in Fig. 1(b), the scaling exponent λ of (S&P, bond rate), (S&P,

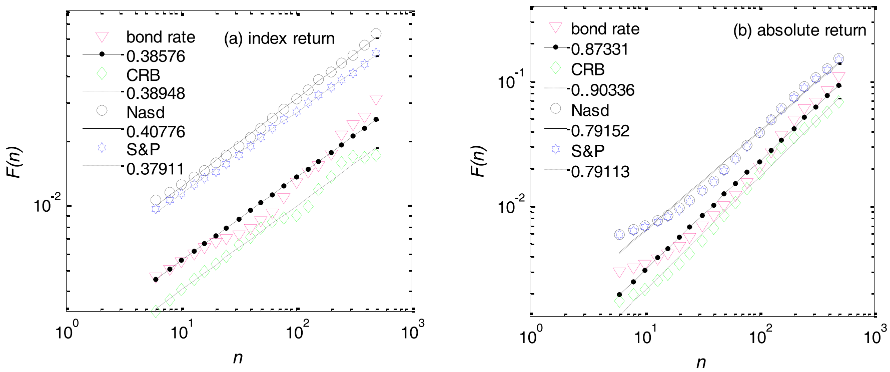

Fig. 1. Cross-correlations between the S&P 500 index and the 10-yr Treasury bond rate, the Reuters Jefferies CRB index, the Nasdaq Composite index and the autocorrelation of the S&P 500 index. Each time series has 3856 daily data points which are in the period from January 3, 1994 to April 24, 2009. The square root of the detrended covariance can be approximated with the function relationship $F(n) \sim n^{\lambda}$. (a) Cross-correlations of paired index return series. (b) Long-range cross-correlations of paired absolute return series. For paired absolute return series, the scaling exponents of (S&P, bond rate), (S&P, CRB), (S&P, Nasdq) and (S&P, S&P) are 0.87331, 0.90336, 0.79152, and 0.79113 respectively. For other paired series, we can obtain similar cross-correlation relationships.

CRB), (S&P, Nasdaq) and (S&P, S&P) are 0.87331, 0.90336, 0.79152, and 0.79113 respectively. These fitting exponents are all between 0.5 and 1, which demonstrates that there are long-range cross-correlations between different financial return series [17]. These results are much in agreement with the magnitude cross-correlations found in Refs. [26–28]. For other paired time series, we performed the detrended cross-correlation analysis and found similar qualitative results.

Furthermore, we employed the Granger causality test to determine whether one return series is useful in forecasting another. Based on the definition of Granger causality, a time series X is said to be Granger-cause Y if it can be shown, usually through a series of F-tests on lagged values of X (and with lagged values of Y also known), that those X values provide statistically significant information about future values of Y [29]. We use the Bayesian information criterion to determine the optimized lag length, and do not use trend analysis in the computational process. Our results indicate that (1) The 10-yr treasury bond rate only Granger-causes the CRB index (2) The S&P 500 index Granger-causes the 10-yr Treasury bond rate and the CRB index (3) both the CRB index and the Nasdaq Composite index Granger-cause all other time series.

3. Forecasting method

Based on the structural risk minimization principle, the SVM is now being widely used to solve classification, regression, and prediction problems [12]. The SVM deals with classification and regression problems through some nonlinear mapping of the input data into high-dimensional feature spaces. Therefore, the originally nonlinear decision boundary is transformed into an optimized separating hyper-plane in the new space. Support vectors are those training examples which are closest to the maximum margin hyper-plane. The remaining training examples are irrelevant in determining the binary class boundaries. The problem of separating the set of training vectors belonging to two separate classes is equivalent to solving the following non-linear classification function:

$$f(x) = \mathrm{Sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + \frac{1}{N_s} \sum_{0<\alpha_j<C} \left(y_j - \sum_{i=1}^{N} \alpha_i y_i K(x_i, x_j)\right)\right), \tag{1}$$

where x_i is the ith input vector; $y_j \in \{-1, 1\}$ is binary target; α_i are the non-negative Lagrange multipliers; N_s is the number of support vectors; $K(x_i, x)$ is defined as the kernel function. There are several different kernels for generating the inner products to construct machines with different types of nonlinear decision surfaces in the input space. Any function satisfying Mercer's condition can be used as the kernel function [12]. In this work, the Gaussian radial basis kernel $K(x, y) = \exp(-\|x-y\|^2/\delta^2)$ is used as the kernel function of the SVM because the radial kernel tends to give good performance under general smoothness assumptions.

Compared with other artificial intelligence technologies, the SVM method has some significant advantages. First, the SVM can overcome the over-fitting problem and eventually achieves a high generalization performance by implementing the structural risk minimization principle to estimate a function. Second, training the SVM is equivalent to solving a linearly constrained quadratic programming problem so that the solution of the SVM is always unique and globally optimal while neural network models may fall into a locally optimal solution. Third, unlike back-propagation neural networks which suffer from a difficulty in selecting a large number of control parameters, there are no parameters to tune except the upper bound for the non-separable cases in linear SVM. Fourth, the SVM can handle nonstationarity, long memory, high-dimension, and multi-scale effects without restrictive assumptions and approximations required by other models, which are especially important for financial applications. Finally, research results on foreign-exchange data and the volatility of the S&P 500 suggested that the SVM can efficiently work with high-dimensional inputs to account for long-term memory and multi-scale effects and is often superior to main-stream volatility models [30,31].

Let us now illustrate how to implement our forecasting model. First, all price series were transformed into return series by calculating the logarithmic change of the price series, $r(t) = \ln P(t) - \ln P(t-1)$, in which $P(t)$ denotes the index price on day t. Then, we denote the ith return value of the 10-yr Treasury bond rate, the Reuters Jefferies CRB index, the Nasdaq Composite index, and the S&P 500 index as $x_i^1, x_i^2, x_i^2, x_i^4$, respectively. We assume that x_i^j $(j = 1, 2, 3, 4)$ can be approximated by a nonlinear function F_j of its historical values:

$$x_i^j = F_j(x_{i-1}^j, \ldots, x_{i-m}^j, \ldots, x_{i-M}^j), \tag{2}$$

where index $i - m$ corresponds to time $(t_i - mdt)$, dt is a time lag interval and $T = mdt$ is the total length of the memory for the mth previous input. Evidently, M represents the dimension of the input vector. In this paper, the largest M is 20. This form of lagged inputs can enable us to examine the forecasting performance improvement when a larger number of lagged index values is being used as inputs, but keeps our model be computationally realistic at the same time.

In order to test the cross-market correlation effects, we assume that x_i^j can be approximated by another nonlinear function G_j of both its own historical values and historical values of other variables:

$$x_i^j = G_j(x_{i-1}^1, \ldots, x_{i-m}^1, \ldots, x_{i-M}^1, x_{i-1}^2, \ldots, x_{i-m}^2, \ldots, x_{i-M}^2, x_{i-1}^3, \ldots, x_{i-m}^3, \ldots, x_{i-M}^3, x_{i-1}^4, \ldots, x_{i-m}^4, \ldots, x_{i-M}^4). \tag{3}$$

Based on expression (2) and (3), we construct two kinds of training datasets and execute the corresponding prediction. We name the forecast procedure based on expression (2) as a single-market prediction and the forecast procedure based on expression (3) as a cross-market prediction. We use the functions of **svmreg** and **svmval** in the SVM-KM library to train sampling data and perform predictions, respectively. Programs can be downloaded from http://asi.insa-rouen.fr/enseignants/~arakotom/toolbox/index.html [32].

In this study, similar to Ref. [33], the Gaussian radial basis function is used as the kernel function of the SVM. There are three parameters in this kind of SVM model, which are the ε-insensitive loss function, the upper bound C and the kernel bandwidth δ. In order to keep comparison, we set $\varepsilon = 0.003$, $C = 50$, and $\delta = 5$ in all forecasting experiments.

Now, we use the above SVM model and parameters to perform forecasts. For both single-market prediction and cross-market prediction, we choose the length of the time window as 1857 transactional days and shift this window with a step of 4 transactional days to examine to which degree the predictive performance is sensitive to for different periods of datasets. There are 500 time windows in total. In each time window, the first 1837 data are used as training datasets, and the remaining 20 data are used as test datasets so as to obtain forecasts. Furthermore, the first prediction is a one-step-ahead forecast. The second prediction is a two-step-ahead forecast obtained by using a recursive regression. Similarly, we can repeat this procedure again until we finish the 20-step-ahead forecast. Eventually, we will obtain 500 predictions for each step-ahead forecast. The predicted data will be used in our forecasting performance comparison.

4. Results

Forecast error is defined as $e_t = z_t - d_t$, where d_t denotes the actual return and z_t denotes the forecasting return at period t. Considering that there are 500 predicting values for each step-ahead forecast, the mean absolute error (MAE) and the root mean squared error (RMSE) is defined as follows:

$$\mathrm{MAE} = \sum_{t=1}^{500} |e_t| / 500, \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\sum_{t=1}^{500} (e_t - \widehat{e})^2 / 500}, \tag{5}$$

where $\widehat{e}$ is the average value of e_t.

The random-walk model is often taken as a benchmark which would forecast a return of zero for each forecast horizon. In order to demonstrate the superiority of the SVM method, we compare the predictive performance of the SVM-based cross-market forecast model with that of a random-walk model. Here, we are not ready to show the comparisons of single-market forecasts and random-walk processes, because we will compare cross-market forecasts and single-market forecasts in the latter. As shown in Fig. 2(a) and (b), whatever the error standard of the MAE or RMSE, the SVM-based model outperforms random-walk model in most case. Taking the CRB index as an example, we can degrade forecast errors by using a SVM-based model, regardless of the forecast horizon varying from 1 to 20. These results indicate that (1) the SVM can capture the non-stationary, unstructured nature, and hidden relationship to some extent (2) a SVM-based forecast model surpasses the random-walk model significantly.

Now, we compare the out-of-sample forecasts of the single-market and the cross-market by computing the disparities in the MAE and RMSE, which are the single-market prediction errors minus the corresponding cross-market prediction errors.

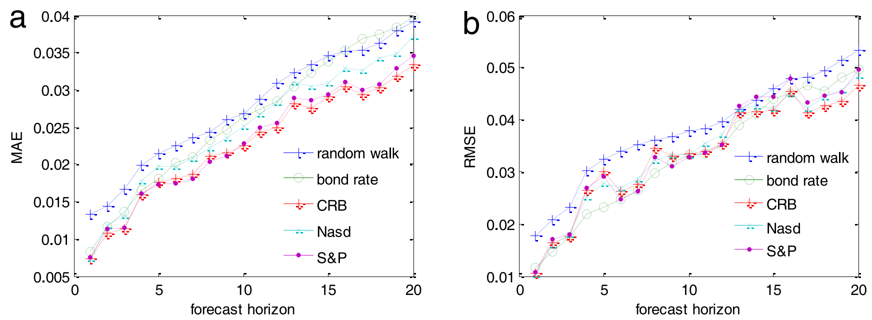

Fig. 2. Comparing the predictive performance of a SVM-based forecast model and that of a random-walk model. (a) The predictive accuracy of cross-market prediction and that of a random-walk model measured by MAE. (b) The predictive stability of cross-market prediction and that of the random-walk model measured by RMSE. In the SVM-based model, the dimension of input vector is set to 1 ($M = 1$). To compare, each financial time series was normalized to zero mean return and standard deviation 0.01. The forecast errors of the random-walk shown in this figure are the averages of the forecast errors of the 10-yr Treasury bond rate, the CRB index, the Nasdaq Composite index, and the S&P 500 index predicted by a random-walk model.

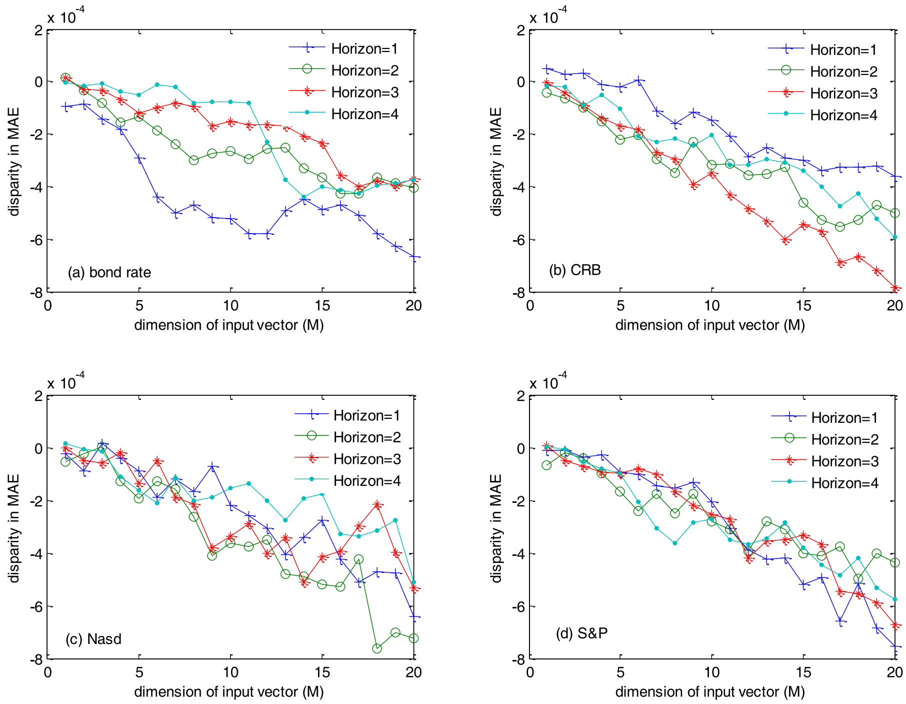

Fig. 3. Comparing the mean absolute errors of the multivariate and the univariate models. Single-market prediction is the univariate model, in which only one financial time series is used in training and prediction. Cross-market prediction is the multivariate model, in which the closing prices of the 10-yr treasury bond rate, the CRB index, the Nasdaq Composite index, and the S&P 500 index are all used in training and prediction. In (a–d), each data point is the MAE obtained by single-market prediction minus the corresponding MAE obtained by cross-market prediction. (a)–(d) show the disparity in MAE for the 10-yr treasury bond rate, the CRB index, the Nasdaq Composite index, and the S&P 500 index, respectively. Most data points being negative indicate that higher predictive accuracy can be obtained by single-market forecasting rather than by cross-market forecasting.

As we can see from Figs. 3 and 4, whatever the MAE or RMSE, single-market predictive performances are better than cross-market predictive performances in most cases, which is contradictory to previous results on forecasting the Taiwan Stock Exchange Capitalization Weighted Stock index [34]. To some extent, it seems anti-intuitive that multivariate information does not improve predictability compared to the univariate case. However, our results only suggest that cross-correlation information may be not helpful to improve predictability. Considering the prediction error of the SVM-based model is influenced by the size of training data, the multivariate model might generate a higher error than the univariate model if they have the same number of training samples. Because the number of input variables used in cross-market prediction is five times of that used in single-market prediction, it is reasonable that the predictive performances of cross-market prediction are often lower than that of single-market prediction. It is worth noting that, we cannot obtain better forecasts by incorporating correlated financial time series into the forecasting model, even though there are Granger causalities among these time series. This can be explained that Granger causality does not imply true causality. If two time series are driven by a

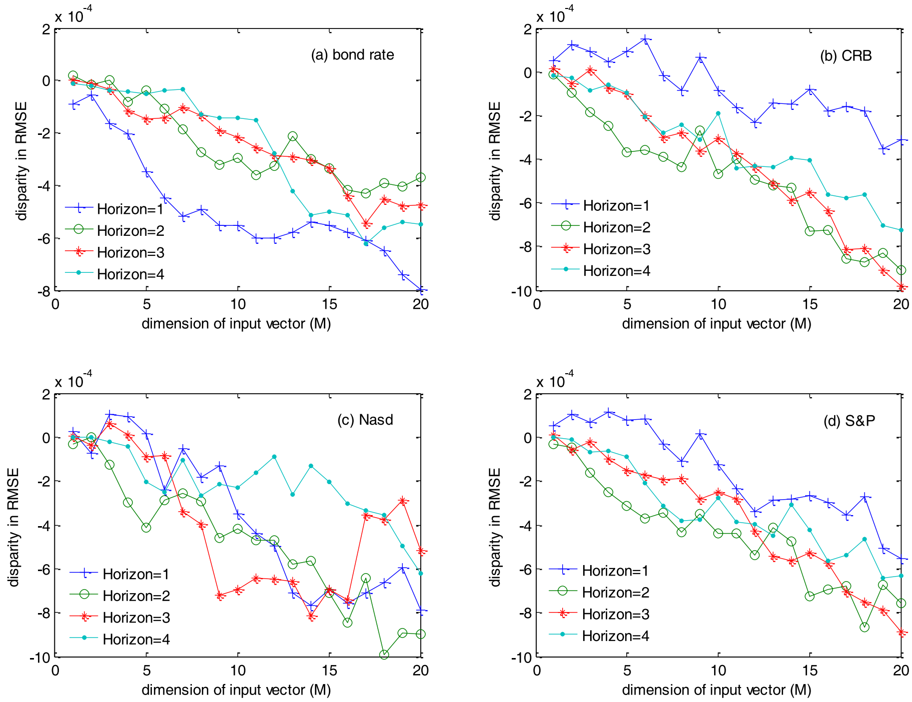

Fig. 4. Comparing the root mean squared errors of the multivariate and the univariate models. In (a–d), each data point is the RMSE obtained by single-market prediction minus the corresponding RMSE obtained by cross-market prediction. (a)–(d) show the disparity in RMSE for the 10-yr Treasury bond rate, the CRB index, the Nasdaq Composite index, and the S&P 500 index, respectively. Most data points being negative indicate that higher predictive stability can be obtained by single-market forecasting rather than by cross-market forecasting.

common third process with different lags, their measure of Granger causality could still be statistically significant. Our results indicate that integrating correlated market information does not improve, and even worsens the predictive performances, which reminds practical forecasters to recognize the complexity of financial forecasts and keep cautiously on the declared high performance forecasting model obtained by integrating multi-market information—more is not always better.

5. Conclusions

People often believe that cross-correlation is related to the predictability of volatility in financial time series. This paper examined whether we can improve the predictive performance of financial returns if we incorporate correlated financial return series into forecasting models. Our results show that the predictive performance of a given financial return series would become worse in most cases when correlated cross-market return series were taken as input variables into the SVM-based forecasting model, which suggests that there is no necessity to take other financial return series into consideration when we perform financial return series forecasts based on the SVM method.

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