THE INFORMATION OF TRADING VOLUME IN THE PREDICTION OF STOCK INDEX RETURNS: A NONPARAMETRIC INVESTIGATION

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ABSTRACT

This paper investigates the predictability of stock index returns by using the multivariate nearest neighbor model which considers the trading volume as well as the stock price. The optimal choice for the embedding dimension, the number of neighbors, and the contribution of the trading volume are determined by the cross validation method which minimizes the mean square error in the training set. The empirical results by using the KOSPI composite index and 16 industry indexes indicate that the multivariate nearest neighbor model provides statistically significant forecast improvements over the random walk model and the univariate nearest neighbor model.

KEYWORDS

Nonparametric; Nearest Neighbor; Time Series Forecasting

1. Introduction

Forecasting the levels and direction of financial terms is of interest to participants in financial markets. There are numerous approaches in the literature, yet when Meese and Rogoff [13] examined an exhaustive set of linear time series, reduced form and structural models, they found no model that consistently produced forecasts superior to the random walk.

An emerging body of research has stressed nonlinearities as one of the potential reasons for such poor performance. Analysis of nonlinearities in the dynamics of short-term stock returns is of great importance at both theoretical and empirical levels. On the other hand, recent advances in both analytic and computational methods have helped empirical analysis of nonlinear models and have encouraged the research in this area, dramatically increasing the number of approaches to forecasting financial terms. One of these approaches are the nearest neighbor predictors.

We employ a nonparametric nearest neighbor model which is known to perform well at forecasting low-dimensional chaotic data generators infected with high levels of noise. Unlike ordinary least squares which fits the regression surface globally, the nearest neighbor model provides a local approximation. In contrast to parametric nonlinear approaches, our nonparametric approach does not impose any specific type of nonlinearity in the forecasting process. Therefore, the nonparametric approach avoids the parametric-model selection problem and allows for a wider array of nonlinear behavior. The basic idea behind these predictors is that pieces of time series sometime in the past might have a resemblance to pieces in the future. The nearest neighbor model uses the data scatter to weight observations near to the dependent variables more heavily.

In this paper, we propose a multivariate nearest neighbor (MNN) model which considers the trading volume as well as the stock price. We measure the forecasting accuracy of our model using both mean absolute prediction error (MAPE) and mean squared prediction error (MSPE) criteria. We compare the forecasting performance of the MNN model with the performance of two benchmark models: the random walk (RW) model and the univariate nearest neighbor (UNN) model. We use a robust test statistic due to Mizrach [14] to evaluate whether forecasts generated by the MNN model are significantly better than forecasts generated by the RW and the UNN models. The optimal choice of embedding dimension, number of neighbors, and the contribution of the trading volume are determined by the cross validation method which minimizes the mean square error in the training set.

The plan of the paper is as follows. Section 2 develops the nearest neighbor methodology. In Section 3 we discuss the relationship between stock price and trading volume and develop the MNN. Section 4 gives the main results of the paper demonstrating out of sample forecast improvements for stock index returns. Section 5 concludes.

2. Forecasting Methodology

The conditional mean of a random variable x, given a vector of conditioning variables w, can be written as $E(x|w) = M(w)$. In parametric estimation, $M(w)$ is typically assumed to be linear in w, but in the nonparametric approach $M(w)$ remains a general functional form. In this paper we take a simple approach to forecasting $M(w)$, using the nearest neighbor model of Stone [20]. Applications of nearest neighbor model include the work of Robinson [16] in a regression context as well as the work of Yakowitz [21] in a time series forecasting context.

The first step in the model is the creation of a state space library that contains the geometric sections that have occurred in the past. The model reviews the time series iteratively using 'embedding dimensions', E. As the number of embedding dimensions increases, the model becomes capable of picking up more complicated attractors. The model uses lagged coordinates to represent each sequence of data points as a vector, $\mathbf{x}_t$, in E-dimensional state space such that

$$\mathbf{x}_t = (x_{t-(E-1)}, x_{t-(E-2)}, \Lambda, x_{t-1}, x_t) \qquad (1)$$

For each embedding dimension, the model retains the time series values of variables for the next time period associated with that E-dimensional vector. Mulhern and Caprara [15] refers to the data for these next time period as the outcome data associated with a particular vector. The outcome data are not future values, but the historical time series values that come in the period immediately following each vector formed by the model. The outcome data represent the historical response of the time series when a particular pattern of behavior, represented by a state space vector, is observed.

The forecast of nearest neighbor model at time t+1 is given by:

$$\hat{x}_{t+1} = \sum_{i=1}^{t-1} w_{it} I[d(\mathbf{x}_i, \mathbf{x}_t) < \eta] x_{i+1} \qquad (2)$$

where I is the indicator binary function, which is 1 if $\mathbf{x}_i$ is neighbor and 0 otherwise, d is the distance of each vector, η is some constant, w_{it} is a sequence of weights, and x_{i+1} is the outcome data of vector $\mathbf{x}_i$.

An important issue is how the nearest neighbors are identified. There are a variety of approaches for doing so. In the studies of Gencay [6] and Barkoulas *et al.* [1], the model calculates the Euclidean distance between the E-dimensional vector and each vector in the state space library and retains a specified number of vectors with the smallest distances. The distance, d, between two vectors in E-dimensional space, often known as a norm, is calculated as

$$d(\mathbf{x}_i, \mathbf{x}_t) = \left(\sum_{k=0}^{E-1} (x_{i-k} - x_{t-k})^2 \right)^{\frac{1}{2}} \qquad (3)$$

where x_{i-k} is the value of the vectors of the state space library, x_{t-k} is the value of the vector for which a prediction is desired, and E is the embedding dimension. Alternatively, Casdagli [2] and Jaditz and Sayers [9] suggested using the supreme norm to calculate distances:

$$d(\mathbf{x}_i, \mathbf{x}_t) = \max_{k=0}^{E-1} |x_{i-k} - x_{t-k}| \qquad (4)$$

Other implementations of the nearest neighbor model advocate local weighting schemes that place greater weights on near observations. Stone [20] formulated the problem of consistent estimation through regularity conditions on weights for the neighbors. As the sample grows large, the number of neighbors, q, must go off to infinity, but at a slower rate than the rate at which the sample size increases. Consistency becomes a matter of imposing a selection rule involving η. As a practical matter, our investigation will look over a range of q's.

Typically one uses the distance of neighbors to compute their weights. We use exponential weighting algorithm of Linden *et al.* [12] that regulates the contribution of each vector by a function of its distance from the original vector:

$$w_i = \frac{e^{-d_i}}{\sum_{j=1}^{q} e^{-d_j}} \qquad (5)$$

where d_i is the distance of each neighbor, q is the number of neighbors. Mulhern and Caprara [15] suggested using the power factor, p, to calculate weights. A negative exponent assures that the greatest weight is given to the neighbor that is closest to the vector for which a prediction is desired:

$$w_i = \frac{d_i^p}{\sum_{j=1}^{q} d_j^p} \qquad (6)$$

We obtain the optimal choice of embedding dimension and number of nearest neighbors by the cross validation method which minimizes the mean square error in the training set.

3. Multivariate Nearest Neighbor Model

There are several explanations for the presence of a causal relation between stock prices and trading volume. First, the sequential information arrival models of Copeland [3] and Jennings *et al.* [10] suggested a positive causal relation between stock price and trading volume in either direction. Second, Lakonishok and Smidt [11] showed that current volume can be related to past stock price changes due to tax- and non-tax-related trading motives. The dynamic relation is negative for tax-related trading motives and positive for certain non-tax-related trading motives. Third, in the mixture of distributions model of Epps and Epps [5], trading volume is used to measure disagreement as traders revise their reservation prices based on the arrival of new information into the market. Their model suggested a positive casual relation running from trading volume to absolute stock returns.

Examining the relation between returns and volume, a positive contemporaneous correlation was found by Rogalski [17] using monthly stock and warrant data and by Epps [4] using transactions data. To explain such results, Epps [4] proposed a theoretical framework consistent with his findings. His framework implied the ratio of volume to returns should be greater for price increases than for price decreases, which was supported by empirical evidence in Smirlock and Starks [18]. More recent empirical work has investigated the lagged relation between price changes and volume. For example, Smirlock and Starks [19], employing individual stock transactions data, documented a strong positive lagged relation between absolute price changes and volume. In addition, Hiemstra and Jones [8] found a new result through the use of nonlinear Granger causality. They found a significant positive relation going in both directions between stock returns and trading volume.

Despite the relation between stock price and trading volume, there have been few stock return forecasting models which include trading volume. In this paper, we propose a multivariate nearest neighbor (MNN) model which considers the trading volume as well as the stock price. Compared with univariate nearest neighbor (UNN) model, the MNN model uses two series of data, price ($\mathbf{p}_t$), and volume ($\mathbf{v}_t$).

$$\mathbf{x}_t = \begin{pmatrix} \mathbf{p}_t \\ \mathbf{v}_t \end{pmatrix} = \begin{pmatrix} r_{t-(E-1)} & \Lambda & r_{t-1} & r_t \\ v_{t-(E-1)} & \Lambda & v_{t-1} & v_t \end{pmatrix} \qquad (7)$$

In the MNN model, the distance between two vectors is calculated as

$$d(\mathbf{x}_i, \mathbf{x}_t) = \left((1-\alpha)\sum_{k=0}^{E-1} (r_{i-k} - r_{t-k})^2 + \alpha \sum_{k=0}^{E-1} (v_{i-k} - v_{t-k})^2 \right)^{\frac{1}{2}} \qquad (8)$$

where r_{i-k} and v_{i-k} are the values of the vectors of the state space library, r_{t-k} and v_{t-k} are the values of the vectors for which a prediction is desired, α is the contribution of the trading volume, and E is the embedding dimension. If $\alpha = 0$, this model becomes the UNN model.

Previous UNN models have used the distance of price vector itself to obtain the neighbors. Our model, however, identifies neighbors by the weighted average of distances of price vector and volume vector.

4. Forecasting Results

There have been some price restrictions in the Korean stock market: until March 1995, prices were allowed to go up only by a fixed amount. Since April 1, 1995 they have been allowed to go up by 6%, depending on the closing price of the security on the last trading day. Price restriction was relaxed to 8% from November 25, 1996, 12% from March 2, 1998, and 15% from December 7, 1998. Under these price restrictions, transactions are interrupted when price reaches the limit. It means that the information obtained may not reflect the market promptly. Hence, the past data which were generated under the strong restrictions cannot explain the present data. In fact, the volatility of present data is much greater than that of past data. To take account of price restrictions, we limit our analysis to data since March 2, 1998 when the restriction was relaxed to 12% of the closing price on the last trading day.

The data used in this paper are based on time series of daily stock prices as well as trading volumes obtained from the Korean Stock Exchange during March 2, 1998 ~ December 28, 1999, for a total of 493 observations. We compute stock returns from daily closing prices for the Korea Composite Stock Price Index (KOSPI) and 16 industry stock price indexes. Industry stock price indexes used in this paper are Fishing (FS), Mining (MI), Food & Beverages (FB), Textile & Wearing Apparel (TW), Wood & Wood Products (WW), Paper & Paper Products (PP), Chemicals & Chemical Products (CC), Non-metallic Mineral Products (NM), Basic Metal Industries (BM), Fabricated Metal Products, Machinery & Equipment (FME), Other Manufacture (OM), Construction (CO), Wholesale Trade (WT), Transport & Storage (TS), Financial Institutions (FI), and Insurance (IN). The summary statistics of the log differences of daily prices and volumes are presented in Table 1 and 2, respectively. All series exhibit slight skewness and high kurtosis, which is common in high frequency financial time series data.

Table 1

Summary statistics for the daily stock indexes prices: log difference, 1998/3/3 ~ 1999/12/28.

Industry	Mean * 100	Standard Deviation	Skewness	Kurtosis	Maximum	Minimum
KOSPI	0.1183	0.0263	0.0700	3.4216	0.0816	-0.0844
FS	0.0744	0.0380	0.1431	3.8137	0.1391	-0.1247
MI	0.0136	0.0479	0.1576	3.1796	0.1200	-0.1285
FB	0.1278	0.0240	0.3418	4.4715	0.1045	-0.0709
TW	-0.0186	0.0251	-0.0884	4.1189	0.0970	-0.1016
WW	-0.1202	0.0425	-0.1093	3.8065	0.1381	-0.1591
PP	-0.0792	0.0299	-0.2069	3.5717	0.0949	-0.1032
CC	0.0898	0.0257	-0.1005	3.4087	0.0815	-0.0857
NM	0.0148	0.0269	0.0903	3.5468	0.1003	-0.0957
BM	0.0600	0.0297	0.1756	5.0830	0.1161	-0.1080
FME	0.0913	0.0299	0.2851	3.7543	0.0966	-0.0874
OM	-0.0418	0.0319	-0.3446	3.7877	0.1045	-0.1116
CO	0.0065	0.0377	0.4791	5.0574	0.1388	-0.1496
WT	0.0360	0.0335	-0.0009	3.7766	0.1125	-0.1012
TS	0.0908	0.0347	0.0300	3.4632	0.1172	-0.1254
FI	-0.0012	0.0356	0.1027	3.4783	0.1134	-0.1231
IN	-0.0129	0.0356	0.2759	4.0352	0.1360	-0.1055

Table 2

Summary statistics for the daily stock indexes volumes: log difference, 1998/3/3 ~ 1999/12/28.

Industry	Mean * 100	Standard Deviation	Skewness	Kurtosis	Maximum	Minimum
KOSPI	0.1942	0.2349	-0.2605	3.9864	0.7853	-0.7635
FS	0.3764	0.5551	0.2104	3.7291	1.9144	-1.5055
MI	0.3814	0.4919	1.1417	8.5727	3.5648	-1.5003
FB	0.3525	0.3510	-0.1496	3.6498	1.0645	-1.1142
TW	0.1684	0.3208	0.1366	3.6279	1.1243	-1.0575
WW	0.0218	0.4996	0.1858	3.4511	1.6266	-1.6702
PP	0.0455	0.3377	0.0474	3.4848	1.1276	-1.0451
CC	0.1693	0.2653	-0.2152	3.7080	0.8317	-0.8852
NM	0.0720	0.3797	-0.1158	5.5214	1.5803	-2.0696
BM	0.1932	0.3298	-0.1280	4.8420	1.3085	-1.5858
FME	0.2164	0.2693	-0.3425	4.3910	1.1121	-1.0077
OM	0.0957	0.4424	0.2531	4.5269	1.8055	-1.8099
CO	0.1704	0.3653	0.3258	5.2900	1.7709	-1.3369
WT	0.1982	0.3321	0.1012	3.8414	1.2549	-1.1709
TS	0.5611	0.4134	0.0882	3.6690	1.4530	-1.3025
FI	0.1392	0.3326	0.2343	3.5215	1.0855	-1.0845

IN	0.2169	0.4517	0.1818	3.1574	1.5680	-1.2757

To Choose the optimal embedding dimension, the number of neighbors, and the contribution of volume, we use the cross validation method which minimizes the mean square error in the training set. The training set is from January 4, 1999 to June 30, 1999. Table 3 summarizes the optimal embedding dimension, the number of neighbors, and the contribution of volume of the UNN and the MNN models.

Table 3
The optimal embedding dimension (E), the number of neighbors (q), and the contribution of volume (α) in the training set: 1999/1/4 ~ 1999/6/30.

Industry	The UNN model		The MNN model		
	E	q	E	q	α
KOSPI	6	50	3	20	0.05
FS	3	40	2	30	0.15
MI	7	60	6	40	0.50
FB	5	40	5	20	0.20
TW	2	50	3	20	0.05
WW	5	40	5	30	0.45
PP	3	90	2	60	0.30
CC	3	80	2	40	0.05
NM	4	30	5	30	0.10
BM	8	30	8	30	0.05
FME	7	60	7	40	0.05
OM	3	90	4	100	0.45
CO	2	70	5	60	0.75
WT	6	10	3	20	0.15
TS	3	20	10	10	0.85
FI	10	100	3	20	0.60
IN	2	90	4	10	0.55

For each stock index, the out-of-sample forecasting performances of the RW, UNN and MNN models are examined. The out-of-sample one-step ahead forecasts are calculated from the prediction set July 1, 1999 ~ December 28, 1999 for a total of 125 observations. As a measure of performance, the MAPE and the MSPE are used. These errors of three models are presented in Table 4. To assess the statistical significance of forecasting performance, we test for the differences in mean squared forecast errors using the approach originally derived by Granger and Newbold [7] and updated by Mizrach [14]. Granger and Newbold [7] pointed out that direct testing of hypotheses about the relative magnitudes of the forecast errors generated by two alternative forecasting methods is complicated by the fact that the forecast errors themselves are likely to be correlated. Let e_{1t} be the forecast residuals from method 1, and let e_{2t} be the forecast residuals from method 2. Suppose that these two forecast residual series are normally distributed and serially uncorrelated. If the forecast errors were from a bivariate normal population (e_{1t}, e_{2t}), with zero means, the correlation ρ, and the standard deviations, σ_1 and σ_2, a straightforward test of the forecast improvement is available. Let $U_t = e_{1t} - e_{2t}$ and $V_t = e_{1t} + e_{2t}$. Then, (U_t, V_t) has a bivariate normal distribution with parameters:

$$\begin{aligned} &E(U_t) = E(V_t) = 0 \\ &Var(U_t) \equiv \sigma_U^2 = \sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2 \\ &Var(V) \equiv \sigma_V^2 = \sigma_1^2 + \sigma_2^2 + 2\rho\sigma_1\sigma_2 \\ &Cov(U_t, V_t) \equiv \sigma_{UV} = \rho\sigma_U\sigma_V \end{aligned} \quad (9)$$

In terms of the original population, $\sigma_{UV} = \sigma_1^2 - \sigma_2^2$. If the mean squared prediction errors in the original population are equal, then the covariance in the transformed population must be zero. Therefore, if the sample correlation s_{UV} is significantly greater (less) than 0, then σ_1^2 is significantly greater (less) than σ_2^2. However, the approach of Granger and Newbold [7] cannot handle our stock return populations. The assumptions of unbiasedness and normality are clearly violated in the population. Moreover, given that we are working with times-series data, the forecast errors are also likely to be serially correlated. Mizrach [14] relaxed the assumptions of Granger and Newbold [7], extending the approach to allow the forecast error series to be biased, non-normal, serially correlated and heteroskedastic. Mizrach [14] showed that the statistic

$$\sqrt{n}\frac{\frac{1}{n}\sum_{j=1}^{n}U_jV_j}{\left[\sum_{t=-k}^{k}\left(1-\frac{|t|}{k+1}s'_{UVUV}\right)\right]^{\frac{1}{2}}} \qquad (10)$$

where

$$s'_{UVUV}=\begin{cases}\frac{1}{n}\sum_{j=t+1}^{n}U_jV_jU_{j-t}V_{j-t} & for \quad j\geq 0\\ \frac{1}{n}\sum_{j=-t+1}^{n}U_{j+t}V_{j+t}U_jV_j & for \quad j<0\end{cases}$$

$$k=k(K) \quad with \quad \lim_{K\to\infty}\frac{k(K)}{\sqrt{K}}=0$$

is distributed asymptotically $N(0, 1)$ when the order of dependence is known to be k.

We apply the Mizrach's test to three forecasting models above and the results are presented in Table 4. Test statistics with positive value indicates that the forecasting performance of the latter model is superior to that of the former model. We make pairwise comparisons between the models. The test results show that the UNN model provides a forecast improvement over the RW model for almost all indexes (except MI, WW, CO). Forecasting improvements of the UNN model over the RW model, however, are statistically significant for TW and BM only. The MNN model provides a forecast improvement for the RW model across all indexes, and forecasting improvements of the MNN model for the RW model are significant for 11 out of 16 indexes. The MNN model is superior to the UNN model in the forecasting of almost all indexes (except BM), and provides statistical significance for FS, FB, FME, and CO.

Table 4
The MAPE, MSPE, and the test statistics of forecasting performances of three models: 1999/7/1 ~ 1999/12/28

Industry	MAPE			MSPE			Test statistics		
	RW	UNN	MNN	RW	UNN	MNN	RW & UNN	RW & MNN	UNN & MNN
KOSPI	1.957	1.975	1.968	6.138	6.115	6.036	0.2398	0.5607	0.4630
FS	2.797	2.778	2.733	13.31	13.02	12.35	1.2046	**2.5281**	**2.0727**
MI	3.114	3.138	3.123	16.53	16.33	16.12	-0.284	0.6351	0.9130
FB	2.180	2.142	2.113	9.067	8.877	8.619	0.9766	**1.8302**	**1.9875**
TW	1.904	1.788	1.757	5.729	5.176	5.152	**2.9011**	**3.0131**	0.2739
WW	2.455	2.457	2.435	9.171	9.082	8.617	-0.629	0.0638	0.6130
PP	2.255	2.225	2.204	8.443	8.246	8.204	1.3494	**1.9339**	1.0727
CC	2.041	2.003	1.987	6.618	6.487	6.398	0.8917	1.4880	1.2592
NM	1.878	1.862	1.854	5.764	5.562	5.502	1.3404	1.5508	0.2152
BM	2.401	2.336	2.337	9.772	9.232	9.300	**2.2901**	**1.7662**	-1.566
FME	2.389	2.381	2.360	9.287	9.050	8.847	1.3726	**1.7548**	**2.0043**
OM	2.615	2.593	2.561	11.29	11.09	10.98	0.8103	**2.6095**	0.8989
CO	2.393	2.385	2.311	11.08	11.10	10.71	-0.023	**3.7842**	**3.1600**
WT	2.800	2.767	2.752	12.95	12.50	12.36	1.0136	**1.7680**	0.7134
TS	2.922	2.892	2.805	13.86	13.56	13.04	0.8662	**1.8733**	1.0675
FI	2.578	2.567	2.588	11.88	11.78	11.43	0.9965	**1.6682**	1.1475
IN	2.915	2.871	2.909	14.98	14.80	14.23	1.0028	1.4693	1.1461

Note: MAPE and MSPE are reported in levels ($\times 10^{-2}$) and ($\times 10^{-4}$), respectively. All statistics are distributed standard normal in large samples. All bold statistics are significant at the 5% level.

5. Conclusion

This paper compares the out-of-sample stock index returns forecasts of the RW, the UNN, and the MNN models. The forecasts generated by the nonparametric models (UNN, MNN) dominate the RW model. Among the nonparametric models, the forecasts of the MNN model dominate those of the UNN model. This suggests the effectiveness of the multivariate nearest neighbor method as a modeling strategy for stock index returns. We find that the forecasts of the MNN model are superior to those of the RW and the UNN models. This evidence therefore establishes the presence of substantial nonlinear mean predictability in the stock index returns as well as the effectiveness of the MNN method as a modeling strategy for stock index returns.

It is preferable to have a sufficiently long time series so that all areas of the attractor appear several times in the time series. This allows the model to select nearest neighbors from many locations in the time series. When the time series is short, however, the number of vectors in any one area of the attractor may be relatively small. Another problem of the Korean stock market data is that the data suffer some forms of price restrictions. Under these restrictions, the information entered into the market may not affect the price and volume promptly. Further research should try different data set, perhaps based on longer periods with less restrictions.

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