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Investment Index Construction from Information Propagation Based on Transfer Entropy

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Abstract In recent years, the number of individual investors continues to increase in financial markets. However, the large information gap between individual and institutional investors unduly impairs individual investors, which may negatively influence the market. In this study, we propose a new investment index that focuses on the relationships among stocks to help manage the risk of individual investors. The relationships among stocks have often been analyzed by a cross-correlation matrix method. However, such methods are strongly influenced by irregular events, including drawdowns. Therefore, we employed a transfer entropy method to analyze the relationships among stocks. Transfer entropy is a sequence analysis method proposed by Schreiber that is robust for irregular events. First, we applied the partial correlation and transfer entropy methods to test the data and confirm robustness for unexpected events. Next, we generated stock-networks by transfer entropy that represents the relationships among stocks. Finally, we proposed an investment index that is calculated from stock-networks which are generated from transfer entropy. We compared the proposed investment index with long positions and obtained higher performance investment by our proposed method than with a long position.

Keywords Transfer entropy · Investment index · Stock networks

1 Introduction

In recent years, the number of individual investors has increased in financial markets. However, a large information gap exists between individual and institutional investors, unduly impairing individual investors, which may have a bad influence on the market.

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There are especially large information gaps on short-term risks. For example, sudden fluctuations in market consensuses caused by rapid political/economical changes strongly affect short-term price changes. In such cases, to build a profitable position, institutional investors exploit their advantages in information collection, creating information gaps. The gap causes big problems for individual investors.

In this study, we propose a new investment index that focuses on the relationships among stocks to help manage the risk of individual investors. In such situations, individual investors must understand the influences to constructing a portfolio to realize risk management. Thus, technology for understanding the relationships among each stock is required to provide support systems for individual investments. For instance, if the short-term influential spread among securities can be captured, individual investors are helped estimate the risk of holding stocks.

In this study, we propose a method that quantifies the relationships among securities that are difficult to predict qualitatively.

To analyze such relationships among securities, a cross-correlation matrix (Plerou et al. 1999) is often used as a general method. However, it suffers from the following limitations:

1. It is affected by the strong influence of drawdowns;
2. It is unable to consider influence from plural securities;
3. It is required to expand its method to be able to analyze causality.

In this study, we employ Schreiberfs transfer entropy (Schreiber 2000) to detect the relationships among securities. Transfer entropy is a method of time-series analysis that effectively detects causality. It uses discrete values that allow the influence of drawdowns to be ignored. Moreover, because transfer entropy has an additivity when the time-series data have stochastic independence, it can also consider the influence from plural securities. With the above characteristics, we develop a new investment index that considers information propagation among securities by transfer entropy. We also evaluate our proposed index using a virtual transaction simulation.

2 Literatures

2.1 Researches of Influence Propagation Among Securities

Plerou et al. (1999) used the random matrix theory to analyze the cross-correlation matrix in the 1995 stock price data from the market capitalization of the top 1000 companies in 1994 on the NY Stock Exchange. Jung et al. (2009) analyzed the correlation among securities from a network topology that was calculated by minimum spanning trees in the stock market data of Korea, Japan, Canada, the United States, Italy, and the United Kingdom.

However, neither study considered the causality of relationships. The studies only focused on long-term relationships that complicate the analysis of such sudden and unexpected incidents as tumbles or the collapse of bubble economies. Therefore these methods are not effective to support individual investor's daily transactions.

2.2 Researches on Transfer Entropy

Many researches use transfer entropy. Bauer et al. (2007) identified the direction of the propagation of disturbances in chemical processes using transfer entropy. Ver Steeg,Galstyan (2012) analyzed the information propagation among nodes using the simple time-series data of Twitter and concluded that transfer entropy is useful for analyzing social data. Ver Steeg,Galstyan (2012) proposed a model on the features of information sharing and load allocation in a supply chain network with transfer entropy.

It has also been widely applied to financial research. Kantz (2002) identified price information flow from the Dow Jones Industrial Average to the DAX index by analyzing transfer entropy. Kwon and Yang (2008) investigated the strength and the direction of information transfers in the U.S. stock market between the composite stock price index of the stock market and the prices of individual stocks using transfer entropy. Kwon and Yang (2008) investigated the relationship between time series among different stock markets by three different types of methods including transfer entropy.

These researches cover the relationships between index and individual stocks or groups of stocks from the viewpoint of long-term analysis. Therefore, these analyses are not suitable for individual investors who are concerned with abrupt market changes.

In our study, we focus on the relationships among individual stocks to clarify that transfer entropy can effectively analyze short-term information propagation.

3 Information Propagation Analysis

3.1 Transfer Entropy

Transfer entropy is one type of quantity of information, which is an index that quantifies the information propagation between two statistical variables as average quantities. Transfer entropy can analyze the causality of two variables, including the direction of the information propagation, which cannot be detected by mutual information.

Transfer entropy is the amount of uncertainty reduced in future values by knowing the past values of another variable. The uncertainty, which was reduced by its past value, is removed and has asymmetry that mutual information does not have.

Consider two discrete stationary processes: $I and J$. When we calculate the $kandl$ samples, transfer entropy $T_{J \to I}$, which goes from J to I, is shown as follows:

$$T_{J \to I} = \sum_{n} p\left(i_{n+1}, i_n^{(k)}, j_n^{(l)}\right) log \frac{p\left(i_{n+1}|i_n^{(k)}, j_n^{(l)}\right)}{p\left(i_{n+1}|i_n^{(k)}\right)}. \tag{1}$$

Here, i_n, j_n are the discrete variables at time n of I, J. $i_n^{(k)}, j_n^{(l)}$) are transfer source variables that represent $i_{n-(k+1)}, j_{n-(l+1)}$.

Probability $p(i_{n+1}, i_n^{(k)}, j_n^{(l)})$ is a joint probability distribution of $i_{n+1}, i_n^{(k)}, j_n^{(l)}$. Probability $p(i_{n+1}|i_n^{(k)}, j_n^{(l)})$ and $p(i_{n+1}|i_n^{(k)})$ are conditional probability distributions of i_{n+1} in the conditions of $i_n^{(k)}$ and $j_n^{(l)}, i_n^{(k)}$.

Transfer entropy $T_{J \to I}$ explains the amount of influence that information J gives to I. In other words, it quantifies how information j_n decreases the uncertainly of the information of I. Eq. (1) can be rewritten as follows:

$$T_{J \to I} = \sum_n H\left\{i_{n+1}|i_n^{(k)}\right\} - H\left\{i_{n+1}|i_n^{(k)}, j_n^{(l)}\right\}, \tag{2}$$

where

$$H(A|B) = -\Sigma_{A,B} P(A, B) log P(A|B). \tag{3}$$

It is easily understood that transfer entropy has asymmetricity to two discrete variables, $i_n and j_n$. The direction of the information propagation between two variables is observable.

3.2 Signed Transfer Entropy

Since we can easily imagine both positive and negative influences between two stocks, we must identify the signs of such influences.

Let us extend transfer entropy to make it possible to identify the signs of information propagation. We employ stock prices to explain the relationships among securities. We define state symbols S_0, S_+, S_- as states with 0, positive and negative price returns, respectively.

Equation (1) can be described as follows based on Bayes' theorem:

$$\begin{aligned} T_{J \to I} &= \sum_n p\left(i_{n+1}, i_n^{(k)}, j_n^{(l)}\right) log \frac{\frac{p\left(i_{n+1}, i_n^{(k)}, j_n^{(l)}\right)}{p\left(i_n^{(k)}, j_n^{(l)}\right)}}{\frac{p(i_{n+1}, i_n^{(k)})}{p(i_n^{(k)})}} \\ &= \sum_n p\left(i_{n+1}, i_n^{(k)}, j_n^{(l)}\right) log \frac{p\left(i_{n+1}, i_n^{(k)}, j_n^{(l)}\right) p\left(i_{n+1}, i_n^{(k)}\right)}{p\left(i_n^{(k)}, j_n^{(l)}) p(i_n^{(k)}\right)} \\ &= \sum_n p_1 log \frac{p_1 p_3}{p_2 p_4}. \end{aligned} \tag{4}$$

Here, we define p_1^+ when the transferred information has the same signs $(i_{n+1}, j_n) = (S_+, S_+)$ or $(i_{n+1}, j_n) = (S_-, S_-)$

$$\begin{aligned} p_1^+ = &\, p(i_{n+1} = S_+) p(j_n^{(l)} = S_+) p(i_n^{(k)}) \\ &+ p(i_{n+1} = S_-) p(j_n^{(l)} = S_-) p(i_n^{(k)}). \end{aligned} \tag{5}$$

and p_1^- when the transferred information has the opposite signs

$$p_1^- = p(i_{n+1} = S_+)p(j_n^{(l)} = S_-)p(i_n^{(k)}) + p(i_{n+1} = S_-)p(j_n^{(l)} = S_+)p(i_n^{(k)}). \tag{6}$$

Then we define positive transfer entropy $T^+_{J\to I}$ and negative transfer entropy $T^-_{J\to I}$ as follows:

$$T^+_{J\to I} = \sum_n p_1^+ log \frac{p_1^+ p_3}{p_2 p_4} \tag{7}$$

$$T^-_{J\to I} = \sum_n p_1^- log \frac{p_1^- p_3}{p_2 p_4}. \tag{8}$$

Finally, we define signed transfer entropy as follows:

$$T^*_{J\to I} = T^+_{J\to I} - T^-_{J\to I}. \tag{9}$$

With signed transfer entropy, we can capture the positive or negative relationships among stocks.

3.3 Combined Transfer Entropy

Transfer entropy is generally defined to detect relationships among two time-series data. We extend it to calculate the influence from plural time series.

The definition of transfer entropy in Eq. (1) can easily be extended to consider the influence from plural time series A, B as follows:

$$T_{A,B\to I} = \sum_n p\left(i_{n+1}, i_n^{(k)}, a_n^{(l)}, b_n^{(m)}\right) log \frac{p\left(i_{n+1}|i_n^{(k)}, a_n^{(l)}, b_n^{(m)}\right)}{p\left(i_{n+1}|i_n^{(k)}\right)}. \tag{10}$$

However, it requires T^s times computational complexity to calculate the influence from s stocks, where $T = k = l = m$ is the delay time of the influence transfer. It is not realistic to consider plural stocks with Eq. (10). Therefore, the following three time series, $A, B, and I$, are considered:

$$T_{A\to I} + T_{B\to I} = \sum H\left\{i_{n+1}|i_n^{(k)}\right\} + H\left\{i_{n+1}|i_n^{(k)}\right\} - \left[H\left\{i_{n+1}|i_n^{(k)}, a_n^{(l)}\right\} + H\left\{i_{n+1}|i_n^{(k)}, b_n^{(m)}\right\}\right]$$

$$
\begin{aligned}
&= \sum H\{i_{n+1}|i_n^{(k)}\} + H\{i_{n+1}|i_n^{(k)}\} \\
&\quad + H\{i_n^{(k)}, a_n^{(l)}\} + H\{i_n^{(k)}, b_n^{(m)}\} \\
&\quad - \Big[H\{i_{n+1}, i_n^{(k)}, a_n^{(l)}\} + H\{i_{n+1}, i_n^{(k)}, b_n^{(m)}\} \Big]. \qquad (11)
\end{aligned}
$$

The information transfer from time serieses A, B to I occur independently:

$$H\{i_{n+1}, i_n^{(k)}, a_n^{(l)}\} + H\{i_{n+1}, i_n^{(k)}, b_n^{(m)}\} = H\{i_{n+1}, i_n^{(k)}, a_n^{(l)}, b_n^{(m)}\} \qquad (12)$$

$$H\{i_n^{(k)}, a_n^{(l)}\} + H\{i_n^{(k)}, b_n^{(m)}\} = H\{i_n^{(k)}, a_n^{(l)}, b_n^{(m)}\}. \qquad (13)$$

From Eqs. (11, 12, 13), is rewritten:

$$
\begin{aligned}
T_{A\to I} + T_{B\to I} &= \sum H\{i_{n+1}|i_n^{(k)}\} + H\{i_{n+1}|i_n^{(k)}\} \\
&\quad + H\{i_n^{(k)}, a_n^{(l)}, b_n^{(m)}\} - H\{i_{n+1}, i_n^{(k)}, a_n^{(l)}, b_n^{(m)}\} \\
&= H\{i_{n+1}|i_n^{(k)}\} + T_{A,B\to I}. \qquad (14)
\end{aligned}
$$

Therefore, the transfer entropy has the following subadditivity:

$$T_{A,B\to I} \leq T_{A\to I} + T_{B\to I}. \qquad (15)$$

The right side is defined as the combined transfer entropy.

4 Efficiency Validation

4.1 Data

In this section, we validate our proposed method based on transfer entropy that has the ability to capture relationships among stocks. We use the following data to test the efficiency of transfer entropy.

The tick data of stock and exchange markets are used as test data. Tick data are time-series data that contain the details of transactions, such as traded volume, agreed price, and so on.

As test data, we used stock data from the market data of the Tokyo Stock Exchange from January 1, 2006 to September 30, 2012. The data were recorded each second during the trading time without opening and closing sessions. The exchange data are the USD-JPY data from May 1, 2010 to December 24, 2010.

4.2 Sign Detection

We validate the ability of signed transfer entropy to detect the signs of information transfer by artificial data.

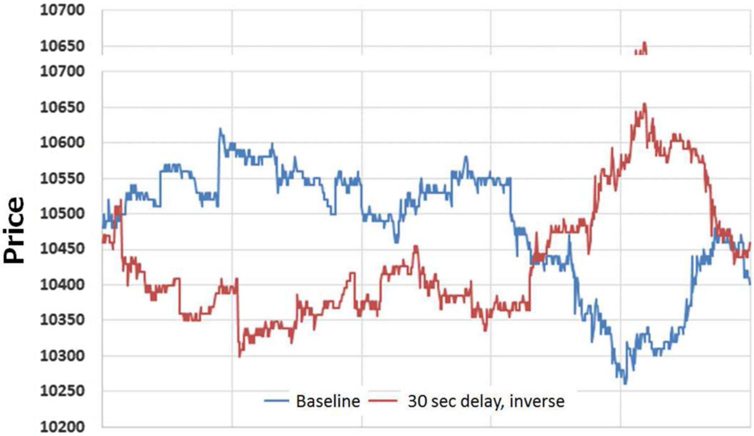

Fig. 1 Test data for sign detection

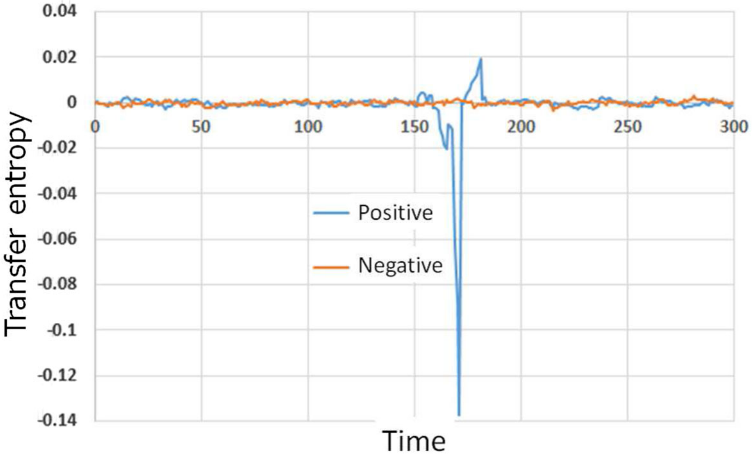

Fig. 2 Result of sign detection

We selected price data as a baseline and created those that move in the inverse direction to the baseline data with a 1–300 s delay. Examples of the baseline and test data are shown in Fig. 1. We calculated the signed transfer entropy from the data. If we can find a negative peak within the defined delay time, we can assume that the signed transfer entropy detects signs.

Figure 2 shows the result of the sign detection test. Only positive transfer entropy $T^{-}_{J\rightarrow I}$ has a negative peak. Signed transfer entropy detected negative peaks in all 1000 trials. Consequently, opposite sign of the information propagation was detected correctly by signed transfer entropy.

4.3 Resistivity to Drawdowns

The partial correlation coefficient is strongly affected by drawdowns. On the other hand, our proposed method is relatively free of influence from drawdowns because

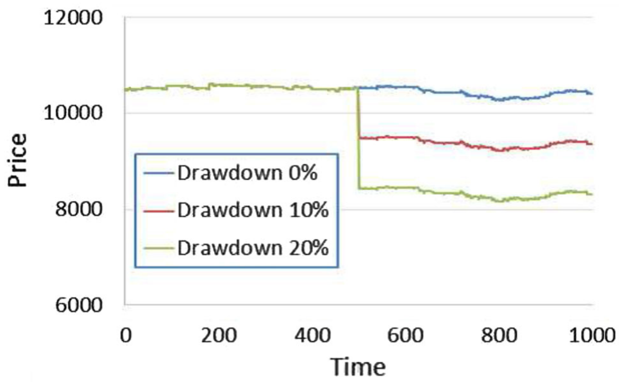

Fig. 3 Test data for drawdown

of discretization processing. Next we analyzed how transfer entropy and the partial correlation coefficient are influenced by drawdowns.

We selected price data as a baseline and created those that move in the same direction to the baseline data with 1–300 s delay and 0–100 % drawdown. Figure 3 shows an example of the baseline and test data with 0, 10, and 20 % drawdown.

As a comparative method, we employed a correlation coefficient with time delays because it is the most basic index to capture relationships between two variables. Also, as shown in Eq. (2), auto correlations were removed from the transfer entropy. Therefore, partial correlation coefficient $C_{J \to I}$ is a correl correlation that removes the influence of autocorrelation as follows (Eq. 16):

$$C_{J \to I} = \frac{R_{I_n J_n^{(l)}} - \left(R_{I_n^{(k)} J_n^{(l)}} R_{I_n^{(k)} I_n} \right)}{\sqrt{1 - R^2_{I_n^{(k)} J_n^{(l)}}} \sqrt{1 - R^2_{I_n^{(k)} I_n}}}, \tag{16}$$

where R_{XY} is the correlation between X and Y.

Figure 4 shows the changes in the size of the peaks that are obtained by transfer entropy and the partial correlation coefficient. There was no change in the size of the peaks calculated by transfer entropy. On the other hand, the size of the peaks became smaller when the drawdown increased. Thus, although the partial correlations are strongly affected by the drawdown, the transfer entropy captured the relationships among stocks.

4.4 Validation by Real Data

Finally, we used real data to validate the transfer entropy.

Foreign exchange rates or commodity significantly affect the price decisions of stock markets (Zong 2009; Zapata et al. 2012). Therefore, we used a well-known relationship among stocks and foreign exchanges to validate transfer entropy.

First, the stocks in the Tokyo Stock Exchange were classified into 28 sectors based on TOPIX Sector Indices. Next, we surveyed the relationships between each sector and

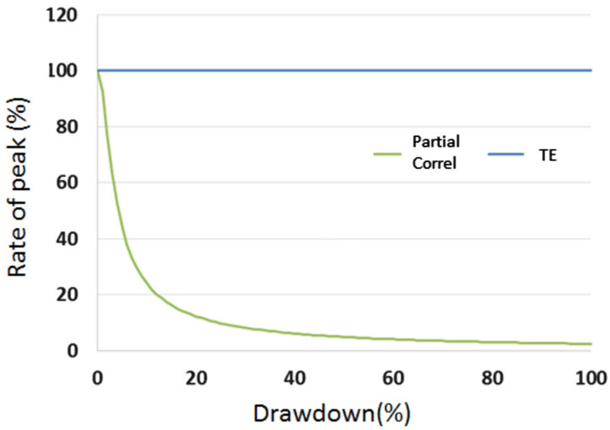

Fig. 4 Result of drawdown tests

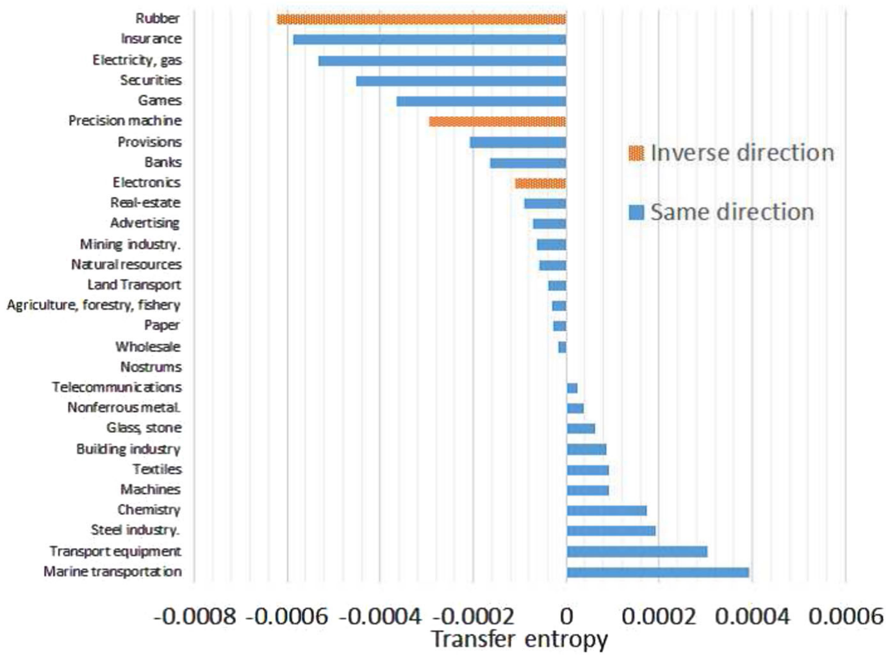

Fig. 5 Relationship between USDJPY and industrial sectors: transfer entropy

the USDJPY exchange from reports by financial institutions (Mizuho Bank Industry Research Division 2014), think tanks (ITOCHU Corporation 2013), and so on. The relationship is defined as positive when a weak yen causes higher stock prices in the sector, and otherwise is negative.

Then we addressed the direction of the influence from the changes in the USDJPY exchange to the stock prices by transfer entropy and the partial correlation coefficient.

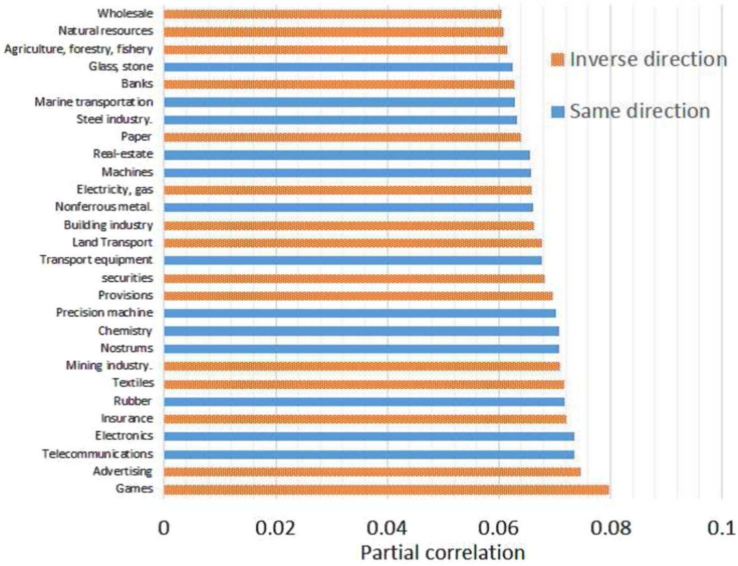

Fig. 6 Relationship between USDJPY and industrial sectors: partial correlation coefficient

The transfer entropy result is shown in Fig. 5; the partial correlation coefficient result is shown in Fig. 6. When the directions by the survey and the analysis method have identical signs, we define them as the same direction and otherwise as the inverse direction.

From the results of the transfer entropy analysis, the signs of 25 sectors agreed with the survey result. On the other hand, the signs of 13 sectors agreed with the partial correlation coefficient.

This indicates that transfer entropy more effectively captures well-known information propagation between exchange and stock markets than partial correlation coefficient.

5 Investment Index Considering Information Propagation Among Stocks

5.1 Investment Method

The purpose of this study is to provide investment information to individual investors. In this section, we propose an investment index, *TE index*, calculated from transfer entropy, and evaluate it by an investment simulation.

An investmentfs decision making is divided into two parts. The first part decides which position to take, long or short, which means buy or sell. The second part decides the volume of the position. In our proposed investment method, two base indexes are developed to separately operate each part.

Investment index $I(t)$ consists of two indexes, $S(t)$ and $V(T)$, which indicate the sign and the volume of the position:

$$I(t) = S(t) \cdot V(t). \tag{17}$$

Sign index $S(t) = \{+1, 0, -1\}$ controls the following position signs: long position, no position, and short position. Volume index $V(t)$ determines the amount of the position that is calculated from the transfer entropy.

Both $S(t)$ and $V(t)$ are calculated from the signed transfer entropy. Here, assume an investment strategy to security i using the information of security j.

First, we define $T_{J \to I}(t)$:

$$T_{J \to I}(t) = \sum_n p\left(i_{n+1}, i_n^{(t)}, j_n^{(t)}\right) log \frac{p\left(i_{n+1}|i_n^{(t)}, j_n^{(t)}\right)}{p\left(i_{n+1}|i_n^{(t)}\right)}. \tag{18}$$

By changing t in the range of $(0 < t \leq \tau)$, we can consider the transfer delay from j to i.

Next, the sign of ten-second returns of stock j is defined as $S_j(t) = \{-1, 0, 1\}$. Then the influence that transferred f to i is defined as

$$T_{J \to I}^{all} = \frac{\sum_{t_d=1}^{T} S_j(t - t_d) \cdot T_{J \to I}(t - t_d)}{\tau}. \tag{19}$$

In this experiment, we employed maximum value $\tau = 300$, which represents five minutes of delay.

Finally, we consider the plural influence of stocks. To decrease the computational complexity, we employ a combined transfer entropy with four stocks with larger transfer entropies. The combined transfer entropy T_c is defined as follows:

$$T_c = \sum_{s=1}^{4} T_{s_j \to I}^{all}, \tag{20}$$

where $s_1 \cdots s_4$ are the top four stocks in descending order of $T_{* \to I}^{all}$.

Now, $S(t)$ and $V(t)$ are calculated from T_c:

$$S(t) = \begin{cases} 1 & T_c > 0 \\ 0 & T_c = 0 \\ -1 & T_c < 0 \end{cases} \tag{21}$$

$$V(t) = \alpha \left\{ 1 + \frac{|T_c - \mu_T|}{\sigma_T} \right\} \quad (0 < V(t) < 2) \tag{22}$$

$$E[V(t)] = 1, \tag{23}$$

where μ_T and σ_T are an average and a standard deviation of the past values of T_c. α is a coefficient to normalize $V(t)$ in the range of $(0, 2)$.

For comparison, we propose *PC index*, which was calculated by partial correlation $C_{* \to i}$, shown in Eq. (16). To calculate the PC index, we rewrite Eqs. (19, 20) as follows:

$$C^{all}_{J\to I} = \frac{\sum_{t_d=1}^{T} S_j(t-t_d)\cdot C_{J\to I}(t-t_d)}{\tau} \tag{24}$$

$$C_c = \sum_{s=1}^{4} C^{all}_{s_J\to I}. \tag{25}$$

Then $S(t)$ and $V(t)$ are calculated using C_c instead of T_c.

5.2 Evaluation Method

To evaluate investments, we used the following four evaluation indexes:

- Win rate
- Max drawdown
- Sharpe ratio
- Total return

Each evaluation index is compared with the standard investment strategy: *Buy and Hold*. In the buy and hold strategy, we assume

$$S(t) = 1 \tag{26}$$

$$V(t) = 1 \tag{27}$$

to decide investments.

5.2.1 Win Rate

The win rate is the rate of positive returns W for all investments:

$$W = \frac{T_p}{T_p + T_n}, \tag{28}$$

where T_p is the number of positive return investments and T_n is the number of negative return investments. The index shows the success rate of the transactions.

5.2.2 Max Drawdown

Max drawdown D is the rate of the drops in a scenario that realizes minimum return:

$$D = \max_{t,t'} \left\{ 1 - \frac{P_{t'}}{P_t} | t < t' \right\}, \tag{29}$$

where P_t, $P_{t'}$ represents a price at time t, t'. This index indicates the investment strategy's risk.

5.2.3 Sharpe Ratio

The sharpe ratio, which indicates the efficiency of the return of investment against the risk, is calculated as follows:

$$S = \frac{R_T}{\sigma}, \tag{30}$$

where σ^2 is a variance estimated by a HAC (Heteroskedasticity and Autocovariance Robust) estimator (Newey and West 1986).

5.2.4 Total Return

Total return is the most basic index to evaluate investment strategy. It is calculated as follows:

$$R = \prod_{k=1} 1 + \left\{ I(t) \cdot (r(t) - 1) \right\}, \tag{31}$$

where $I(t)$ is the investment index at time T and $r(t)$ is the price return of the investment target stock at time t.

5.3 Investment Simulation Result

The signed transfer entropy, which was used to calculate the investment indexes, is discretized every ten seconds. Thus, trades are done every ten seconds. The stocks to trade in the simulation were chosen randomly on random days. This simulation ignores commissions.

We simulated 500 trials to calculate the average evaluation values. The simulation result is shown in Fig. 7.

The win rate, the sharpe ratio, and the total return increased, and the drawdown became smaller than in the buy and hold strategy. This result shows that an investment

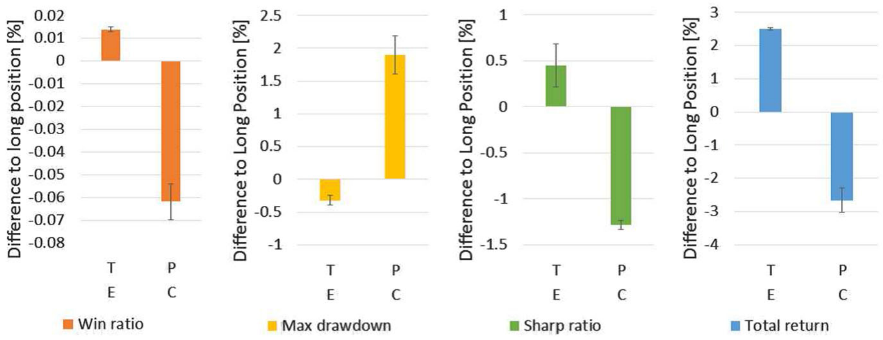

Fig. 7 Result of investment simulation

strategy that uses transfer entropy realizes more efficient investment than the buy and hold strategy. It also realizes fewer risks and higher returns than investments using partial correlation.

6 Conclusion

We proposed an investment index that uses transfer entropy to provide effective information to individual investors.

First, we applied the partial correlation and transfer entropy methods on test data to confirm their robustness for unexpected events. Next, we generated stock-networks by a transfer entropy that represents the relationships among stocks. Finally, we proposed an investment index that is calculated from stock-networks which were generated from transfer entropy. We compared our proposed investment index with long positions and obtained higher performance investment with our proposed method than with the buy and hold strategy.

Our study showed the effectiveness of our proposed strategy. However, it is impossible for individual investors to change their positions every ten seconds, as we proposed in the strategy. Therefore, we must propose a more realistic investment strategy using transfer entropy.

We also employed combined transfer entropy to consider plural influences. However, since combined transfer entropy is a simplified method, its accuracy might not be satisfactory. We must propose a more accurate method to calculate plural influences.

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