2016 International Symposium on Nonlinear Theory and Its Applications,
NOLTA2016, Yugawara, Japan, November 27th-30th, 2016

# Technical Trading Strategy Using Reactions to Stock Price Jumps 

Tokimaru Tsuruta and Tomoya Suzuki<br>Graduate School of Science and Engineering, Ibaraki University<br>4-12-1, Nakanarusawa-cho, Hitachi-shi, Ibaraki, Japan<br>Email: \{16nm929h, tomoya.suzuki.lab\}@vc.ibaraki.ac.jp


#### Abstract

As a technical indicator, the BPV ratio has been proposed to dynamically detect market price jumps. In the present study, we first confirmed the existence of an anomaly in Japanese and American stock markets where stock price movements are often biased to react on price jumps. Next, we applied this anomaly to decide the dealing position (long or short) by foreseeing this biased reaction of a price movement. Finally, we confirmed the efficiency of this trading strategy through some investment simulations, and also confirmed the validity of the decided dealing positions and their timings by bootstrap statistical tests.


## 1. Introduction

In financial markets, dealing prices sometimes jump suddenly due to significant news such as natural, political, or financial accidents. According to behavioral economics, market jumps are sometimes caused by overreaction of traders to new information. If so, the following prices might be reversed to the appropriate price by the efficiency of market. To detect these jumps, some techniques [1, 2] have been proposed, and, as one of them, the BPV ratio[3] was proposed as a technical indicator to decide the investment timing. Moreover, our previous study[4] found out that the significant reaction happens right after a market jump detected by the BPV ratio[3], and then showed the validity of the investment strategy applying this significant reaction. However, its validity has been confirmed only in the Japanese stock market. For this reason, in the present study, we investigate the generality of the given results by analyzing real stocks listed on the Japanese Stock Exchange and the American Stock Exchange.

In Sec.3, we analyze 617 Japanese stocks and 1232 American stocks to confirm whether both markets have the anomaly that unnatural reactions happen right after the market jump. Next, as an application of this biased reaction, in Sec.4, we discuss some technical trading strategies based on the market jumps detected by the BPV ratio, and confirm its efficiency through some investment simulations. Finally, in Sec.5, we also perform the statistical significance test to examine the validity of the dealing positions and their timings decided by our trading strategy, comparing to its randomized strategies. In particular, this statistical test is considered quite important to prove the validity of technical analysis, and this approach has been known as the evidence-based technical analysis[5]. Until
now, both positive and negative results have been shown in many previous studies[6], and therefore this topic is very controversial and important in the field of quantitative economics.

## 2. BPV ratio

This section introduces the technical indicator proposed in Ref.[3], which uses the ratio of the realized volatility (RV) and the bipower variation (BPV). First, let us denote the stock price at the time of $t$ as $s(t)$, and then its return rate $r(t)$ can be defined by

$$
\begin{equation*}
r(t)=\log \frac{s(t)}{s(t-1)} \tag{1}
\end{equation*}
$$

Then, the $\mathrm{RV} v(t)$ is defined by

$$
\begin{equation*}
v(t)=\frac{1}{N} \sum_{a=1}^{N} r^{2}(t-a+1) \tag{2}
\end{equation*}
$$

and the $\mathrm{BPV} b(t)$ is defined by

$$
\begin{equation*}
b(t)=\frac{1}{N-1} \sum_{a=1}^{N-1}|r(t-a+1)||r(t-a)| \tag{3}
\end{equation*}
$$

where $N$ is the temporal period of the latest historical data, and we set $N=10$ in the present study. This BPV was proposed by Ref.[1] as a new volatility to detect market jumps, and is composed by two absolute values of temporally adjacent return rates. Therefore, the BPV is less sensitive to large price movements, i.e., market jumps than the RV. Namely, if a market jump occurs, their ratio $b(t) / v(t)$ becomes smaller. On the other hand, if $r(t)$ has no jumps or no specific trends during the latest temporal period, that is, $r(t)$ obeys the normal stochastic process, the ratio $b(t) / v(t)$ converges into $2 / \pi$ under the condition of $N \rightarrow \infty$ [1].

For this reason, Ref.[3] proposed the BPV ratio $c(t)$ so as to converge into one under the condition:

$$
\begin{equation*}
c(t)=\frac{\pi}{2} \times \frac{b(t)}{v(t)}, \quad \text { where } \lim _{N \rightarrow \infty} c(t)=1 \tag{4}
\end{equation*}
$$

However, because $N$ is a finite value in actual trading, the convergence value is not exactly equal to one. As a solution, we compose the distribution of the latest $c(t-i)$, $i=0 \sim I-1$, and calculate its mean value $m(t)$ and standard
deviation $\sigma(t)$. If $c(t-1)>m(t-1)$ and $c(t)<m(t)-k \cdot \sigma(t)$, we consider that a market jump happens at the time $t$ because $c(t)$ becomes smaller than the average level $m(t)$. Here, we set $k=1$ and $I=120$ as the same as Ref.[4].

## 3. Biased Reactions to Market Jumps

According to behavioral economics, market jumps are sometimes caused by overreaction of traders to new information. If so, the following prices might be reversed to the appropriate price. To confirm this possibility, we analyzed 617 Japanese stocks and 1232 American stocks in 20002006.

We classified market jumps into two types: the daytime jump and the nighttime jump. The daytime jump means the jump from the opening price to the closing price in the same day, and its reaction is observed at the next opening price. Similarly, the nighttime jump means the jump from the closing price to the opening price, and its reaction is observed until the next closing price. In addition, we classified market jumps into two types: rising jump and falling jump. To detect jumps, we used the BPV ratio.

Table 1 shows the results. We can see that the reversal behavior tends to be happened right after a market jump occurs especially at nighttime. This tendency is almost the same in both the Japanese market and the American market. It might be caused by the over-reaction of traders and its modification into the appropriate price. During the nighttime, because markets are closed, any traders cannot make a deal even if important news happens. In this case, new orders are reserved at night, and all of them are concentratedly dealt with at the next opening time. This over-reaction to news causes an excessive nighttime jump. However, due to the efficiency of the market, this nighttime jump is immediately modified into the proper level. This modification might be a reason why the reversal reaction to the nighttime jump is most clearly shown in Table 1.

## 4. Technical Trading Strategy with Biased Reactions

As shown in Sec.3, because the stock price tends to move reversely to market jumps (especially to the nighttime jump), we apply this biased reaction to a technical trading strategy. In this section, we prepare the following four strategies for comparison.
(A) We take a short (sell) position at $t$ if $c(t)$ indicates a daytime rising jump.
(B) We take a long (buy) position at $t$ if $c(t)$ indicates a daytime falling jump.
(C) We take a short position at $t$ if $c(t)$ indicates a nighttime rising jump.
(D) We take a long position at $t$ if $c(t)$ indicates a nighttime falling jump.

Table 1: Reaction of the price movement right after a rising or falling jump based on (a) 617 Japanese stocks and (b) 1232 American stocks. Each market jump was observed during the daytime or the nighttime. Bold figure means more than $50 \%$ in each category.
(a) Japanese stocks

|  | Daytime |  | Nighttime |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Rising | Falling | Rising | Falling |
| Follow | $44.3 \%$ | $34.9 \%$ | $35.6 \%$ | $34.2 \%$ |
| Do not move | $15.2 \%$ | $15.7 \%$ | $6.6 \%$ | $7.7 \%$ |
| Reverse | $40.5 \%$ | $49.5 \%$ | $\mathbf{5 7 . 7 \%}$ | $\mathbf{5 8 . 1 \%}$ |

(b) American stocks

|  | Daytime |  | Nighttime |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Rising | Falling | Rising | Falling |
| Follow | $39.5 \%$ | $37.9 \%$ | $43.1 \%$ | $39.1 \%$ |
| Do not move | $17.4 \%$ | $15.4 \%$ | $5.3 \%$ | $5.0 \%$ |
| Reverse | $43.2 \%$ | $46.7 \%$ | $\mathbf{5 1 . 6 \%}$ | $\mathbf{5 5 . 9 \%}$ |

In our strategies (A)-(D), we immediately close the position at the next time $t+1$. According to Table 1, we consider that the strategies (C) and (D) will work well.

Next, as another idea to obtain many trading opportunities, we invest all of the stocks where $c(t)$ indicates a price jump in each time $t$. For example, if price jumps are recognized in three stocks at the same time, we invest these three stocks by the same allocation rate, which is called the dynamically-allocated investment in this study.

To compare the trading performance of four trading strategies (A)-(D), we perform investment simulations using the same kind of stocks analyzed in Sec.3. However, because Sec. 3 used the stock data during 2000-2006 to discover the biased reactions, another period should be used for the invest simulation as out-of-sample data. Therefore, we use the following new stock data during 2007-2013 for the invest simulation.

The result is shown in Table 2 and Figure 1. Here, $F$ is the number of days when any trade was executed by the BPV's signal, and these days are denoted as $t^{*}$. Then, $R$ is the total return rate [\%] during the investment period, and $\bar{R}$ is the average return rate [\%] per day, that is, $\bar{R}=R / F$. Moreover, the winning percentage $W$ [\%] , the payoff ratio $\phi$, and the profit factor $\psi$ are calculated by

$$
\begin{align*}
W & =\frac{\left|\left\{t^{*} \mid r\left(t^{*}+1\right)>0\right\}\right|}{\left|\left\{t^{*} \mid r\left(t^{*}+1\right) \neq 0\right\}\right|},  \tag{5}\\
\phi & =\frac{\left\langle\left\{R\left(t^{*}+1\right) \mid R\left(t^{*}+1\right)>0\right\}\right\rangle}{\left\langle\left\{R\left(t^{*}+1\right) \mid R\left(t^{*}+1\right)<0\right\}\right\rangle},  \tag{6}\\
\psi & =\frac{\sum\left\{R\left(t^{*}+1\right) \mid R\left(t^{*}+1\right)>0\right\}}{\sum\left\{R\left(t^{*}+1\right) \mid R\left(t^{*}+1\right)<0\right\}}=\phi \cdot \frac{W}{1-W}, \tag{7}
\end{align*}
$$

where $r\left(t^{*}+1\right)$ is the return of the stock invested at $t^{*}$, and $R\left(t^{*}+1\right)$ is our return obtained by closing the position at $t^{*}+1$. Then, $\{\cdot\}$ means a set, and its number, its average,

Table 2: Investment performance by the strategies (A)-(D) to 617 Japanese stocks and 1232 American stocks. Bold figure means the best score in each category.

|  | Japanese stocks |  |  |  | American stocks |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $(\mathrm{A})$ | $(\mathrm{B})$ | $(\mathrm{C})$ | (D) | (A) | $(\mathrm{B})$ | $(\mathrm{C})$ | $(\mathrm{D})$ |
| $F$ | 1367 | 1272 | 1184 | 1034 | 1587 | 1563 | 1525 | 1559 |
| $R[\%]$ | -19.4 | 181 | $\mathbf{3 3 5}$ | 330 | 34.4 | 198 | 772 | $\mathbf{9 4 4}$ |
| $\bar{R}[\%]$ | -0.01 | 0.14 | 0.28 | $\mathbf{0 . 3 2}$ | 0.02 | 0.13 | 0.51 | $\mathbf{0 . 6 1}$ |
| $W[\%]$ | 45.9 | 56.9 | 58.6 | $\mathbf{5 9 . 9}$ | 51.3 | $\mathbf{5 6 . 3}$ | 55.1 | $\mathbf{5 6 . 3}$ |
| $\phi$ | 1.02 | 0.99 | 1.03 | $\mathbf{1 . 1 4}$ | 0.92 | 1.10 | 1.36 | $\mathbf{1 . 5 2}$ |
| $\psi$ | 0.97 | 1.37 | 1.47 | $\mathbf{1 . 6 4}$ | 0.72 | 1.47 | 2.02 | $\mathbf{2 . 1 9}$ |
| $M[\%]$ | 59.1 | 19.2 | 12.4 | $\mathbf{1 2 . 0}$ | 62.8 | $\mathbf{8 . 3 2}$ | 9.90 | 9.59 |



Figure 1: Temporal change of the asset growth rate by the strategies (A)-(D).
and its sum are respectively denoted as $|\{\cdot\}|,\langle\{\cdot\}\rangle$, and $\sum\{\cdot\}$. In addition, we calculate the maximum drawdown rate $M$, which is the maximum rate of the cumulative losses since the previous largest profit. As expected in Table 1, the strategies (C) and (D) show better investment performance in both markets. Therefore, the biased reactions especially to the nighttime jump are useful to compose technical trading strategies.

## 5. Statistical Significance Tests for Evidence-based Technical Analysis

Although we could confirm that our strategies, especially (C) and (D), are profitable by using the biased reactions to market jumps, we next confirm their validities by the statistical significance test from the following viewpoints: the investment position of long/short and the investment timing.

### 5.1. Validity of Investment Positions

First, we investigate whether each trading strategy can take long/short positions properly in the dynamicallyallocated investment. For this propose, we randomly shuffle all of the original positions, but keeping each trading timing $t^{*}$, and then we evaluate the trading performance by
the same measures as Sec.4. For example, if we use $R$ as a measure, we calculate $R_{r}(r=1 \sim 10,000)$ for 10,000 randomized strategies shown in Fig.2. Then, we compare them with $R$ given by the original strategy in the statistical significance test. This method is a sort of nonparametric bootstrap tests.

However, by randomly shuffling the trading positions, the number of each position decided by the randomized strategies becomes different from that for the original strategy. This difference gives either advantage or disadvantage to the randomized strategies. Therefore, we have to modify each investment performance given by the $r$ th randomized strategy. For example,

$$
\begin{align*}
R_{r} & \leftarrow R_{r}+\alpha  \tag{8}\\
\alpha & =\sum_{i=1}^{I} \alpha_{i},  \tag{9}\\
\alpha_{i} & =\left(L_{o, i}-L_{r, i}\right) \cdot \bar{r}_{i}-\left(S_{o, i}-S_{r, i}\right) \cdot \bar{r}_{i} \tag{10}
\end{align*}
$$

where $\bar{r}_{i}$ is the average return rate of the $i$ th stock during the investment period, and $I$ is the total number of stocks (i.e., $i=1 \sim I$ ). Then, $L_{o, i}$ and $S_{o, i}$ are the numbers of taking long and short positions of the $i$ th stock by the original strategy, and $L_{r, i}$ and $S_{r, i}$ are those by its $r$ th randomized strategy. Similarly,

$$
\begin{align*}
\bar{R}_{r} & \leftarrow \frac{1}{F}\left[R_{r}+\alpha\right]  \tag{11}\\
W_{r} & \leftarrow W_{r}+\frac{1}{F} \sum_{i=1}^{I} \beta_{i},  \tag{12}\\
\beta_{i} & =\left(L_{o, i}-L_{r, i}\right) \cdot w_{i}-\left(S_{o, i}-S_{r, i}\right) \cdot w_{i}  \tag{13}\\
w_{i} & =\frac{\left|\left\{t^{*} \mid r_{i}\left(t^{*}+1\right)>0\right\}\right|-\left|\left\{t^{*} \mid r_{i}\left(t^{*}+1\right)<0\right\}\right|}{\left|\left\{t^{*} \mid r_{i}\left(t^{*}+1\right) \neq 0\right\}\right|}  \tag{14}\\
\psi_{r} & \leftarrow \phi_{r} \cdot \frac{W_{r}}{1-W_{r}} \tag{15}
\end{align*}
$$

where Eq. (15) is modified by using $W_{r}$ given in Eq. (12), but $\phi_{r}$ does not need any modification because it is calculated only by the average values in Eq. (6), and therefore the numbers of long and short positions are not essential. Then, it is so hard to modify $M$ that the maximum draw down is not used in this test.

By comparing the trading performance given by the original strategy to those given by its random strategy, we can evaluate the $p$-value, that is, the percentage that the random strategies can win against the original strategy. If the $p$-value is less than $5 \%$, we can conclude that the original strategy is statistically valid. Table 3 shows each $p$-value given by the same measure as Table 2. As a result, we can confirm the validity of our strategies (C) and (D) very clearly in terms of almost all measures.

### 5.2. Validity of Investment Timings

Next, we investigate whether each strategy can decide investment timings properly in the dynamically-allocated

| The original Strategy |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Time $t$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| $R$ |  | L | L |  | L | L |  | L |  | L |

Its randomized strategies

| $R_{1}$ |  | S | L |  | L | S | L | L | S |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $R_{2}$ |  | S | L |  | L | L |  | S |  | L |
| $\vdots$ |  |  |  |  |  |  |  |  |  |  |
| $R_{10000}$ |  | L | L |  | S | S |  | L |  | S |

Figure 2: Example of randomized strategies where the original investment positions (long or short) were randomly shuffled. Here, "L" means a long position and "S" means a short position.

Table 3: The $p$-value to confirm the validity of investment positions (long or short), where the original strategies (A)(D) were compared to their randomized strategies. Bold figure means the $p$-value is less than the significance level of $5 \%$.

|  | Japanese stocks |  |  |  | American stocks |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (A) | (B) | (C) | (D) | (A) | (B) | (C) | (D) |
| R | 62.2\% | 0.00\% | 0.00\% | 0.00\% | 40.7\% | 0.00\% | 0.00 | 0.00\% |
| $\bar{R}$ | 66.2\% | 0.00\% | 0.00\% | 0.00\% | 40.7\% | 0.00\% | 0.00\% | 0.00\% |
| W | 99.9\% | 0.00\% | 0.00\% | 0.00\% | 0.00\% | 0.00 | 0.00\% | 0.00\% |
| $\phi$ | 43.5\% | 56.7\% | 37.4\% | 2.71\% | 57.3\% | 14.2\% | 0.00 | 0.00\% |
| $\psi$ | 34.1\% | 0.18\% | 0.00\% | 0.00\% | 28.8\% | 0.02\% | 0.00 | 0.00\% |


| The original strategy |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Time $t$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| $R$ |  | L | L |  | L | L |  | L |  | L |

Its randomized strategies

| $R_{1}$ | L | L |  | L |  | L | L |  |  | L |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $R_{2}$ | L |  | L |  | L | L |  | L | L |  |
| $\vdots$ |  |  |  |  |  |  |  |  |  |  |
| $R_{10000}$ |  | L |  |  | L | L | L |  | L | L |

Figure 3: The same as Fig.2, but the original investment timings were randomly shuffled. In this case, the modifications of Eqs.(8)-(15) are unnecessary because the number of investment positions does not change from the original strategy.

Table 4: The same as Table 3, but shows the validity of investment timings.

|  | Japanese stocks |  |  | American stocks |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (A) | (B) | (C) | (D) | (A) | (B) | (C) | (D) |
| $R$ | $\mathbf{0 . 5 6} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 5} \%$ | $\mathbf{2 . 1 1} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ |
| $\bar{R}$ | $\mathbf{0 . 7 7} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 5} \%$ | $\mathbf{1 . 6 2} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ |
| $W$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ |
| $\phi$ | $74.7 \%$ | $17.7 \%$ | $18.8 \%$ | $\mathbf{0 . 5 1} \%$ | $91.5 \%$ | $8.09 \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ |
| $\psi$ | $\mathbf{0 . 5 7 \%}$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 5} \%$ | $\mathbf{1 . 0 9} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ |
| $M$ | $\mathbf{2 . 7 0} \%$ | $\mathbf{0 . 2 2} \%$ | $\mathbf{0 . 6 9} \%$ | $\mathbf{0 . 0 0} \%$ | $75.0 \%$ | $\mathbf{0 . 0 4} \%$ | $\mathbf{0 . 0 0} \%$ | $\mathbf{0 . 0 0} \%$ |

more detail, we performed the statistical significance tests by comparing it to its randomized strategies. As a result, we could confirm the validity in terms of the investment positions (long or shot) and their investment timings. These results are general in financial markets because these were confirmed in two major markets.

This research was partially supported by JSPS KAKENHI Grant Number 16K00320.

## References

[1] O. E. Barndorff-Nielsen and N. Shephard: Journal of Financial Econometrics 2(1), 1, 2004.
[2] S. S. Lee and P. A. Mykland: Review of Financial Studies 21(6), 2535, 2008.
[3] M. Yamada and T. Suzuki: Technical Analysts Journal 1, 1, 2014.
[4] H. Koizumi and T. Suzuki: Technical Analysts Journal 2, 1, 2015.
[5] D. Aronson: Evidence-Based Technical Analysis, Wiley, 2006.
[6] C. H. Park and S. H. Irwin: Journal of Economic Surveys 21(4), 786, 2007.

