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Assessing the Profitability of Timely Opening Range Breakout on Index Futures Markets

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ABSTRACT This paper presents a timely open range breakout (TORB) strategies for index futures market trading via using one-minute intraday data. We observe that the trading volumes and fluctuations in returns on each one-minute interval of trading hours in the futures markets reach their peaks at the opening and closing of the underlying stock markets. With these observations, we align the active hours of an index futures market with its underlying stock market and test the proposed TORB strategies on the DJIA, S&P 500, NASDAQ, HSI, and TAIEX index futures from 2003 to 2013. In the experiments, the proposed strategy achieves over 8% annual returns with p-values less than 3% in all of the five markets; the best performance, 20.28% annual returns at a p-value of 3.1×10^{-5}%, is reached in the TAIEX. For each market, we also find the best probing time, which is relatively short in the U.S. market and relatively long in Asian markets. Furthermore, we conduct experiments on a TAIEX futures transaction dataset to analyze the relationship between the TORB signals and trader behavior, and find that the TORB signals are in the same direction as institutional traders, especially foreign investment institutions.

INDEX TERMS Index futures, open range breakout, technical analysis, traders' behavior, trading strategy.

I. INTRODUCTION

With the development of information technology, a considerable amount of data has been generated and thus can be utilized to produce useful information and insights to better solve various problems in many fields including finance, social science, and environmental science [1]. Data science provides a scientific way to capture and verify the information behind the data, which promotes productivity, improves efficiency, and supports innovation [2]. In the filed of finance, many studies, including research related to trading, credit rating, and fraud detection, have been done through various data analytic techniques [3], among which backtesting on historical data is a common approach to calculate the profitability of a trading system and is used to find profitable strategies [4].

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In this paper, we propose several TORB (timely open range breakout) strategies for index futures market trading which are profitable in recent years, in which we use one-minute transaction data in more than ten years to assess the profitability of the proposed strategies. The parameters for the TORB strategies are selected based on the following three observations. First, trading volumes and fluctuations in returns on each one-minute interval during trading hours on the futures markets reach their peaks at the opening of the underlying stock markets. Thus, we provide two market fluctuation measurements for each one-minute interval during the trading hours: the per-minute mean volume, denoted by **PMMV** and the per-minute variance of return, denoted by **PMVR**. These two measurements are used to define a time period with high volumes and large fluctuations as active hours; we observe that a futures market's active hours are the same as the opening hours of the underlying stock market. Second, stock market fluctuations are influenced by events occurring during and after the market. Although the markets do not respond in real time to events occurring after the market, it seems that the market picks up the information in the early stage of market opening, and impacts market dynamics on the same day. Finally, the higher frequency data contains more information for technical analysis [5], which means that using higher frequency data may improve the performance of a technical trading strategy. Based on these three observations, the following hypothesis is proposed. The dynamic of prices in the early stage of market opening reveals more information in a trading day; therefore, it is profitable by using the information in the one-minute movements in prices during this period to forecast the price for the rest time on the same day.

To test this hypothesis, we set up the TORB strategy parameters using the information picked up by the market in the early stage of market opening and then conduct profitability tests on the Dow Jones Industrial Average Index (DJIA), Standard & Poor's 500 (S&P 500), NASDAQ, Hang Seng Index (HSI), and Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) index futures markets from 2003 to 2013. The experimental results show that the TORB strategy in each market achieves over 8% annual return with a p-value of less than 3% of t-test with transaction costs, significantly rejecting the null hypothesis that the return from TORB strategies equals zero; additionally, the best performance in our experiments reaches a 20.28% annual return in the TAIEX with p-value equal to $1 \times 10^{-4}\%$. Furthermore, experiments in sub-periods from 2003 to 2007 and from 2007 to 2013 are conducted to demonstrate that the performance of TORB strategies does not change before or after the financial crisis.

Moreover, the experiments indicate that the TORB strategies perform better than the TRB strategies defined in [6]. While TRB and TORB strategies share the same concept, TRB strategies set up the parameters by using daily data. The results show that there are no significant results (p-value less than 5%) in a profitability test of TRB strategies on the DJIA, S&P 500, HSI, and TAIEX futures indexes in the full time period. The only exception is the NASDAQ index future, which earns significant profits using TRB strategies; however, there are no significant results in the two sub-period tests. Overall, the annual returns from the best TRB strategies are smaller than the annual returns from TORB strategies in all of the five futures markets tested in the experiments. Our experimental results are consistent with the findings in [5], which states that higher frequency data contains more information for technical analysis.

In addition to attesting the profitability of the TORB strategies, we also investigate the relationship between TORB signals and the behavior of informed traders. Generally speaking, informed traders are those who can predict market returns using private information. Previous literature has investigated what kind of traders are informed traders, e.g., [7]–[11]. In 2014, Hendershott *et al.* [11] show that institutional traders are informed by investigating the net buy positions of institutions from 2003 to 2005 for NYSE-listed stocks with all news announcements from Reuters. They find that institutions' net buy positions increases (decreases) more than five days prior to the announcement of good (bad) news, as measured by the sentiment of the news. This implies that institutions tend to trade in the same direction more than five days before the news breaks. Additionally, Chang *et al.* [9] use data from Taiwan to show that institutional traders are informed, and also find that foreign institutional investors have greater predictive power than other kinds of institutional traders. Tsai *et al.* [12] present the persistent behavior hypothesis for financial markets, which is tested statistically on five stock indices from 2001 to 2014; they also study the impact of investor behavior over market price of TAIEX futures. In the experiments, we use a unique one-minute transaction data set from the TAIEX futures market to investigate the relationship between TORB signals and the net buy positions of different kinds of traders. It is worth mentioning that the signals from the best TORB strategy are positively related to the net buy positions of institutional traders before and after breakout, meaning that TORB signals catch the trading direction of institutional traders, which is positively related to the market return; the inverse results are found for individual traders.

The rest of the paper is organized as follows. Section II presents the related work, and Section III presents the parameter settings for the proposed TORB strategies. Empirical data and experimental results are introduced and discussed in Section IV. Section V concludes the paper.

II. LITERATURE REVIEW

Technical analysis is one of the most popular methods for developing trading strategies [13]. In contrast to fundamental analysis, which uses macroeconomics and corporate information regarding assets including earnings per share (EPS), sales margins, dividend yields and other information, technical analysis forecasts the future movement of prices using present and past prices. For instance, in 2009, Schulmeister [5] investigates how technical trading systems exploit momentum and reversal effects in the S&P 500 spot and futures markets and finds that technical trading systems using 30-minute-price information perform better than those using lower-frequency information. In 2018, Alhashel and Hansz [14] apply various popular technical trading rules to Asian property market indices to investigate the profitability of these rules and find that technical indicators are predictive in some markets and thus can generate returns that exceed the buy-and-hold strategy.

The profitability of technical analysis strategies has been studied extensively. In 1992, Brock *et al.* [6] test two of the most popular trading rules – the moving average (MA) and trading range break (TRB) – using 90 years of Dow Jones Index data and find significant results in profitability tests with both standard statistical analysis and bootstrap techniques. In 2009, Zhu and Zhou [15] modify the MA trading rule to adjust asset allocation. In the same year, Neely *et al.* [16] use previously studied trading rules, such as

MA, to test the inter-temporal stability of excess returns in the foreign exchange market and find positive excess returns from MA during the 1970s and 1980s, though the profit opportunities disappeared in the early 1990s. They conclude that this outcome is consistent with the adaptive markets hypothesis [17]. In 2010, Szakmary *et al.* [18] investigate commodity futures markets using a monthly dataset spanning 48 years and 28 markets; the results show that trend-following trading strategies yield positive mean excess returns net of transactions costs in at least 22 out of the 28 markets. In 2018, Ahmad *et al.* [19] test the applicability of moving average (MA) investment timing strategy on individual stocks and portfolios, and they find MA strategy substantially beats the buy-and-hold strategy by yielding higher average returns and Sharpe ratios, lower standard deviations, and much success ratios across portfolios.

Open range breakout (ORB) [20] is a common technical trading strategy based on momentum effects. A trader sets a predetermined threshold of upper and lower bounds to denote the open range, and the trading strategy is to long (or short) a position as the market price moves beyond the upper (or lower) bound. Several ORB variants have been discussed in recent studies (see [21]–[23]). In 2010, Cekirdekci studies various trading strategies based on 30-minute open range breakouts, and demonstrates profitability by back-testing on 250 stocks from various industry groups between 2005 and 2010 [21]. Two ORB variants based on average true range and volatility breakout are considered in [22], which provides the evidence for the ORB strategy profitability in the Bucharest Exchange Trade index. Chang *et al.* show the ORB strategy profitability based on a normally distributed return on the day the open range is broken; their result shows the characteristics of an increased success rate in a fair game [23]. However, it has been shown in the literature that the performance of technical analysis has been deteriorating in recent years (see [5], [16], [21], [24]). For the ORB trading strategy, Borda *et al.* in 2010 state that 22 stocks perform well with ORB from 2005 to 2010 in U.S. markets; but these 22 stocks are from 250 stocks of their test, which means most of the stocks are unprofitable [21]. Moreover, their strategies are limited to stock trading and cannot be used in derivatives trading. In 2017, Lundström *et al.* [25] study the returns of ORB across volatility states for long time series data of crude oil and S&P 500 future contracts, and their results indicate that the average ORB return increases with the volatility of the underlying asset.

III. METHODOLOGY

In this section, we describe the mechanism to set the parameters of TORB strategies in futures markets. Section III-A defines the two variables **PMMV** and **PMVR** which are used to identify active hours for futures market trading. In Section III-B, we describe the trading rules of the proposed TORB strategies.

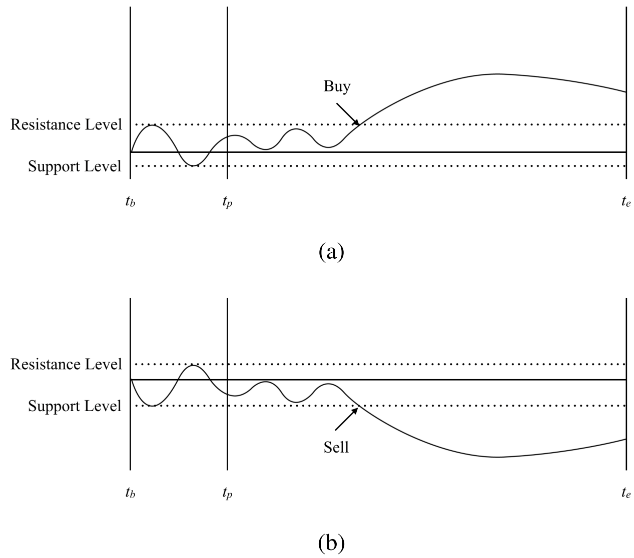

FIGURE 1. **The (a) long (buy) and (b) short (sell) positions in TORB. The curve denotes the futures price; t_b and t_e denote the beginning and the ending of the observed period, respectively; t_p denotes the end of the observed period and is an independent variable in our experiments. The resistance/support levels are the highest/lowest prices of the duration $[t_b, t_p]$, and the time of entering the market is the time that the price crosses over the resistance level. (a) Long (buy) position.**

A. DEFINITIONS OF PMMV AND PMVR

We first define the two variables **PMMV** and **PMVR** that measure the fluctuations of futures markets. Let $V_{t,d}$ be the trading volume in the one-minute interval t on day d, where $t_0 < t < T$ and t_0 and T are the open and the close times of the futures markets, respectively. **PMMV** is defined as

$$PMMV_t = \frac{\sum_{d=1}^{N} V_{t,d}}{N}, \tag{1}$$

where N is the total number of trading days. Let $P_{t,d}$ be the close price in the one-minute interval t on day d. Thus, the one-minute return is denoted as

$$r_{t,d} = \log(P_{t,d}) - \log(P_{t-1,d}).$$

PMVR is defined as

$$PMVR_t = Var(r_{t,d}). \tag{2}$$

The above two measures in Equations (1) and (2) are used to identify active hours for futures market trading.

B. TORB TRADING RULES

The TORB trading signals are illustrated in Figure 1 and described as follows: We set the resistance (support) levels as the highest (lowest) prices for a predetermined period termed the observed period. The trading signal is revealed once the price exceeds the upper bound or falls below the lower bound. We consider two cases:

1) If the price moves above the resistance level, then the buying strength is greater than the selling pressure, and the price will continue to move up with this trend.

TABLE 1. E-mini DJIA daily returns.

Return	Full samples	Sub-period (03–07)	Sub-period (07–13)
Number of observations	2693	978	1714
Mean	0.0002	0.0004	0.0001
SD	0.012	0.008	0.013
Skewness	−0.030	−0.040	−0.013
Kurtosis	12.745	4.766	11.207
Serial correlations			
$\rho(1)$	-0.109^{***}	−0.049	-0.123^{***}
$\rho(2)$	−0.029	−0.013	−0.030
$\rho(3)$	0.047^{**}	0.037	0.046^{**}
$\rho(4)$	−0.028	0.036	-0.037^{*}
$\rho(5)$	−0.029	-0.067^{**}	−0.021

2) If the price drops below the support level, then the selling strength is greater than the buying pressure, and the price will continue to move down with this trend.

To build a TORB strategy with the intraday data, we must determine three time points: the beginning time-point of the observed period, the end time point of the observed period, and the time point of the closing position. The beginning of observed period, denoted as t_b, is set to the beginning of the active hours, and the time point of the closing position, denoted as t_e is set to the end of the active hours; the end of the observed period is the probe time t_p, where $t_b < t_p < t_e$. The sufficient conditions for the buying and selling signals of day d are

$$P_{t',d} > \max(P_{t_b,d}, \cdots, P_{t_p,d}) \Rightarrow \text{Buy}, \quad (3)$$
$$P_{t',d} < \min(P_{t_b,d}, \cdots, P_{t_p,d}) \Rightarrow \text{Sell}, \quad (4)$$

where $P_{t',d}$ is the price at time t' on day d and $t_p < t' < t_e$. If there is a trading signal on a day, the position closes at t_e on that day.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

Two data sets are adopted in our experiments: The first one contains one-minute intraday data of the five futures markets and the second one contains transaction data for the TAIEX index futures. For the first data set, we investigate the spot month E-mini futures of the DJIA (from 2003/1/2 to 2013/12/2), S&P 500 (from 2001/1/2 to 2013/12/2), and NASDAQ 100 (from 2001/1/2 to 2013/12/2) plus two spot month futures indexes, the HSI in Hong Kong (from 2003/1/2 to 2011/3/4),[1] and the TAIEX in Taiwan (from 2001/1/2 to 2013/11/28). In addition to the full time period, to account for the global financial crisis during 2007 to 2008, test results are presented for the two sub-periods before and after 2007/1/1. The second data set contains transaction data

TABLE 2. E-mini S&P daily returns.

Return	Full samples	Sub-period (01–07)	Sub-period (07–13)
Number of observations	3181	1465	1715
Mean	0.000085	0.000031	0.000140
SD	0.013	0.011	0.015
Skewness	−0.148	0.082	−0.227
Kurtosis	10.629	5.738	10.880
Serial correlations			
$\rho(1)$	-0.084^{***}	−0.021	-0.114^{***}
$\rho(2)$	-0.037^{**}	−0.034	−0.038
$\rho(3)$	0.029	0.026	0.030
$\rho(4)$	-0.039^{**}	-0.056^{**}	−0.031
$\rho(5)$	−0.012	0.002	−0.018

TABLE 3. E-mini-NASDAQ daily returns.

Return	Full samples	Sub-period (01–07)	Sub-period (07–13)
Number of observations	3181	1465	1715
Mean	0.000092	−0.00025	0.00039
SD	0.017	0.020	0.015
Skewness	−0.027	0.040	−0.112
Kurtosis	7.640	6.007	9.958
Serial correlations			
$\rho(1)$	-0.031^{*}	0.010	-0.090^{***}
$\rho(2)$	-0.060^{***}	-0.091^{***}	−0.015
$\rho(3)$	0.022	0.026	0.015
$\rho(4)$	-0.029^{*}	−0.026	−0.035
$\rho(5)$	0.002	−0.001	0.007

TABLE 4. HSI daily returns.

Return	Full samples	Sub-period (03–07)	Sub-period (07–11)
Number of observations	2018	989	1028
Mean	0.00045	0.00079	0.00011
SD	0.017	0.011	0.021
Skewness	−0.031	−0.225	0.032
Kurtosis	9.128	4.386	6.873
Serial correlations			
$\rho(1)$	−0.016	−0.011	−0.017
$\rho(2)$	−0.028	−0.023	−0.029
$\rho(3)$	−0.009	−0.006	−0.009
$\rho(4)$	-0.068^{***}	0.042	-0.074^{**}
$\rho(5)$	0.018	−0.007	0.024

for the TAIEX index futures from 2006/7/1 to 2013/12/31,[2] which is utilized to test the relationship between TORB signals and trader behavior.

This section presents the experimental results, including the identification of active hours in Section IV-A, the TORB profitability tests in Section IV-B, and the relationships

[1] Although the spot month futures data for HSI is from 2003/1/2 to 2013/12/2, due to the changes in trading times beginning on 2011/3/7, we conduct experiments only on the data from 2003/1/2 to 2011/3/4.

[2] The data is non-public and customized by Taiwan Futures Exchange, summarizing the one-minute transactions of the buys and sells of all traders, dealers, domestic institutions, and foreign investment institutions.

TABLE 5. TAIEX daily returns.

Return	Full samples	Sub-period (01–07)	Sub-period (07–13)
Number of observations	3203	991	2211
Mean	0.00017	0.00023	0.00015
SD	0.016	0.019	0.015
Skewness	−0.219	−0.019	−0.398
Kurtosis	6.444	4.960	7.429
Serial correlations			
$\rho(1)$	−0.019	−0.035	−0.008
$\rho(2)$	0.007	0.011	0.003
$\rho(3)$	0.016	0.046	−0.006
$\rho(4)$	−0.022	0.028	−0.057***
$\rho(5)$	−0.022	−0.023	−0.021

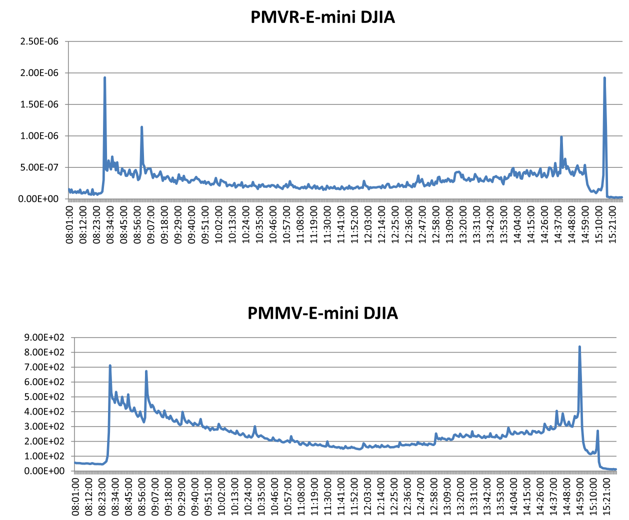

FIGURE 2. E-mini DJIA PMMV and PMVR. There are three major peaks for PMMV and PMVR from 2003 to 2013, including 8:30 (the opening time of the underlying market), 9:00, and 15:00 (the closing time of the underlying market).

TABLE 6. Best strategies in the full samples test of TORB.

Market	Probe time (minute)	#Trading	Return (annual)	t-statistic	p-value
DJIA	4	2,677	12.89 %	2.98	0.15 %
S&P	1	3,096	8.95 %	2.00	2.29 %
NASDAQ	1	3,099	17.51 %	2.76	0.3 %
HSI	151	1,381	10.32 %	3.87	0.01 %
TAIEX	37	3,038	20.28 %	4.99	0.000031 %

between TORB signals and trader behavior in Section IV-C. Before we present the experimental results, Tables 1 to 5 show the statistics of daily returns of the five future markets, in which returns are measured as percentage differences in the logarithm of the future prices. In the five futures, the means of the daily returns are positive, except for the E-mini NASDAQ in the 2003–2007 sub-period, which also shows the largest standard deviation. In the full time period,

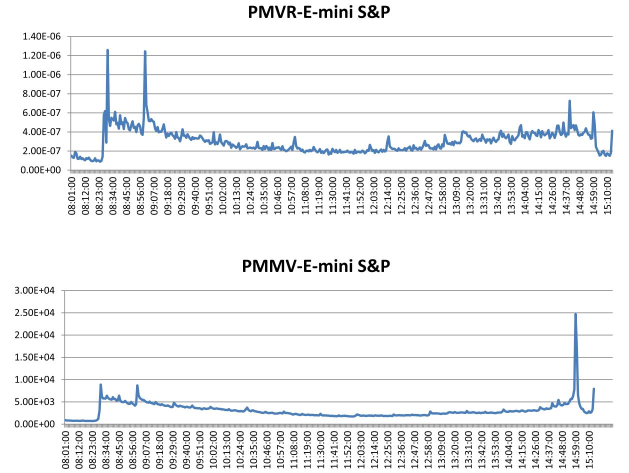

FIGURE 3. E-mini S&P PMMV and PMVR. There are two major peaks for PMVR in E-mini S&P, including 8:30 (the opening time of the underlying market) and 9:00. Also, there are two small corresponding peaks for PMMV. For the case of PMMV, there is a major peak near the closing time (15:00) of the underlying market.

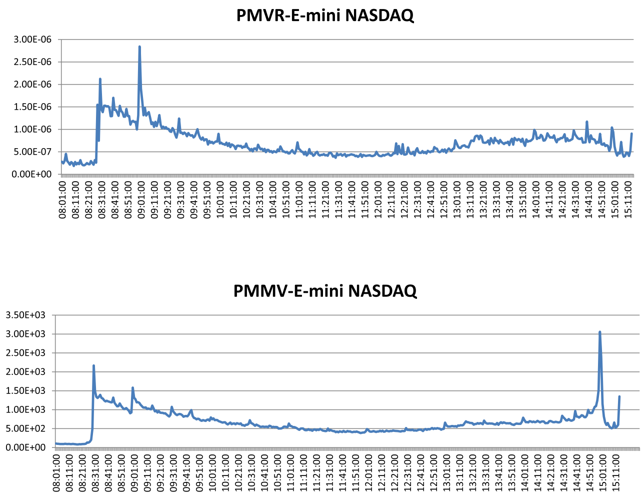

FIGURE 4. E-mini NASDAQ PMMV and PMVR. There are two major peaks for PMVR, including 8:30 (the opening time of the underlying market) and 9:00. Also, there are two small corresponding peaks for PMMV. For the case of PMMV, there is a major peak near the closing time (15:00) of the underlying market.

TABLE 7. Best strategies in the sub-period (01–07) test of TORB.

Market	Probe time (minute)	#Trading	Return (annual)	t-statistic	p-value
DJIA	4	965	5.31 %	1.01	15.71 %
S&P	1	1,382	10.95 %	2.00	2.31 %
NASDAQ	1	1,386	21.2 %	1.96	2.52 %
HSI	151	623	8.67 %	3.18	0.08 %
TAIEX	37	1,419	28.79 %	4.47	0.00042 %

all five futures markets have negative skewness; in sub-periods 2007 to 2013, except for the HSI, all futures have negative skewness, which is probably due to the global financial crisis. However, the skewness values are small in all

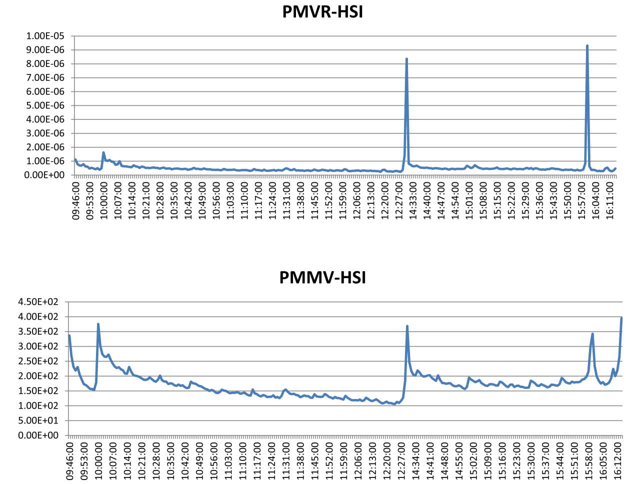

FIGURE 5. **HSI PMMV and PMVR. There are two major peaks for PMVR, including 12:30 (the start time of the lunch break of the underlying market) and 16:00 (the closing time of the underlying market). For the case of PMMV, there are five major peaks, including 09:45 and 16:15 (the opening and the closing time of the futures market), 10:00 and 16:00 (the opening and the closing time of the underlying market), and 12:30 (the start time of the lunch break of the underlying market).**

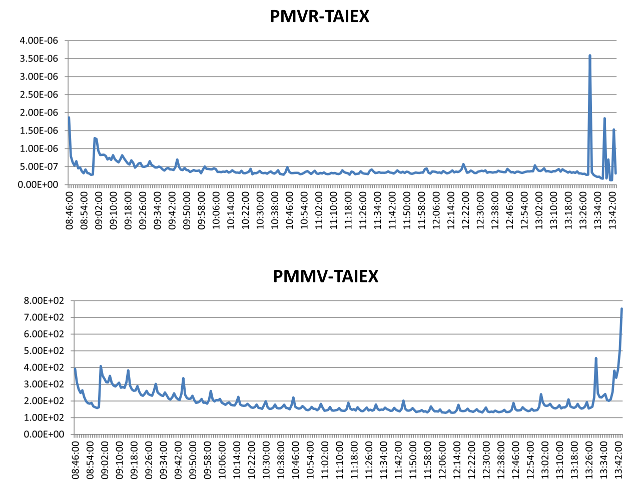

FIGURE 6. **TAIEX PMMV and PMVR. There are four major peaks for PMVR and PMMV, including 08:45 and 09:00 (the opening time of the futures market and the underlying market), 13:45 and 13:30 (the closing time of the futures market and the underlying market).**

TABLE 8. **Best strategies in the sub-period (07–13) test of TORB.**

Market	Probe time (minute)	#Trading	Return (annual)	t-statistic	p-value
DJIA	4	1,712	17.23 %	2.82	0.24 %
S&P	1	1,714	7.23 %	1.05	14.62 %
NASDAQ	1	1,713	14.35 %	1.96	2.48 %
HSI	151	758	11.52 %	2.77	0.29 %
TAIEX	37	1,619	12.98 %	2.53	0.578557 %

futures except the TAIEX. In addition, $\rho(i)$ denotes the estimated i days lag auto-correlation, and the marks *, **, and *** represent the significance at the 10, 5, and 1% levels,

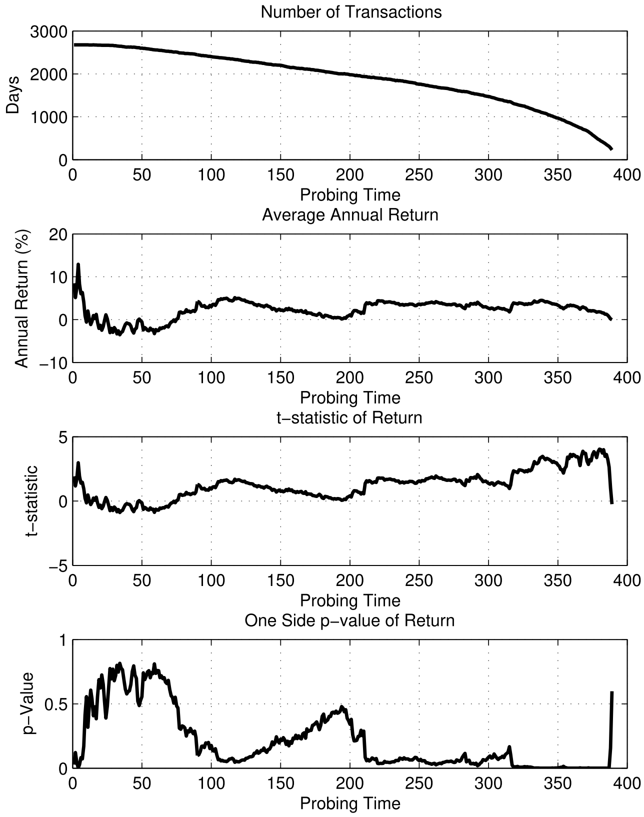

FIGURE 7. **Trading number, average annual return, and one-tailed *p*-value of DJIA in the full samples test.**

respectively. As shown in the tables, for the E-mini DJIA, the first-order serial correlations in both the full time period and the second sub-period are significantly negative, but the other-order serial correlations are rather small; for the E-mini S&P 500 and the E-mini NASDAQ, there are significant negative serial correlations in the first two orders.

A. ACTIVE HOURS

Figures 2 to 6 illustrate the **PMMV** and **PMVR** for each minute for the five futures markets. Figure 2 shows for both **PMMV** and **PMVR** a peak around 8:30, which is the opening time of the underlying market, and the values between 8:30 and 9:00 are generally larger than those at other time points; additionally, there is another **PMMV** peak around 15:00, the closing time of the underlying market, and a **PMVR** peak around 15:15, the closing time of the E-mini DJIA. For both E-mini S&P in Figure 3 and E-mini NASDAQ in Figure 4, there are peaks for both **PMMV** and **PMVR** around the opening and closing times of the underlying markets. Observe from Figure 5 for HSI that there are peaks not only around the opening (10:00) and closing (16:00) times of the underlying market, but also a peak around 14:30 for both **PMVR** and **PMMV**, which is due to the lunch break from 12:30 to 14:30. Figure 6 shows that the TAIEX has four peaks: Two around the opening time (9:00) and closing time (13:30) of the underlying market, and the other two

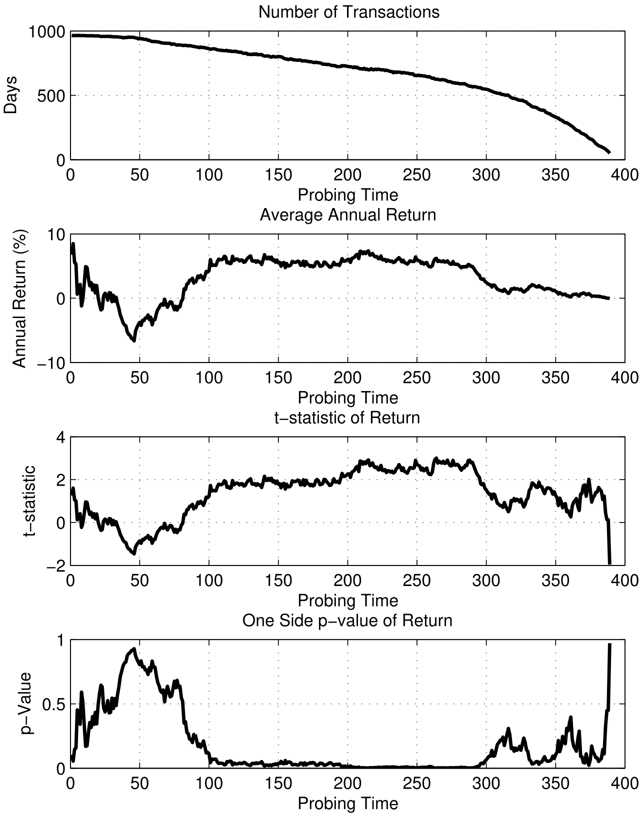

FIGURE 8. Trading number, average annual return, and one-tailed *p*-value of DJIA in the sub-period (03–07) test.

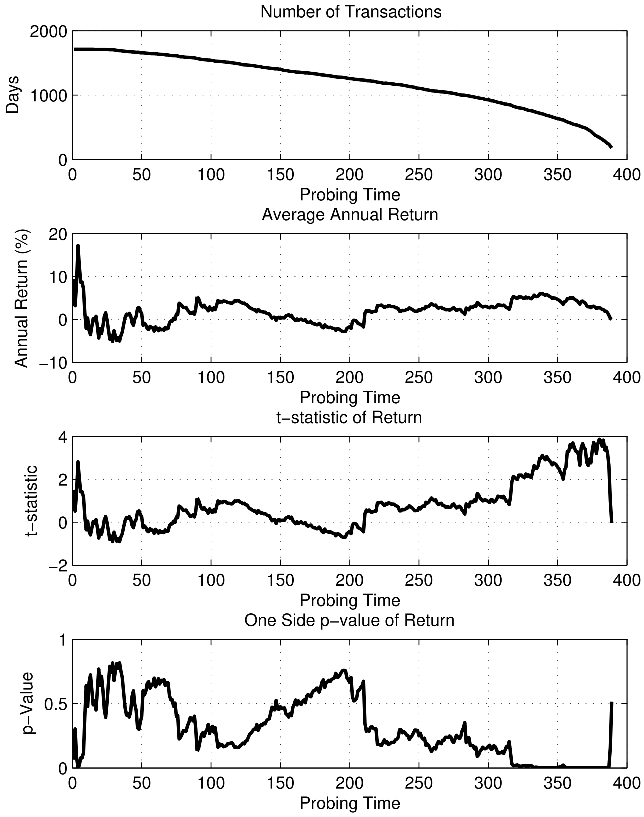

FIGURE 9. Trading number, average annual return, and one-tailed *p*-value of DJIA in the sub-period (07–13) test.

TABLE 9. Best strategies in the full samples test of TRB.

Market	Test838 (D, X)	#Trading	Return (annual)	t-statistic	p-value
DJIA	(135,0.01)	20	0.48 %	0.21	41.69 %
S&P	(5,0)	291	0.49 %	0.1	45.98 %
NASDAQ	(164,0)	87	5.58 %	1.73	4.37 %
HSI	(149,0)	56	3.12 %	0.99	16.3 %
TAIEX	(7,0)	278	8.99 %	1.55	6.12 %

TABLE 10. Best strategies in the sub-period (01–07) test of TRB.

Market	Test (D, X)	#Trading	Return (annual)	t-statistic	p-value
DJIA	(135,0.01)	2	−0.2 %	−0.14	54.79 %
S&P	(5,0)	177	3.29 %	0.38	35.39 %
NASDAQ	(164,0)	47	7.92 %	1.32	9.72 %
HSI	(149,0)	30	−1.12 %	−0.24	59.4 %
TAIEX	(7,0)	127	4.37 %	0.46	32.31 %

TABLE 11. Best strategies in the sub-period (07–13) test of TRB.

Market	Test (D, X)	#Trading	Return (annual)	t-statistic	p-value
DJIA	(135,0.01)	16	0.97 %	0.28	39.21 %
S&P	(5,0)	113	−1.87 %	−0.38	64.8 %
NASDAQ	(164,0)	36	2.7 %	0.9	18.78 %
HSI	(149,0)	19	6.39 %	1.67	5.59 %
TAIEX	(7,0)	150	12.22 %	1.73	4.29 %

around the opening time (8:46) and closing time (13:44) of the futures market. To summarize the results of **PMVR** and **PMMV** in these five futures markets, we conclude that there are peaks around the opening and closing times of the underlying market; therefore, we set the active hours as the opening to closing times of the underlying market for each future market in the following experiments.

B. TORB PROFITABILITY TEST

After establishing the active hours, we use Equations (3) and (4) to build TORB strategies with the probe time as a parameter. Figure 7 shows the back-testing results for the DJIA in the full time period. The top of the figure shows the numbers of the TORB transactions, in which the number of transactions decreases when the probe time moves away from the beginning of the active hours; in this case, the boundary is larger, and the probability decreases for the price to break out of the boundary on the same day. The second illustrates the average annual returns of the TORB strategies with transaction costs;[3]

[3]Here we follow Schulmeister's estimation to assume an overall transaction cost of 0.01% (per trade) [5].

TABLE 12. Average daily volumes (buy positions plus sell positions).

All	Dealers		Domestic		Foreign		Institutional		Individual	
Volume	Volume	Ratio	Volume	Ratio	Volume	Ratio	Volume	Ratio	Volume	Ratio
175663.5	32793.5	18.45%	1073.5	0.67%	27522.2	14.60%	61389.1	33.72%	114274.4	66.28%

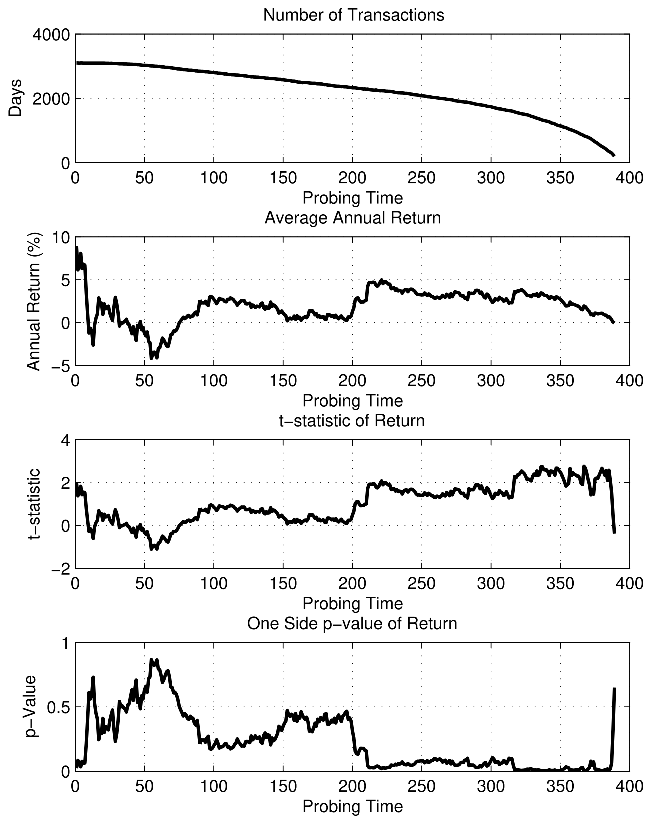

FIGURE 10. Trading number, average annual return, and one-tailed *p*-value of S&P in the full samples test.

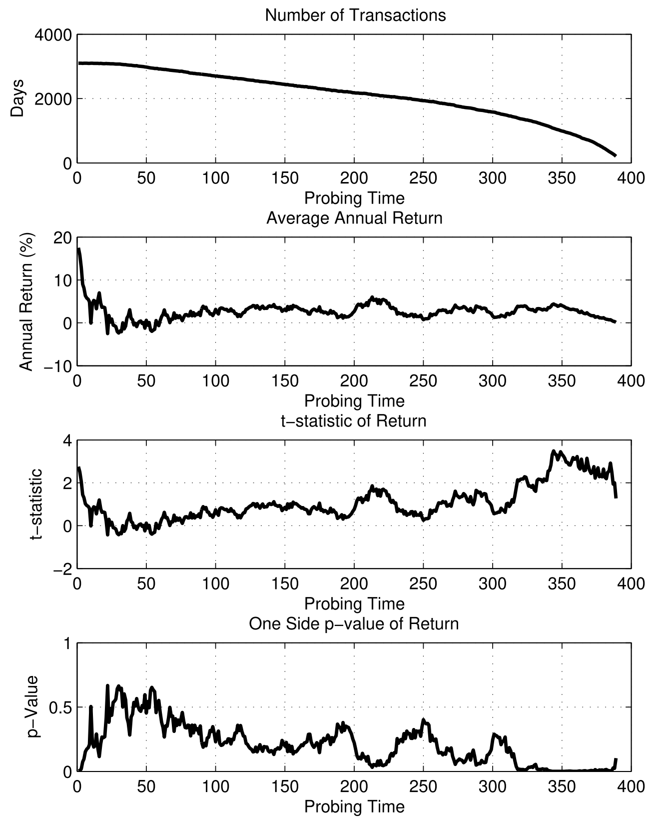

FIGURE 11. Trading number, average annual return, and one-tailed *p*-value of NASDAQ in the full samples test.

from the figure, we observe that strategies with the probe time in the early stages earn a significantly higher annual return. The third and the bottom ones are the t-statistic and the one-tailed p-value of the t-test, respectively, with respect to the null hypothesis that the TORB returns equal zero. When the probe time is within five minutes, there are four strategies that significantly reject the null hypothesis with the p-value less than 5%. Note that since the sub-period results are similar to those of the full time period (see Figures 8 and 9), we show only the results for the full time period for the rest of the markets. Figures 10 and 11 are the results for the S&P 500 and the NASDAQ, respectively, in which the results are similar to those for the DJIA, and again the probe time within the first 5 minutes earns the highest annual returns with significant p-values. Similar to the results in the US market, as shown in Figure 13, TORB strategies on the HSI earn significantly higher returns in the early stages of the stock market opening; additionally, TORB strategies also earn significantly higher returns with probe times around 150 minutes. The phenomenon may be due to the difference in market structures and market efficiency; for example, the lunch break from 12:30 to 14:30 in the Hong Kong market may affect the performance of the technical analysis. Figure 13 shows that the strategies on the TAIEX with probe times less than 200 minutes earn significantly higher returns.

Table 6 tabulates the best strategies in the five markets in the full time period, where the best strategies are defined as those that earn the most profit in the full time periods. The best strategies for the E-mini DJIA, E-mini S&P 500, and E-mini NASDAQ are all with short probe times (4, 1, and 1 minutes, respectively), whereas for the HIS and the TAIEX, the probe times of the best strategies are 151 minutes and 37 minutes, respectively. The average annual returns of the best strategies in all markets are greater than 8%, with p-values less than 3%. Additionally, as shown in Tables 7 and 8, except for the E-mini DJIA in the sub-period

TABLE 13. TORB returns and net buy positions of different traders.

	TORB returns (bps)		#Positions of all traders		#Positions of institutional traders		#Positions of individual traders	
	BB	AB	BB	AB	BB	AB	BB	AB
Buy signals (GB)	51.696	8.052	238.45	113.314	1440.501	542.428	−1202.05	−429.114
	(20.911)***	(1.763)*	(6.427)***	(1.281)	(13.597)***	(3.691)***	(−13.634)***	(−3.949)***
Sell signals (GS)	−54.797	−5.181	−173.279	−18.146	−924.304	−262.431	751.025	244.285
	(−19.57)***	(−1.689)*	(−5.812)***	(−1.12)	(−12.491)***	(−3.337)***	(12.699)***	(3.643)***
Mean [all data]	−4.23	1.102	22.228	44.277	198.606	119.75	−176.379	−75.474
SD [all data]	67.81	88.131	783.213	1263.409	2193.129	2645.795	1795.393	2048.436

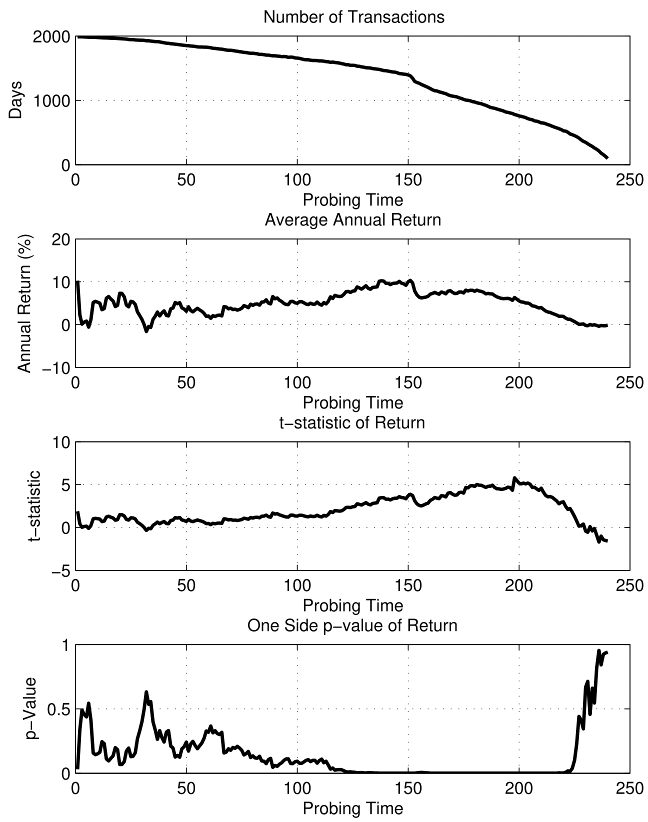

FIGURE 12. Trading number, average annual return, and one-tailed *p*-value of HSI in the full samples test.

from 2003 to 2007 and the E-mini S&P in the sub-period from 2007 to 2013, the best strategies earn significantly higher returns.

To compare the TORB strategies with TRB strategies, we briefly describe the TRB strategies in [6]: The TRB initiates a buy (sell) signal when the price is greater (less) than the product of $(1+X)$ and the local maximum (minimum) of the price in the previous D days, where X is the percentage band (e.g., 0, 1, 2%). When the buy (sell) signals are revealed, we open the positions and hold them for ten days.[4] Table 9 demonstrates the best TRB strategies in the five markets in the full time period. The experimental results suggest that there is no significant result (p-value less than 5%) in the profitability tests for all TRB strategies on the DJIA, S&P 500, HSI, TAIEX futures indexes in the full time periods. Although the best strategy in the full time period on the NASDAQ earns significant profits ($p - value = 4.37\%$), the annual return 5.58% is much less than the annual return 17.51% of the best TORB strategy on the same market. In addition, in the two sub-period tests shown in Tables 10 and 11, there is no significant result on the NASDAQ. We therefore conclude that there is no consistently significant result from the probability tests of TRB strategies on these five futures markets in these two sub-period tests.

[4]In the experiments, we test $D = 2$ to $D = 200$ with bands as $X = 0$ or $X = 1\%$.

C. RELATIONSHIP BETWEEN TORB SIGNALS AND TRADER BEHAVIOR

This subsection examines the relationship between TORB signals and trader behavior with the transaction and price data from the TAIEX futures market. Table 12 summarizes the daily volumes (buy positions plus sell positions) for different kinds of traders. From the table, the average daily volume of all traders is about 175,663.5; we observe that the daily volume for individual traders is about twice that for institutional traders.

Table 13 shows the returns of the TORB strategies (second column) and the net buy positions for different kinds of traders (third, fourth, and fifth columns) before breakout (BB) and after breakout (AB). The data is group by the TORB buy (sell) signals and the data with the TORB buy (sell) signals is tabulated in the row of GB (GS, respectively). The numbers in parentheses are the t-statistics of the t-test under the null hypothesis that the data in GB (GS) and the all data have equal means and equal but unknown variances. As shown in the table, while the numbers of the net buy positions for institutional traders are positively related to the TORB returns before and after breakout, those for individual traders are negatively related to the TORB returns before and after breakout. The results suggest that by following the TORB signals, one trades in the same direction as institutional traders, and thus obtains positive returns. Additionally, in Table 14,

TABLE 14. TORB returns and net buy positions of different types of institutional traders.

	TORB returns (bps)		#Positions of dealers		#Positions of domestic traders		#Positions of foreign traders	
	BB	AB	BB	AB	BB	AB	BB	AB
Buy signals (GB)	51.696	8.052	733.331	77.434	−16.572	87.654	723.742	377.339
	(20.911)***	(1.763)*	(13.279)***	(1.116)	(1.365)	(2.47)***	(7.729)***	(2.567)***
Sell signals (BS)	−54.797	−5.181	−469.431	−65.787	−67.192	−61.648	−387.681	−134.996
	(−19.57)***	(−1.689)*	(−12.581)***	(−1.054)	(−1.218)	(−2.37)**	(−7.018)***	(−2.355)***
Mean [all data]	−4.23	1.102	101.692	2.221	−43.155	9.247	140.07	108.282
SD [all data]	67.81	88.131	1123.51	1516.788	451.434	709.977	1763.323	2397.936

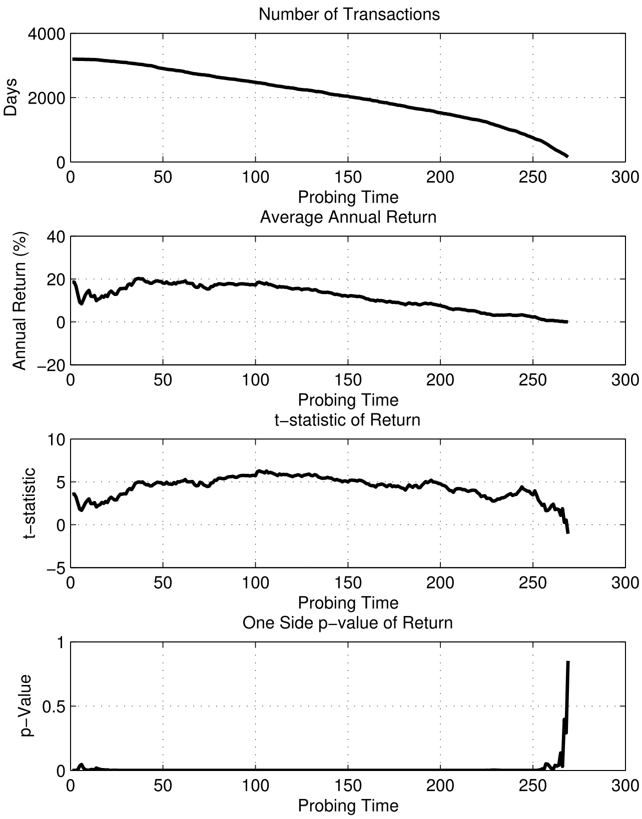

FIGURE 13. Trading number, average annual return, and one-tailed *p*-value of TAIEX in the full samples test.

we detail the returns of the TORB strategies and the numbers of the net buy positions for different types of institutional traders before and after breakout. We observe that the returns of the TORB strategies are all positively related to the three types of institutional traders after breakout; in particular, the returns are significantly and positively related to foreign investment institutions both before and after breakout. These results are consistent with the findings in [9], which claim that the TORB signals are positively related to the trading direction of foreign investment institutions, who are usually considered the most informed traders in the Taiwan market.

Lots of analysts and traders in investment institutions have conducted in-depth analysis to develop trading strategies. However, the directions of trading positions of TORB signals are almost the same as those of the positions of investment institutions. In addition, we use statistical verification (t-statistic, p-value) to assess the profitability of our proposed solution, TORB. Previous experiments in five futures markets have shown that the TORB strategy has significant profitability in all markets to achieve higher returns than the TRB strategy does. Further, we propose PMMV, PMVR to observe the market volatility, and align the active hours of TORB at the most appropriate times which are the opening and closing time of the underlying index market. At the last time parameter (t_p), probing time, we examine all the parameters to get the best return and confidence in profitability. Based on the observations of the markets (PMMV, PMVR), statistical verification of profitability (t-statistics, p-values) and the analogy analysis of trader behavior, the proposed TORB strategy is attested to be profitable.

V. CONCLUSIONS

This paper proposes profitable TORB strategies for trading on the index futures market. We test the profitability of the proposed strategies with E-mini-DJIA, E-mini S&P 500, E-mini NASDAQ, HSI, and TAIEX. The profitability tests show that the TORB strategies in each futures market achieve an over 8% annual return with p-value less than 3% in the t-test; the best performance, a 20.28% annual return with a $1 \times 10^{-4}\%$ p-value, is reached in the TAIEX. In addition, the TORB strategies perform consistently in the two sub-periods before and after the financial crisis in 2007; in contrast, there is no consistent result in the probability test of the TRB strategies in these five futures markets, which is in line with the findings in [5]. Our experimental results suggest that by using the one-minute price information, TORB strategies capture more useful information than TRB strategies, and thus earn significantly higher profits. We also conduct experiments on unique transactions data from the TAIEX futures market, one interesting finding of which is that by following the TORB signals, we trade in the same direction as institutional traders, especially foreign investment institutions.

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