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# Market Intraday Momentum with New Measures for Trading Cost: Evidence from KOSPI Index

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**Abstract:** Evidence on Market Intraday Momentum (MIM) has been documented in the United States and in some, but not all, major economies. The main results on MIM are broadly robust against transaction costs, which are measured by either quoted spread or effective spread. By using two new spread measures obtained from high and low prices, we show that these measures of transaction cost tend to become smaller toward the end of a trading day, thus establishing MIM in more than 10 years of the 30 min KOSPI index. We also report the solid profitability of such MIM-based trading strategies.

**Keywords:** market intraday momentum; transaction costs; effective spread; intraday pattern; range



**Citation:** Lai, Chien-Yuan, Zhen-Yu Lin, Cheoljun Eom, and Ping-Chen Tsai. 2022. Market Intraday Momentum with New Measures for Trading Cost: Evidence from KOSPI Index. *Journal of Risk and Financial Management* 15: 523. <https://doi.org/10.3390/jrfm15110523>

Academic Editor: Joanna Olbrys

Received: 5 October 2022

Accepted: 2 November 2022

Published: 8 November 2022

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## 1. Introduction

Market momentum was first documented by Jegadeesh and Titman (1993), who showed that buying stocks that have increased in value and selling those that have lost value would generate significant and positive returns over the next 3 to 12 months. More recently, Moskowitz et al. (2011) found that returns from the previous 12 months can predict future returns. Gao et al. (2018) was the first to identify momentum at an intraday level—the first 30 min return can have predictive power on the last 30 min return in a trading day.

Many subsequent studies then tested the existence of Market Intraday Momentum (MIM) for different economies, such as Zhang et al. (2019) for the Chinese stock market, Li et al. (2021) for 16 developed markets and Ho et al. (2021) for the Australian market. While the main results on MIM in Gao et al. (2018) were robust against many factors for the United States market, subsequent studies did not present a consistent conclusion. Ho et al. (2021) did not find MIM in the Australian stock market, which could be due to the relatively smaller trading volume compared with the U.S. market. Li et al. (2021) identified that 12 out of 16 developed markets display MIM. Zhang et al. (2019) showed that for the Chinese market, the penultimate 30 min return has higher predictive power than the first one. Other studies on MIM include Elaut et al. (2018) for the FX market, Wen et al. (2021) for the crude oil futures market and Wen et al. (2022) for the intraday momentum and reversal in Bitcoin prices.

The above studies also vary in terms of how trading costs are accounted for in establishing MIM. Gao et al. (2018) used the quoted spread from TAQ data and saw a lower but still positive profit from their trading strategies. Li et al. (2021), on the other hand, estimated the range-based effective spread of Corwin and Schultz (2012) and showed that the effect of MIM is stronger in markets with a larger spread (lower liquidity). There is no explicit consideration of transaction costs in Ho et al. (2021), Zhang et al. (2019) and Wen et al. (2021). Elaut et al. (2018) only mentioned in a footnote that the transaction costs would be similar for their MIM-based strategy and a benchmark.

In this study, we make a contribution to the literature by identifying MIM in South Korea's spot KOSPI index and show that it is robust to transaction cost. Transaction cost is an important factor in establishing the economic value of MIM, yet many of the above-

mentioned papers do not consider the profit—net of transaction cost—from their MIM-based strategies. We use two new effective spread measures as a proxy for transaction cost that are calculated from the high and low prices, and show that the profitability of MIM-based strategies remains intact after these costs are accounted for.

Specifically, like Gao et al. (2018), we confirm the existence of MIM in the KOSPI index, which is robust to sensitivity analysis on key market variables such as liquidity, volume and volatility. In addition, when the sum of the overnight and the first 30 min return is different from zero, we can use the overnight and the second 30 min return to predict the last 30 min return of a trading day. On the other hand, if this sum is close to zero, the last 30 min return can be predicted by the penultimate 30 min. This finding on the predictive power of KOSPI's second 30 min return is consistent with the results on the J-shape pattern in Lee et al. (2017).

Unlike Gao et al. (2018) or Li et al. (2021), however, we directly look at the intraday pattern of estimated effective spreads using the range-based methods in Corwin and Schultz (2012) and Li et al. (2018). We find that, consistent with the prediction from the Glosten and Milgrom (1985) model, the estimated spread values tend to become smaller toward the end of a trading day. Hence, a MIM-based trading strategy can still be profitable as its trading costs measured by the effective spread generally become smaller toward the end of trading hours. This result is robust in the two methods considered and also across various sampling frequencies.

The paper is organized as follows. Section 2 describes our data and research methods. Section 3 presents our main results, and Section 4 provides a robustness check and a discussion on our approach in relation to similar topics on intraday momentum. Section 5 concludes.

## 2. Data and Research Methods

### 2.1. Data and Summary Statistics

Our data consist of 1 min index values and trading volume from the KOSPI Index of Korea Stock Exchange (KSE) on 2 January 2004 and 30 June 2016. The KSE opens at 09:00 a.m. and closes at 15:00 p.m. (local time), with the first available price at 09:01:00. After deleting some incomplete trading days, we were left with 3087 trading days, or 1,111,320 1 min observations. A 30 min return is given as:

$$r_{t,i} = \ln(P_{t,i}) - \ln(P_{t,i-1}), \text{ for } t = 1, \dots, 3087, i = 1, \dots, 12, \tag{1}$$

with  $P_{t,0}$  the open price on day  $t$ . We also constructed a high–low range for 30 min, hourly, bi-hourly and half-daily intervals from the 1 min values as:

$$\text{range}_{t,j} = \ln(H_{t,j}) - \ln(L_{t,j}), \text{ for } j = 1, \dots, M, \tag{2}$$

where  $H_{t,j}$  and  $L_{t,j}$  are respectively the highest and lowest 1 min index level for the  $j$ -th interval on day  $t$ . The number of intervals per day  $M$  is thus 12, 6, 3 and 2 for the four frequencies considered.

Table 1 reports the summary statistics of 30 min returns and overnight returns. We define the overnight returns to be the log difference between today's opening price and yesterday's closing price. The first 30 min return  $r_{t,1}$  has the lowest mean and minimum value, but has the largest standard deviation; the last 30 min return  $r_{t,12}$  has the highest mean and maximum value. All 30 min returns are highly non-Gaussian, and interestingly, the values of kurtosis in the afternoon are significantly higher than those in the morning.

**Table 1.** Summary statistics of 30 min and overnight returns for the KOSPI Index.

	$r_{t,ovn}$	$r_{t,1}$	$r_{t,2}$	$r_{t,3}$	$r_{t,4}$	$r_{t,5}$	$r_{t,6}$	$r_{t,7}$	$r_{t,8}$	$r_{t,9}$	$r_{t,10}$	$r_{t,11}$	$r_{t,12}$
Mean (%)	0.081	−0.038	−0.006	−0.014	−0.007	−0.009	−0.016	−0.013	0.003	−0.012	0.002	0.011	0.047
Median (%)	0.124	−0.031	−0.004	−0.003	−0.002	−0.002	−0.010	−0.005	0.003	−0.002	0.007	0.022	0.045
Min (%)	−6.542	−4.515	−1.963	−1.649	−2.738	−1.674	−3.650	−2.249	−2.218	−3.512	−2.981	−3.224	−2.434
Max (%)	6.872	2.997	2.048	2.224	2.225	1.409	1.947	2.251	1.506	3.044	3.629	1.403	4.124
SD (%)	0.868	0.429	0.310	0.288	0.281	0.242	0.221	0.203	0.223	0.268	0.252	0.256	0.293
Skewness	−0.615	−0.477	0.039	−0.334	−0.091	−0.348	−1.594	−0.461	−0.594	−0.777	0.144	−1.475	0.488
Kurtosis	10.600	10.153	7.030	7.460	12.342	8.201	36.406	19.832	13.303	35.935	30.581	19.278	23.026

To conduct a sensitivity analysis on MIM, we looked at three measures on market condition—volatility, liquidity and trading volume—for the first 30 min of a trading day. We calculated realized variance (RV) for 30 min intervals from 1 min returns:

$$RV_{t,i} = \sum_{k=1}^{30} r_{t,i,k}^2 \tag{3}$$

where  $r_{t,i,k}^2$  is squared 1 min returns from the  $i$ -th 30 min interval on day  $t$ . For measuring liquidity, we used the illiquidity measure of Amihud (2002):

$$Illiquidity_{t,i} = \frac{RV_{t,i}}{V_{t,i}}, \tag{4}$$

with  $V_{t,i}$  the trading volume. Table 2 reports the summary statistics of RV, Amihud illiquidity measure and trading volume when they are classified into high, medium and low groups. The average volatility of the highest group was about nine times higher than that of the lowest group. The difference between the highest and lowest Amihud measures was nearly 10 times; the volume of the highest group was on average 2.3 times higher than the lowest group. We therefore analyzed MIM by different subgroups in volatility, liquidity and volume from the first 30 min interval.

**Table 2.** Summary statistics of RV, Amihud illiquidity and trading volume for the first 30 min of a trading day.

	RV (%)			Amihud Illiquidity			Volume (In Millions)		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
Mean	0.004	0.001	0.000	1.1e−10	3.8e−10	1.1e−09	100.62	65.54	43.86
Median	0.002	0.001	0.000	1.1e−10	3.7e−10	9.2e−10	93.68	65.38	45.67
Min	0.001	0.001	0.000	2.5e−24	2.3e−10	5.6e−10	76.55	55.92	17.75
Max	0.096	0.001	0.001	2.3e−09	5.6e−10	5.2e−09	319.32	76.46	55.92
SD	0.005	0.000	0.000	6.6e−11	9.4e−11	6.1e−10	24.73	5.89	8.84
Skewness	9.743	0.277	−0.266	0.07	0.19	2.18	2.33	0.10	−0.65
Kurtosis	153.341	1.908	2.241	1.83	1.89	9.35	12.69	1.81	2.58

Table 3 reports the summary statistics of the range for log prices from different intervals. As expected, the mean and standard deviation of range decreased when the sampling frequency increased. The values of skewness and kurtosis suggest the distribution of range is highly non-Gaussian. Notably, the values of autocorrelation function (ACF) of range at lag 1 were highly significant at around 0.60 across frequencies.

**Table 3.** Summary statistics of range for log prices from different intervals.

	M = 2	M = 3	M = 6	M = 12
No. of Obs.	6174	9261	18,522	37,044
Mean	0.0090	0.0070	0.0047	0.0031
Median	0.0073	0.0057	0.0038	0.0024
SD	0.0068	0.0054	0.0037	0.0026
Max	0.1227	0.0901	0.0704	0.0605
Min	0.0013	0.001	0.0005	0.0004
Skewness	4.0446	3.5325	3.7753	4.1112
Kurtosis	33.0979	24.2368	29.2609	37.1143
ACF, lag = 1	0.6215	0.5718	0.6137	0.6023

2.2. Research Methods

There are two stages in our research methodology. In the first stage, we established MIM by following Gao et al. (2018) and estimated ordinary linear regressions with  $r_{t,12}$  as dependent variable. However, unlike Gao et al. (2018), we separately had  $r_{t,ovn}$ ,  $r_{t,1}$ ,  $r_{t,2}$  and  $r_{t,11}$  as independent variables:

$$r_{t,12} = b_0 + b_{ovn}r_{t,ovn} + b_1r_{t,1} + b_2r_{t,2} + b_{11}r_{t,11} + \varepsilon_t, \tag{5}$$

where the innovation  $\varepsilon_t$  has  $E[\varepsilon_t] = 0$ ,  $\text{var}(\varepsilon_t) = \sigma_\varepsilon^2$  and is serially uncorrelated. This model in (5) was the baseline model for estimating MIM. We then looked at the regression results for different subgroups classified as high, medium and low RV, Amihud illiquidity and trading volume. In addition, we constructed a trading strategy based on the MIM results and evaluated its profitability.

In the second stage, we estimated the trading costs incurred in a MIM-based strategy and calculated the range-based spread measure given by Corwin and Schultz (2012), hereafter CS, and the basic high–low (BHL) spread estimator of Li et al. (2018). The CS estimator assumes that a highest price is given by buy order and a lowest price from a sell order. The observed high and low prices are thus equal to the actual prices adjusted by half of spread:

$$\left[ \ln \left( \frac{H_{t,j}^O}{L_{t,j}^O} \right) \right]^2 = \left[ \ln \left( \frac{H_{t,j}^A(1 + S/2)}{L_{t,j}^A(1 - S/2)} \right) \right]^2, \tag{6}$$

where  $H_t^O$  and  $H_t^A$  denote the observed and actual highest prices, respectively. Note that the lefthand side of (6) is given by the square of range in our definition (2). CS follow Parkinson (1980) and assume traded price follows a driftless Geometric Brownian Motion; their key observation is that while the variance component of range is proportional to the length of time interval, the spread component is not. Thus, CS consider the relationship in (6) over a two-interval period and with two equations, the two unknowns volatility and spread can be solved. As a result, the CS analytic solution of spread is for a two-interval period  $(j, j + 1)$  on day  $t$ :

$$S_{t,(j,j+1)}^{CS} = \frac{2(e^\alpha - 1)}{1 + e^\alpha}, \text{ with } \alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}, \tag{7}$$

where

$$\beta = E \left\{ \left[ \ln \left( \frac{H_{t,j}^O}{L_{t,j}^O} \right) \right]^2 + \left[ \ln \left( \frac{H_{t,j+1}^O}{L_{t,j+1}^O} \right) \right]^2 \right\} \text{ and } \gamma = \left[ \ln \left( \frac{H_{t,(j,j+1)}^O}{L_{t,(j,j+1)}^O} \right) \right]^2 \tag{8}$$

The CS estimator looks at the quadratic relationship in (6). On the other hand, the BHL estimator of Li et al. (2018) makes the same assumptions as in CS and also the theoretical

results in Parkinson (1980), but instead obtains spread as a linear function of the high and low prices:

$$S_{t,(j,j+1)}^{BHL} = \frac{1}{\sqrt{2}-1} E \left[ \sqrt{2} \ln \left( \frac{H_{t,j}^o}{L_{t,j}^o} \right) - \ln \left( \frac{H_{t,(j,j+1)}^o}{L_{t,(j,j+1)}^o} \right) \right], \tag{9}$$

The CS and BHL spread estimators were originally applied to daily and bi-daily data. The assumption that variance over a two-day interval is twice of that for a single day may not hold due to, for example, a large overnight return. The estimated spread values therefore can be negative. However, both Corwin and Schultz (2012) and Li et al. (2018) suggest circumventing this issue by simply setting the negative spreads to zero. For our purpose, we applied the two methods to intraday intervals and thus avoided the occurrences of negative spreads due to overnight returns.

### 3. Results

#### 3.1. Results on MIM Regression

In Table 4, we report the regression results from equation (5), with individual regressors in each column and all the predictors in the right-most column. Note that hereafter we drop the subscript for day  $t$  in the variables. We found that the overnight return  $r_{ovn}$  and  $r_{11}$  can have some predictive power on  $r_{12}$ , but not  $r_1$ . In Gao et al. (2018), they combine  $r_1$  with  $r_{ovn}$  since they believe it will take some time for the overnight effect to be fully digested by the market. We also conducted this regression with combined  $r_1$  and  $r_{ovn}$ , but the result was not significant and so we did not report it here to save space. As a result, we inferred that a separate overnight return  $r_{ovn}$  was more relevant in predicting  $r_{12}$  for our KOSPI data.

**Table 4.** Estimation results of Market Intraday Momentum.

	$r_{ovn}$	$r_{t,1}$	$r_{t,2}$	$r_{t,11}$	All
$b_0$	4.5e−4 (1e−10) ***	4.6e−4 (1e−10) ***	4.7e−4 (1e−10) ***	4.6e−4 (1e−10) ***	4.5e−4 (1e−10) ***
$b_{ovn}$	0.0127 (0.0378) *	-	-	-	0.0135 (0.0267) *
$b_1$	-	−0.0121 (0.3290)	-	-	−0.0030 (0.8109)
$b_2$	-	-	0.0977 (8e−9) ***	-	0.0985 (8e−9) ***
$b_{11}$	-	-	-	0.0423 (0.0400) *	0.0405 (0.0485) *
$R^2$ (%)	0.1392	0.0307	1.0670	0.1360	1.3630

Note: \*\*\* and \* denote significance at 0.1% and 5% level.

Another finding in Table 4 is that we can use  $r_2$  to predict  $r_{12}$  with a significantly positive effect. This result was consistent with Lee et al. (2017), who found that for the KOSPI200 index, when intraday returns display a J-shape pattern, the MIM will be stronger. Moreover, the individual regressions in Table 4 have  $R^2$  values that sum up approximately to the  $R^2$  of the regression with all predictors. This result, which was consistent with Gao et al. (2018), indicates that the individual regressors are close to independent and complementary events.

To further investigate the degree of MIM in the KOSPI index, we classified our sample by the sum of the overnight and the first 30 min return; if  $|r_{ovn} + r_1| < 0.1\%$ , we considered there was not much information in the overnight period and vice versa. Tables 5 and 6 report the regression results when  $|r_{ovn} + r_1| \geq 0.1\%$  and when  $|r_{ovn} + r_1| < 0.1\%$ . We find predictive power from  $r_{ovn}$  and  $r_2$  for the last 30 min return in Table 5. On the other hand, when  $|r_{ovn} + r_1| < 0.1\%$  in Table 6 we see  $r_{12}$  can be predicted by  $r_{11}$  with a higher R-squared value.

**Table 5.** Estimation results of Market Intraday Momentum for days with  $|r_{ovn} + r_1| \geq 0.1\%$ .

	$r_{ovn}$	$r_{t,1}$	$r_{t,2}$	$r_{t,11}$	All
$b_0$	4.6e−4 (4e−15) ***	4.7e−4 (1e−10) ***	4.8e−4 (4e−16) ***	4.7e−4 (1e−15) ***	4.6e−4 (3e−15) ***
$b_{ovn}$	0.0123 (0.0497) *	-	-	-	0.0139 (0.0253) *
$b_1$	-	−0.0110 (0.4010)	-	-	−0.0004 (0.9757)
$b_2$	-	-	0.1122 (8e−10) ***	-	0.1140 (6e−10) ***
$b_{11}$	-	-	-	0.0146 (0.5060)	0.0111 (0.6124) *
$R^2$ (%)	0.1467	0.0270	1.4260	0.0169	1.6280

Note: \*\*\* and \* denote significance at 0.1% and 5% level. There are 2603 daily in our sample with  $|r_{ovn} + r_1| \geq 0.1\%$ .

**Table 6.** Estimation results of Market Intraday Momentum for days with  $|r_{ovn} + r_1| < 0.1\%$ .

	$r_{ovn}$	$r_{t,1}$	$r_{t,2}$	$r_{t,11}$	All
$b_0$	3.7e−4 (0.0025) **	3.8e−4 (0.0024) **	3.8e−4 (0.0016) **	3.4e−4 (0.0045) **	3.0e−4 (0.0133) *
$b_{ovn}$	0.0335 (0.4352)	-	-	-	0.1150 (0.5785)
$b_1$	-	−0.0298 (0.4878)	-	-	0.0635 (0.7600)
$b_2$	-	-	−0.0246 (0.5941)	-	−0.0139 (0.7578)
$b_{11}$	-	-	-	0.3340 (4.6e−8) ***	0.3380 (3.7e−8) ***
$R^2$ (%)	0.1296	0.1025	0.0600	6.1640	6.5110

Note: \*\*\*, \*\* and \* denote significance at 0.1%, 1% and 5% level. There are 472 days in our sample with  $|r_{ovn} + r_1| < 0.1\%$ .

To make our results on MIM more robust, we ran the regression (5) for the three different groups (high, medium, low) of volatility, liquidity and volume from the first 30 min in a trading day. Table 7 reports the estimation results. Under the classification of volatility, we found that  $r_{ovn}$  and  $r_2$  can predict  $r_{12}$  when volatility is high, and  $r_{11}$  can predict  $r_{12}$  when volatility is low. In addition, we saw higher  $R^2$  values under high and low volatility than in Table 4; in particular, estimated  $R^2$  rose from 1.3630% in Table 4 to 2.8740% when volatility was high.

When liquidity in the first 30 min of a day was high,  $r_{ovn}$ ,  $r_1$  and  $r_{11}$  could predict  $r_{12}$ ; when liquidity was low, only  $r_{11}$  could effectively predict  $r_{12}$  but with a larger  $R^2$  value. This result was again consistent with Gao et al. (2018), who found that MIM was more pronounced when liquidity was low. On the other hand, we found a stronger MIM when the first 30 min of trading volume was high or medium, in terms of estimated  $R^2$  values. This result was consistent with Gao et al. (2018) and Sun et al. (2016). Specifically,  $r_2$  was the most significant predictor for  $r_{12}$  when volume was relatively large.

Overall, our results in Table 7 confirmed the findings in previous papers. For example, Gao et al. (2018) found that it was easier to predict  $r_{12}$  when volatility was high and/or volume was high. Zhang et al. (2019) also found a more pronounced MIM in the Chinese market during periods of high volatility and low liquidity.



**Table 7.** Estimation results of Market Intraday Momentum with grouping for volatility, liquidity and volume.

	Volatility (RV)			Liquidity (Amihud Measure)			Volume		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
$b_0$	4.3e−4 (6e−4) ***	5.4e−4 (7e−13) ***	3.7e−4 (7e−8) ***	4.6e−4 (9e−12) ***	3.7e−4 (4e−6) ***	4.9e−4 (5e−5) ***	4.9e−4 (2e−6) ***	3.8e−4 (2e−5) ***	4.9e−4 (4e−9) ***
$b_{ovn}$	0.0186 (0.0641)	0.0026 (0.8074)	0.0175 (0.1705)	0.0202 (0.0460) *	0.0162 (0.1290)	0.0129 (0.2180)	0.0100 (0.2892)	0.0380 (2e−4) ***	−0.0194 (0.1074)
$b_1$	2.9e−4 (0.9887)	−0.0051 (0.8192)	0.0269 (0.3247)	0.0537 (0.0206) *	0.0078 (0.7270)	−0.0105 (0.6130)	0.0300 (0.1805)	0.0015 (0.9373)	−0.0610 (0.0081) **
$b_2$	0.1520 (2e−7) ***	0.0162 (0.5754)	0.0568 (0.0740)	0.0188 (0.5179)	0.0332 (0.2820)	0.1610 (5e−8) ***	0.1240 (5e−5) ***	0.1400 (7e−7) ***	0.0439 (0.1383)
$b_{11}$	−0.0200 (0.5438)	0.1260 (0.0013) **	0.1524 (6e−4) ***	0.1428 (3e−4) ***	0.0885 (0.0150) *	−0.0215 (0.5300)	0.0835 (0.0241) *	0.0160 (0.6274)	−0.0420 (0.2477)
$R^2$ (%)	2.8740	1.0480	1.7240	2.0890	0.9680	3.1600	2.2230	3.6360	1.3440

Note: \*\*\*, \*\* and \* denote significance at 0.1%, 1% and 5% level.

### 3.2. MIM-Based Trading Strategies

To assess the effectiveness of MIM, we constructed trading strategies that use  $r_{ovn}$ ,  $r_2$  and  $r_{11}$  as signals in trading the last 30 min spot KOSPI index. Specifically, the payoff function  $\eta$  from individual and the joint signals are:

$$\eta(r_k) = \begin{cases} r_{12}, & \text{if } r_k > 0 \\ -r_{12}, & \text{if } r_k < 0 \end{cases} \text{ with } k = ovn, 2 \text{ and } 11, \tag{10}$$

and

$$\eta(r_{ovn}, r_2, r_{11}) = \begin{cases} r_{12}, & \{r_{ovn} > 0\} \cap \{r_2 > 0\} \cap \{r_{11} > 0\} \\ -r_{12}, & \{r_{ovn} < 0\} \cap \{r_2 < 0\} \cap \{r_{11} < 0\} \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

In (10), if the individual signals  $r_k > 0$ , for  $k = ovn, 2$  and  $11$ , we will buy at the beginning of the last 30 min of a trading day, and when  $r_k < 0$  we will sell. The position will be closed at the end of trading hours on day  $t$ . When the joint signals are used in (11), we will buy when the signals are all positive and sell when they are all negative.

We report the results of MIM-based trading strategies in Table 8, including summary statistics of returns and Sharpe ratio. In Panel A, we see that  $\eta(r_{ovn})$  delivered a 5.46% return, with a winning percentage of 54.3%. For  $\eta(r_2)$  and  $\eta(r_{11})$ , the returns were 3.76% and 6.68%, respectively. When we considered the joint signal provided by  $r_{ovn}$ ,  $r_2$  and  $r_{11}$ , the average return reached a much higher 16.77%. These results were compared to a benchmark strategy, in which we always took a long position at the beginning of the last 30 min of a trading day and sold it at market close. This *always-long* strategy gave a return of 12.33%, and was outperformed by our joint-signal strategy  $\eta(r_{ovn}, r_2, r_{11})$ .

We could improve the performance of our MIM-based strategies by separating the long and short positions. In particular, we found that MIM is more suitable for a long position and therefore works better in predicting positive returns. In panel B, where we conducted *long-only* strategies, returns from individual signals were now similar to those of  $\eta(r_{ovn}, r_2, r_{11})$  in panel A, and higher than the benchmark. Moreover, the joint-signal strategy with long positions could achieve a 27.2% return. On the other hand, in panel C, the results indicate that MIM is not suitable for conducting short positions or to predict negative returns. Strategies based on individual signals give negative returns, and the joint-signal could deliver a low return of 1.33%.

**Table 8.** Results from MIM-based trading strategies.

	Average Return (%)	Annual S.D. (%)	Sharpe Ratio	Skewness	Kurtosis	No. of Trades	Success Rate (%)
<b>Panel A: long &amp; short</b>							
$\eta(r_{ovn})$	5.46	0.298	0.057	0.835	18.098	3086	54.30
$\eta(r_2)$	3.76	0.298	0.342	0.875	18.067	3087	50.77
$\eta(r_{11})$	6.68	0.297	0.073	0.855	18.128	3087	53.97
$\eta(r_{ovn}, r_2, r_{11})$	16.77	0.344	0.167	1.952	33.351	772	58.80
<b>Panel B: long only</b>							
$\eta(r_{ovn})$	15.4	0.276	0.191	1.366	25.581	1834	62.27
$\eta(r_2)$	16.9	0.301	0.193	1.212	23.666	1520	61.25
$\eta(r_{11})$	17.6	0.282	0.214	1.357	25.443	1731	62.62
$\eta(r_{ovn}, r_2, r_{11})$	27.2	0.315	0.291	4.163	51.054	482	66.81
<b>Panel C: short only</b>							
$\eta(r_{ovn})$	−7.45	0.319	−0.109	0.499	12.355	1252	42.73
$\eta(r_2)$	−7.50	0.288	−0.091	0.529	12.988	1567	40.69
$\eta(r_{11})$	−5.69	0.309	−0.088	0.504	12.544	1356	43.02
$\eta(r_{ovn}, r_2, r_{11})$	1.33	0.382	0.003	0.083	17.995	290	45.52
Benchmark: <i>always long</i>	12.33	0.295	0.144	0.387	18.812	3087	60.13

Note: the table reports the returns generated from MIM-based trading strategies in (10) and (11).

The standard deviations of  $\eta(r_k)$  and  $\eta(r_{ovn}, r_2, r_{11})$  in panel A were: 0.298%, 0.298%, 0.297% and 0.344%, respectively, which were similar to those in other panels. The Sharpe ratios were 0.057, 0.342, 0.073 and 0.167; for the benchmark it was 0.144. All the strategies in panel B outperformed the benchmark in terms of the Sharpe ratio, with the highest Sharpe ratio 0.291 given by the joint strategy  $\eta(r_{ovn}, r_2, r_{11})$ .

Overall, our results in Table 8 suggest that MIM-based strategies can outperform a simple benchmark, especially in predicting positive returns. The joint strategy  $\eta(r_{ovn}, r_2, r_{11})$  gave superior risk-adjusted profitability, but with a stringer condition—it could only be applied to 772 and 482 days in the sample.

### 3.3. The Intraday Distribution of Effective Spreads

To further strengthen our results on MIM-based strategies, in this section we evaluated the transaction costs that would incur in such strategies. Specifically, the transaction costs were measured by the CS and BHL spread in (7) and (9); Table 9 reports the summary statistics from 3087 days in our sample calculated at three different frequencies. In the table,  $M = 2, 3, 6$  corresponds to half-daily, bi-hourly and hourly intervals. Hence, for  $M = 2$ , we obtain daily spread estimates, but for  $M = 3$  and 6, the spread values are for the two-interval period  $(j, j + 1)$ . Following Corwin and Schultz (2012), we set negative spread values to zero.

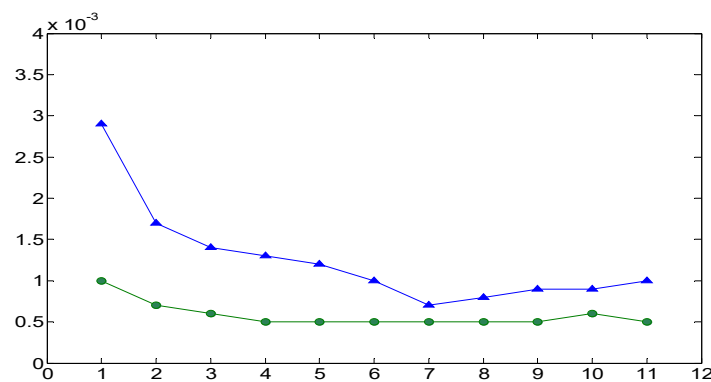
One clear pattern emerged for both the CS and BHL spreads in Table 9: the mean and median values tend to decrease toward the later intervals in a trading day. For example, the average CS spread values calculated from the hourly range declined from 0.0013 to 0.0009, while the BHL values declined from 0.0040 to 0.0013. The standard deviations displayed a similar pattern. Therefore, we showed that transaction costs measured by spread tended to be small toward the end of trading hours. This empirical finding was consistent with the classic Glosten and Milgrom (1985) model, which predicted that market makers will quote smaller spreads after more trades are made in the market, as more information has been revealed through the trading process; see also the review in Tsai and Tsai (2021). The same empirical observation was also found by Bouchaud et al. (2018), who used tick-y-tick data and documented an “L” shape decline of spread from market open to close.



**Table 9.** Summary statistics of intraday spread measures.

	<i>M</i> = 2	<i>M</i> = 3		<i>M</i> = 6				
CS Spread ( <i>j, j</i> + 1)	-	<i>j</i> = 1	<i>j</i> = 2	<i>j</i> = 1	<i>j</i> = 2	<i>j</i> = 3	<i>j</i> = 4	<i>j</i> = 5
Mean	0.0020	0.0013	0.0013	0.0013	0.0009	0.0009	0.0008	0.0009
Median	0.0008	0.0006	0.0005	0.0006	0.0002	0.0003	0.0002	0.0002
SD	0.0032	0.0020	0.0021	0.0019	0.0014	0.0013	0.0012	0.0015
Max	0.0477	0.0227	0.0453	0.0246	0.0125	0.0174	0.0123	0.0232
Min	0	0	0	0	0	0	0	0
Skewness	3.9167	2.9891	5.4647	3.0293	2.8231	3.3434	3.0974	4.0682
Kurtosis	30.548	14.360	73.090	17.379	12.583	19.474	15.078	31.453
Negatives (%)	42.47	43.28	44.77	43.28	47.42	43.31	46.71	45.87
BHL Spread ( <i>j, j</i> + 1)	-	<i>j</i> = 1	<i>j</i> = 2	<i>j</i> = 1	<i>j</i> = 2	<i>j</i> = 3	<i>j</i> = 4	<i>j</i> = 5
Mean	0.0053	0.0053	0.0017	0.0040	0.0023	0.0018	0.0011	0.0013
Median	0.0041	0.0046	0.0000	0.0032	0.0013	0.0007	0.0000	0.0000
SD	0.0063	0.0056	0.0036	0.0045	0.0032	0.0027	0.0022	0.0028
Max	0.0650	0.0648	0.0510	0.0576	0.0364	0.0544	0.0301	0.0511
Min	0	0	0	0	0	0	0	0
Skewness	2.7433	2.6258	5.1969	2.6951	2.9801	4.9029	4.4756	5.4851
Kurtosis	14.586	15.010	45.384	17.830	17.366	59.184	34.732	56.710
Negatives (%)	29.77	20.63	58.31	28.41	38.52	41.95	57.08	58.96

For 30 min intervals, we present the plot of average spread estimates in Figure 1; the two spread measures declined toward the end of a trading day, with values about 0.0005 (CS) and 0.0010 (BHL). The half of these spread values were then the transaction costs when we bought and sold at the last 30 min using our MIM-based strategy; when compared with the KOSPI index level, which was well above 1000 for most of our sample period, these transaction costs were small and profits from our strategies should remain intact. The overall results in Table 9 and Figure 1 thus provide evidence that MIM-based trading strategies can generate profit after accounting for transaction costs.



**Figure 1.** Average intraday spread over a trading day. Note: CS spread (green) and BHL spread (blue).

#### 4. Robustness Check and Discussion

##### 4.1. Robustness Check

It is well known that intraday trading volume and volatility display a U-shape pattern (Andersen and Bollerslev 1997; Taylor and Xu 1997). In this section, we first removed the effect of the intraday volatility pattern (IVP) in returns and tested whether these standardized returns still display MIM.

To do so, we considered the 30 min range of log price in (2) and defined standardized return as:

$$\overline{r}_{t,j} = \frac{r_{t,j}}{range_{t,j}}$$

As we could not calculate range for the overnight period, we only considered the standardization of  $\bar{r}_1$ ,  $\bar{r}_2$ ,  $\bar{r}_{11}$  and  $\bar{r}_{12}$ . We performed the regression in (5) using these  $\bar{r}_{t,i}$  and report the results in Table 10. As before, we see that  $\bar{r}_{12}$  can still be predicted by  $\bar{r}_2$  and  $\bar{r}_{11}$ . This result confirmed the robustness of MIM with respect to the U-shape IVP.

**Table 10.** Estimation results of Market Intraday Momentum, standardized returns.

	$\bar{r}_{t,1}$	$\bar{r}_{t,2}$	$\bar{r}_{t,11}$	All
$b_0$	1.1e−4 (1e−10) ***	1.1e−4 (1e−10) ***	1.0e−4 (1e−10) ***	1.0e−4 (1e−10) ***
$b_1$	0.0172 (0.3940)	- -	- -	0.0262 (0.1952)
$b_2$	- -	0.0736 (0.0002) ***	- -	0.0721 (0.0002) ***
$b_{11}$	- -	- -	0.0831 (3.5e−5) ***	0.0819 (4.3e−5) ***
$R^2$ (%)	0.0235	0.4590	0.5520	1.1740

Note: \*\*\* denote significance at 0.1% level.

#### 4.2. Discussion

Here we discuss the limitation of our approach in the context of previous works on momentum. Since our method was based on transaction-level data such as trade prices and volume, we could not directly verify the relationship between intraday momentum and the traditional momentum proposed by [Jegadeesh and Titman \(1993\)](#). Specifically, traditional momentum can be induced by investors’ behavior, i.e., transactional patterns of institutional investors or the psychological biases of individual investors. That is, the traditional momentum can be due to investment behavior of investors such as overreaction to private information ([Daniel et al. 1998](#); [Lewellen 2002](#)) and underreaction to public information ([Barberis et al. 1998](#); [Hong and Stein 1999](#); [Chen and Hong 2002](#)). Therefore, if the high-frequency transaction data for each investor-type is available, this can help future research explore the source of the intraday momentum and furthermore, establish an investment strategy based on intraday momentum.

With respect to the effect of COVID-19 pandemic on momentum, we note that profit from the investment strategies of traditional momentum was significantly affected by the persistence of common factors and their risk exposure; moreover, limitation of the negative momentum is well-known ([Grundy and Martin 2001](#); [Daniel and Moskowitz 2016](#)). On the other hand, as a method that can reduce exposure from common factors in the momentum investment, idiosyncratic momentum using residuals orthogonal to common factors that are known to explain the variations in stock returns was introduced as an alternative ([Gutierrez and Prinsky 2007](#); [Blitz et al. 2011](#)). Based on these studies, we expect future research will analyze the effects of the common factors’ persistence and their risk exposure on intraday momentum.

#### 5. Conclusions

Market Intraday Momentum is found in over 10 years of the KOSPI index data, by looking into the predictability of intraday 30 min returns and overnight returns on the last 30 min return of a trading day. The evidence that emerged from classification for volatility, liquidity and volume was in general consistent with the previous studies.

Trading strategies based on MIM can generate risk-adjusted profits that are higher than a benchmark method; moreover, the MIM is more suitable for predicting positive returns than negative ones. The MIM-based strategies were also robust against transaction costs, which were estimated using two intraday spread measures based on the highest and lowest prices. We showed that the averages of estimated spreads become smaller toward the end of trading hours and their sizes are small compared with the price level of the

KOSPI index. We thus established empirical evidence on MIM in the KOSPI index, with a new method of accounting for transaction costs.

Our findings also reflect an important regulatory implication. When MIM is present, it is vital for investors to be able to construct a market-timing strategy and make a profit from it. Transaction costs in the form of a large spread could impede this profitability. Our result that spread values tend to become smaller after several hours of trading suggests that exchanges should allow for a sufficient amount of time for trading. Those that currently have rather short trading hours, such as the Taiwan Stock Exchange (9:00 a.m.–1:30 p.m.), may consider extending the trading hours.

**Author Contributions:** Conceptualization, P.-C.T.; data curation, C.-Y.L., Z.-Y.L., C.E. and P.-C.T.; formal analysis, C.-Y.L. and Z.-Y.L.; investigation, C.-Y.L. and Z.-Y.L.; methodology, C.-Y.L. and P.-C.T.; project administration, P.-C.T.; resources, C.E. and P.-C.T.; supervision, P.-C.T.; validation, P.-C.T.; writing—original draft, C.-Y.L. and Z.-Y.L.; writing—review and editing, P.-C.T. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** Data will be available from the correspondent author upon request.

**Acknowledgments:** We thank three anonymous reviewers for their comments that helped improve the content of this paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

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