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Market intraday momentum: APAC evidence

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ABSTRACT

This study examines the market intraday momentum, where the first half-hour return predicts the last half-hour return, in exchange-traded funds (ETFs) from the selected Asia-Pacific (APAC) markets including China, Hong Kong SAR, Japan, Singapore and South Korea. Intraday momentum is mainly evident in China and Japan. There is weak evidence of the momentum effect in South Korea, while Hong Kong SAR and Singapore appear to have no intraday momentum. When both volatility and trading volume are considered, it is found that volatility has a stronger influence on intraday momentum than trading volume in the APAC markets. Finally, we show that the intraday momentum effect is weaker in the COVID-19 crisis period for the APAC markets that exhibit intraday momentum. Overall, the intraday momentum effect is not as pervasive in the APAC markets when compared to the US evidence.

1. Introduction

The efficient market hypothesis (Fama, 1970) advocates that an efficient market is one whereby current security prices fully reflect all available information. In particular, the market is expected to be at least weak form efficient, since past (price) information is readily available. However, a recent study by Gao et al. (2018) documents market intraday momentum (IMOM) in the US market over the period 1993–2013, based on the Standard & Poor's (S&P) 500 exchange-traded fund (ETF). Specifically, the IMOM effect indicates that the market's first half-hour return (from the close of the previous trading day) predicts the last half-hour return in the current trading day. Furthermore, the authors find that the effect is stronger when the market is more volatile, when the trading volume is high, and on recession days.

The IMOM effect is another evidence of the well-documented price momentum and consequently motivates us to carry out the analysis for the Asia-Pacific (APAC) markets. Earlier studies have found that the price momentum of Jegadeesh and Titman (1993) is weaker in Asian markets than in the United States and Europe (e.g., Hameed and Kusnadi, 2002; Brown et al., 2008; Chui et al., 2010). Most recent studies find that momentum exists in different formats in Asian equity markets (e.g., Pan et al., 2013; Chiao et al., 2020). Accordingly, in this replication study, we conduct the analysis in five of the largest APAC markets, including China, Hong Kong SAR, Japan, Singapore, and South Korea. Evidence from these APAC markets provides a validation test on samples that have been previously documented to have a weaker momentum effect. Gao et al. (2018) point out that a financial crisis is an outlier in the time series of market returns, which could affect price momentum. We therefore include the COVID-19 crisis period in our analysis to provide further

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insights on the IMOM effect. This study complements and extends the recent international study on intraday momentum by Li et al. (2021), who show that intraday momentum is prevalent in 16 developed markets.[1]

We first utilise the US data to replicate and validate our empirical methods, and our results are largely consistent with those of Gao et al. (2018). We also confirm the role volatility and trading volume play in IMOM. Finally, the IMOM effect remains robust during the COVID-19 crisis period in the US market. Having confirmed the validity of our approach based on the US market, we then examine the ETFs from the selected APAC markets. We document the IMOM effect in China, Japan, and South Korea. Both the first half-hour and the second-to-last half-hour returns significantly predict the last half-hour return in China and Japan, which is similar to the US evidence. In South Korea, the IMOM effect is relatively weak, since the first half-hour return only marginally predicts the last half-hour return. The IMOM effect is not observed in Hong Kong SAR or Singapore over the whole sample.

When the first half-hour trading volume is controlled for, there is no evidence that the IMOM effect increases with the first half-hour trading volume in the APAC markets. The IMOM effect is found to be stronger in the medium-volume group in China, and in high- and low-volume groups in Japan. The remaining markets show no to weak signs of the IMOM effect across volume groups. The results for the first half-hour volatility are more consistent with the US evidence, where the IMOM effect increases with first-hour volatility in Japan and South Korea. Over the COVID-19 crisis period, among the APAC markets exhibiting intraday momentum, the IMOM effect only persists in Japan. The IMOM effect becomes significant in Singapore, whereas China does not show any IMOM effect in this period. These results differ from the main findings, suggesting that the COVID-19 crisis may have significantly affected intraday momentum in the APAC markets. Overall, we document that the IMOM effect is not as pervasive in the APAC markets when compared to the US evidence. The predictive power of the first half-hour return on the last half-hour return is mainly observed in China and Japan in our sample.

2. Data and summary statistics

Our results include both replicating the main analysis of Gao et al. (2018) and conducting similar analyses with data obtained for China, Hong Kong SAR, Japan, South Korea, and Singapore.[2] The ETF data are obtained from DataScope. Starting with the US market, we obtain S&P 500 ETF data over the period January 1996 to December 2013 to establish the baseline results.[3] As Gao et al. (2018) indicate, the US intraday trading hours are from 9:30 a.m. to 4:00 p.m. Eastern Time, and the trading hours can thus be divided into 13 half-hour intervals. The returns used in the analysis are from three intervals*:* from the previous day's close at 4:00 p.m. to 10:00 a.m. on day *t* (denoted as r_1), from 3:00 p.m. to 3:30 p.m. (denoted as r_{12}), and from 3:30 p.m. and 4:00 p.m. (denoted as r_{13}).

For each APAC market in our study, we select the ETF that tracks the major market index in each market and spans an extended period ending in April 2021. Table 1 shows the information of different markets, including the ETFs analyzed, their trading hours, and the summary statistics of the trading volume, trade size, and volatility in the first-half trading hour, as well as the number of trades throughout the day for the ETFs. As shown in Panel A, the trading hours vary across the APAC markets. Among the markets selected, China has a total of four trading hours, the shortest period among the selected markets, while Singapore has a total of seven trading hours, the longest among the selected markets. Except for South Korea, all the Asian equity markets examined in this study have a lunch break. For example, in China, the market has two trading sessions. The morning session starts at 9:30 a.m. local time and finishes at 11:30 a.m. The afternoon session then resumes at 1:00 p.m. and closes at 3:00 p.m. In Singapore, the market runs from 9:00 a.m. to 5:00 p.m., with a one-hour break in between (i.e., 12:00 p.m. to 1:00 p.m.). For consistency, we follow Gao et al. (2018) and calculate returns every 30 min. Accordingly, the number of half-hour intervals varies across the markets in our sample. For instance, in China, the market has eight 30-min intervals, and in Singapore, the market has 14 30-min intervals.[4]

Panel B of Table 1 shows the descriptive statistics of the trading volume in the first-half trading hour for all the ETFs over their respective sample periods. The results from the US market are similar to those reported by Ho et al. (2021). The ETF in China has the largest trading volume in the first half hour in our sample and undoubtedly dominates the ETFs in the other APAC markets. To gain further understanding of the trading of the APAC markets, we present in Panel C the trade size in the first half hour for all the ETFs. Considering both the trading volume and trade size, the S&P 500 ETF is the most actively traded, as evident from its relatively smaller trade size given the trading volume.[5] For the APAC markets, the ETF in China is the most actively traded market, given its trading volume and average trade size. Each trade in Hong Kong SAR's ETF is considerably large in quantity, but the trading frequency is lower

[1] The markets investigated include Australia, Austria, Canada, France, Germany, Ireland, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

[2] The markets selected in this paper are slightly different from those in the pitch. The main reason why we dropped Malaysia, Thailand, and Taiwan is because their intraday data are very illiquid and include mostly stale prices, especially when compared to the selected markets.

[3] It is important to note that Gao et al. (2018) obtained their data from the Trade and Quote database, which starts in February 1993. The DataScope data start in January 1996.

[4] The trading hours in Hong Kong SAR exhibit a change during our sample period. The market opens at 10:00 a.m. prior to 2011 and opens at 9:30 a.m. after 2011. There are also changes in the duration of the lunch break. The closing time of the market remains at 4 p.m. throughout the sample period. Our calculation for the first half-hour return in Hong Kong SAR reflects the opening time throughout the period.

[5] The frequency of trading is determined by both the trading volume and trade size (i.e., the number of trades equals the trading volume divided by the trade size). For example, in Panels B and C, China has an average trading volume of 110.54 million and an average trade size of 363.76 (in hundreds) in the first half hour. China's trading volume is the largest of all the markets. However, considering the trade size, China's ETF has a lower number of trades in the first half hour when compared to the S&P 500 ETF. This also suggests that there are a few large block trades in the first half hour (i.e., larger trade size) in China's ETF. We thank an anonymous referee for this comment.

Table 1
Summary statistics.

Panel A: Market statistics					
Market	ETF	Ticker	Sample Period	Trading Hours	Market CAP (in US $Billion)
US	S&P500 ETF	SPY	JAN1996-DEC2013	9:30 AM-4:00 PM	$40,720.00
China	Huatai-PB CSI 300	510300.SS	MAY2012-APR2021	9:30–11:30 AM & 1:00–3:00 PM	$12,214.00
Japan	Nikko ET 225	1330	SEP2001-APR2021	9:00–11:30 AM & 12:30–3:00 PM	$6718.00
Hong Kong SAR	HK Hang Seng HSI	2800.HK	JAN2000-APR2021	9:30–12:00 PM & 1:00–4:00 PM	$6130.00
South Korea	KOSEF 200	102110	APR2008-APR2021	9:00 AM-3:30 PM	$2176.00
Singapore	PDR Straits Time	ES3.SI	APR2002-APR2021	9:00 AM-12:00 PM & 1:00–5:00 PM	$652.60

Panel B: Summary statistics on first half-hour trading volume					
Market	N	MIN	MAX	MEAN	STD
US	4485	0.01	175.58	15.91	17.77
China	2157	7.64	1310.20	110.54	117.51
Japan	4005	0.00	0.82	0.05	0.06
Hong Kong SAR	5216	0.00	122.83	6.30	9.38
South Korea	3098	0.00	3.47	0.14	0.18
Singapore	3547	0.00	11.67	0.08	0.27

Panel C: Summary statistics on first half-hour average trade size					
Market	N	MIN	MAX	MEAN	STD
US	4485	2.33	877.56	23.35	32.43
China	2157	36.45	1463.41	363.76	266.25
Japan	4005	0.40	37.27	5.09	3.69
Hong Kong SAR	5216	5.83	3487.32	280.43	296.36
South Korea	3098	0.01	166.68	6.98	5.75
Singapore	3547	1.00	6676.67	48.49	156.81

Panel D: Summary statistics on first half-hour volatility					
Market	N	MIN	MAX	MEAN	STD
US	4485	0.00	82.43	0.21	1.66
China	2157	0.00	10.29	0.22	0.62
Japan	4005	0.00	50.18	0.35	1.56
Hong Kong SAR	5216	0.00	222.18	0.55	3.22
South Korea	3098	0.00	56.70	0.24	1.66
Singapore	3547	0.00	802.30	0.40	13.49

Panel E: Summary statistics on the average daily number of trades					
Market	N	MIN	MAX	MEAN	STD
US	4485	0.07	2293.26	185.59	262.97
China	2157	2.13	133.65	14.98	14.44
Japan	4005	0.05	4.57	0.50	0.32
Hong Kong SAR	5216	0.04	19.97	1.03	1.26
South Korea	3098	0.00	41.66	2.10	2.45
Singapore	3547	0.00	4.10	0.13	0.25

This table reports the basic information of the selected APAC markets, including the specific ETFs and their sample periods, trading hours, and the total market capitalisation (in US $Billion, as of April 2021). The ETF data is obtained from DataScope. Panels B, C, D and E report the summary statistics on trading volume (in millions), trade size (in hundreds) and volatility (multiplied by 1000) of the first half trading hour, and daily number of trades (in thousands) for all the ETFs, respectively. N is the number of valid trading days over the sample period.

when compared to China. There is a big gap between China's ETF and the ETFs in the other APAC markets in relation to trading activities. Based on trading volume and trade size, the ETFs for Hong Kong SAR and Singapore have the smallest number of trades in their first half hour in our sample. Overall, the results from both Panels B and C indicate that, except for China, the trading frequency is relatively low among the ETFs in the APAC markets when compared to that of the United States.

Panel D of Table 1 shows the descriptive statistics for the first half-hour volatility computed based on one-minute returns. The ETFs of the United States and China are observed to have a lower first half-hour volatility than the other markets. Although this result seems to contradict the trading volume findings, it is driven by infrequent trading within the half-hour interval, as evident in Panels B and C.[6] Finally, Panel E shows the descriptive statistics for the daily number of trades in the ETFs. The results confirm that China's ETF is the most actively traded in our APAC sample. Singapore's ETF has the least trading during the day in our sample, consistent with the

[6] The realized volatility is calculated based on valid one-minute returns within the first half-hour interval. In our sample, it is possible for a market to have only a few valid one-minute returns due to infrequent trading.

results from the first half hour. Overall, in our samples, the ETFs in China and the United States are the most actively traded, while the ETF trading activities of the other APAC markets are relatively low. For brevity, in the subsequent sections, we use the respective markets to refer to the ETFs in our sample.

3. Methods

Following Gao et al. (2018), on each trading day *t*, we calculate the first half-hour return based on the period from the previous day's ETF close price to the price at the end of the first 30-min interval after the market opens. Subsequently, we calculate the returns for day *t* at every 30-min interval from the market open to the market close. This process results in the following return for a total of *n* half-hour observations per trading day:

$$r_{j,t} = \frac{p_{j,t}}{p_{j-1,t}} - 1, j = 1, \ldots, n$$

where *n* is the number of 30-min intervals in the specific market.

A. *IMOM Main Regression Analysis*

Following Gao et al. (2018), we run three predictive regressions to investigate whether intraday momentum exists. The following model is used to examine the relation between the first half-hour return (r_1) and the last half-hour return (r_n):

$$r_{n,t} = \alpha + \beta_{r_1} r_{1,t} + \varepsilon_t, t = 1, \ldots, T \tag{1}$$

where $r_{1,t}$ and $r_{n,t}$ are the first and last half-hour returns on day *t*, and *T* is the total number of trading days in the sample. We exclude trading days with fewer than 500 trades, as specified by Gao et al. (2018) for the US sample. Similar to Gao et al. (2018), who use a trade cutoff to exclude infrequent trading days, we apply a trade cutoff of the fifth percentile for all the APAC markets.[7]

Gao et al. (2018) also document that the second-to-last half hour (in this paper denoted as r_{n-1}) can potentially affect the last half-hour return (r_n), provided strong momentum during the day. Hence, we replace r_1 with the return of the second-to-last half hour (r_{n-1}) in the following model:

$$r_{n,t} = \alpha + \beta_{r_{n-1}} r_{n-1,t} + \varepsilon_t, t = 1, \ldots, T \tag{2}$$

Finally, we combine the two predictors to examine whether the first and second-to-last half-hour returns (r_1 and r_{n-1}) have independent and separate explanatory power on the last half-hour return (r_n):

$$r_{n,t} = \alpha + \beta_{r_1} r_{1,t} + \beta_{r_{n-1}} r_{n-1,t} + \varepsilon_t, t = 1, \ldots, T \tag{3}$$

B. *Out-of-Sample Predictability*

Following Gao et al. (2018), we calculate out-of-sample R^2 values to assess whether the return predictability persists out-of-sample. Gao et al. run recursive regressions to forecast returns at time *t,* using data only up to time $t-1$. The initial estimation period is five years, and we progressively add one month of returns at a time to calculate the out-of-sample R^2. The window of the estimation initially uses observations up to December 2000. It is important to note that the selected ETFs for the APAC markets have shorter sample periods and are traded less frequently than the US market. Thus, we require at least 500 trading days in the initial estimation window to run recursive regressions to calculate out-of-sample R^2 values. The out-of-sample R^2 is specified as

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T} \left(r_{n,t} - \widehat{r}_{n,t}\right)^2}{\sum_{t=1}^{T} \left(r_{n,t} - \overline{r}_{n,t}\right)^2} \tag{4}$$

where $\widehat{r}_{n,t}$ is the forecasted last half-hour return from the predictive regressions estimated through period $t-1$, and $\overline{r}_{n,t}$ is the historical average forecast estimated from the sample mean through period $t-1$. The numerator is the variation between actual returns and the predicted returns generated from the regressions, and the denominator is the variation between actual returns and the historical sample means. Since the out-of-sample R^2 is one minus the ratio, a positive R^2_{OS} value indicates that the out-of-sample predictability from the regression is superior to the estimation from the historical average.

[7] In the US market, the 500-trade cutoff is approximately the fifth percentile, and we therefore apply the fifth percentile cutoff to our APAC markets. The number of trades at fifth percentile is 3597 for China, 116 for Hong Kong SAR, 182 for Japan, 53 for South Korea and 8 for Singapore. We also applied a 10th percentile cutoff as a robustness check, given that the APAC markets are not as active as the US market. Our results, which are available upon request from the authors, are robust to the alternative cutoff rule.

4. Empirical results

A. *US Market Replication*

We first replicate Table 1 of Gao et al. (2018) over the period 1996 to 2013. Panel A of Table 2 shows the results based on Models (1) to (3). The results show that the first half-hour return, r_1, positively predicts the last half-hour return, r_n. The coefficient is 7.15, statistically significant at the 1% level, and the model has an R^2 of 1.7%. The 12th half-hour return, r_{n-1}, is also able to predict the last half-hour return, r_n, statistically significant at the 5% level, but with a lower R^2 of 0.9%. When both r_1 and r_{n-1} are included in the regression (Model (3)), they are significant at least at the 5% level with an R^2 of 2.6%, and the r_{n-1} coefficient is larger than the r_1 coefficient. Finally, we compute the out-of-sample R^2, as described in Eq. (4), following Gao et al. (2018), to assess the out-of-sample predictive power of Eq. (3). The R^2_{OS} value is 1.7% when we use the r_1 return alone. When we use r_{n-1}, R^2_{OS} is 0.5%. When both r_1 and r_{n-1} are included in the regression, the R^2_{OS} value is the highest, at 2.3%. In general, the R^2_{OS} values are close to but lower than the in-sample R^2, and the magnitudes are similar to those reported by Gao et al. (2018). Overall, our results indicate successful replication of the results of Gao et al. (2018).

B. *APAC Markets: Main Regressions*

Panels B to F of Table 2 display the results for the APAC markets. Column (1) in each panel tabulates the results of Model (1). The results suggest that the first half-hour return, r_1, significantly predicts the last half-hour return in China and Japan, which are the largest markets in our APAC sample.[8] The second-to-last half-hour return, r_{n-1}, also exhibits predictive power in these two markets. When both r_1 and r_{n-1} are included in the regression, the magnitude and significance of the regression slopes are similar to their individual regression counterparts. The in-sample R^2 values range from 2.3% to 5.5% in China and from 0.6% to 1.5% in Japan. The R^2 value from Model (3) is approximately equal to the sum of the individual R^2 values from Models (1) and (2), indicating that r_1 and r_{n-1} are independent and complementary in forecasting r_n. This finding is consistent with that reported by Gao et al. (2018).

The coefficients of r_1 are marginally significant at the 10% level when r_1 is used as a sole variable and in the combined model for South Korea. While these results suggest some predictive power of the first-half hour return, the evidence is much weaker when compared to China and Japan. Both Hong Kong SAR and Singapore show no intraday momentum and r_{n-1} is also found to be negative in these two markets. Avramov et al. (2006) suggest that less liquid stocks tend to undergo substantially greater reversals than liquid stocks. We postulate that this result may be due to stale prices and the infrequent trading of the ETFs in these markets, as evident in Table 1. The in-sample R^2 values for these two markets range from close to 0% (no predictive power) to approximately 15.7%. However, these results should be interpreted with caution, due to the issue of illiquidity.

The regression results provide two main takeaways. First, the relation between r_1 and r_n is not pervasive across the APAC markets. However, this relation in China is found to be comparable to the US result. Second, r_{n-1} also predicts r_n across the APAC markets, except for South Korea. The effect is independent and remains robust when r_1 is included. Since the IMOM effect is the predictability of the first half-hour return on the last half-hour return, our results suggest that IMOM exists only in China and Japan in our sample.

We next examine whether the models are useful for generating out-of-sample forecasts. The R^2_{OS} values are displayed at the bottom of each panel. The values of the R^2_{OS} are lower than the in-sample R^2 values across the APAC markets, similar to the US finding. The differences are smaller for China, Japan, and South Korea. These R^2_{OS} values suggest that the predictive power of r_1 or both r_1 and r_{n-1} in the combined model is significant not only in sample but also out of sample. It is worth noting that some R^2_{OS} values are negative, especially in Singapore, where the IMOM effect is absent.

C. *Trading Volume Subsample Analysis*

Table 3 shows the results from Model (3) for the subsamples based on the first half-hour trading volume partitions. Following Gao et al. (2018), we split the trading days into low, medium, and high terciles based on the first half-hour trading volume year by year, to form three volume groups. Panel A shows the results for the US market. Similar to Table 3 of Gao et al. (2018), Model (3) performs best in the high tercile, with both r_1 and r_{n-1} being significant, and with the highest R^2 value. For the APAC markets, the signs of the coefficients are largely consistent with the main results across the trading volume groups. However, except for Japan, there is no evidence that the predictive power of r_1 on r_n is stronger in the high-volume group for the APAC markets. For the Chinese market, the effect is found to be strongest in the medium tercile. This also seems to be the case for South Korea. The result also suggests that there is no relation between intraday momentum and the first half-hour trading volume in Hong Kong SAR, and Singapore.

D. *Volatility Subsample Analysis*

Table 4 shows the results from Model (3) in the subsamples based on the first half-hour volatility partitions. Following Gao et al. (2018), all the trading days in the sample are sorted based on the first half-hour volatility and subsequently divided into three groups (terciles). Panel A shows that Model (3) performs best in the high group, with both r_1 and r_{n-1} being significant, and with the highest R^2

[8] The finding for the Japanese market is similar to that of Li et al. (2021).

Table 2
Main regression results.

Panel A: US	[1]	[2]	[3]
Intercept	−1.143	−1.020	−1.415
	[0.402]	[0.459]	[0.318]
r_1	7.150***		7.090***
	[0.000]		[0.000]
$r_{n\text{-}1}$		9.480**	9.330**
		[0.024]	[0.024]
R^2	0.017	0.009	0.026
R^2_{OS}	0.017	0.005	0.023
N	4094	4094	4094
5% PCT	500	500	500

Panel B: China	[1]	[2]	[3]
Intercept	−3.969*	−4.185*	−4.448**
	[0.070]	[0.056]	[0.040]
r_1	7.740***		7.160***
	[0.000]		[0.000]
$r_{n\text{-}1}$		18.990**	18.140***
		[0.040]	[0.002]
R^2	0.023	0.036	0.055
R^2_{OS}	0.020	0.028	0.045
N	2049	2049	2049
5% PCT	3597	3597	3597

Panel C: Hong Kong SAR	[1]	[2]	[3]
Intercept	−1.735	−0.648	−0.698
	[0.250]	[0.657]	[0.637]
r_1	0.704		0.287
	[0.412]		[0.736]
$r_{n\text{-}1}$		−18.230***	−18.200***
		[0.000]	[0.000]
R^2	0.000	0.039	0.040
R^2_{OS}	−0.002	0.029	0.027
N	4959	4959	4959
5% PCT	116	116	116

Panel D: Japan	[1]	[2]	[3]
Intercept	0.720	1.167	0.876
	[0.519]	[0.295]	[0.434]
r_1	2.170***		2.080***
	[0.000]		[0.001]
$r_{n\text{-}1}$		8.510**	7.960**
		[0.024]	[0.031]
R^2	0.010	0.006	0.015
R^2_{OS}	0.010	−0.002	0.007
N	3804	3804	3804
5% PCT	182	182	182

Panel E: South Korea	[1]	[2]	[3]
Intercept	−0.449	−0.300	−0.424
	[0.484]	[0.637]	[0.499]
r_1	2.090*		2.060*
	[0.092]		[0.084]
$r_{n\text{-}1}$		5.600	5.570
		[0.114]	[0.110]
R^2	0.006	0.013	0.019
R^2_{OS}	0.001	0.008	0.009
N	2944	2944	2944
5% PCT	53	53	53

Panel F: Singapore	[1]	[2]	[3]
Intercept	0.657	0.592	0.569
	[0.584]	[0.611]	[0.623]
r_1	−0.714		−0.648
	[0.248]		[0.258]
$r_{n\text{-}1}$		−32.570***	−32.450***
		[0.000]	[0.000]
R^2	0.157	−0.032	0.152
R^2_{OS}	−0.002	0.000	−0.001
N	3261	3261	3261
5% PCT	8	8	8

This table reports the main regression results of the three models for the US market, and the selected APAC markets. In all models, r_n is the dependent variable. r_1 is the first half-hour return and $r_{n\text{-}1}$ is the second-to-last half-hour return. The intercepts are annualized and in percentage, and the slope coefficients are scaled by 100. The p-values are in parentheses, with ***, **, and * indicating the statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period for each market is as indicated in Table 1. N is the number of observations after the application of the 5% percentile trade cut-off. 5% PCT is the daily number of trades at the 5% percentile. The *p*-values are generated after correcting for Newey and West (1987) standard errors.

Table 3
IMOM and volume.

Panel A: US	Low	Medium	High
Intercept	−3.319*	−2.029	0.967
	[0.054]	[0.305]	[0.775]
r_1	6.090***	6.030***	7.570***
	[0.004]	[0.000]	[0.003]
r_{n-1}	2.750	2.180	15.740**
	[0.163]	[0.618]	[0.017]
R^2	0.011	0.016	0.039

Panel B: China	Low	Medium	High
Intercept	−2.542	−8.859**	−2.201
	[0.351]	[0.022]	[0.633]
r_1	6.080	9.630***	6.840***
	[0.149]	[0.007]	[0.003]
r_{n-1}	22.240*	26.590***	9.870
	[0.068]	[0.010]	[0.188]
R^2	0.060	0.096	0.038

Panel C: Hong Kong SAR	Low	Medium	High
Intercept	2.583	−0.822	−3.897
	[0.289]	[0.778]	[0.172]
r_1	−0.194	−0.948	1.170
	[0.871]	[0.443]	[0.373]
r_{n-1}	−23.870***	−17.630***	−13.830***
	[0.000]	[0.000]	[0.003]
R^2	0.075	0.039	0.022

Panel D: Japan	Low	Medium	High
Intercept	2.120	−1.366	2.155
	[0.207]	[0.419]	[0.351]
r_1	1.740**	0.947	2.490***
	[0.047]	[0.264]	[0.005]
r_{n-1}	−0.1877	1.330	14.460**
	[0.974]	[0.748]	[0.028]
R^2	0.004	0.002	0.035

Panel E: South Korea	Low	Medium	High
Intercept	0.071	−1.538	0.768
	[0.946]	[0.145]	[0.532]
r_1	−0.737	3.260*	2.350
	[0.702]	[0.058]	[0.121]
r_{n-1}	−4.510	2.700	19.280***
	[0.192]	[0.272]	[0.009]
R^2	0.004	0.021	0.091

Panel F: Singapore	Low	Medium	High
Intercept	−0.871	0.816	0.718
	[0.511]	[0.704]	[0.750]
r_1	−0.051	0.116	−3.770
	[0.403]	[0.934]	[0.064]
r_{n-1}	−17.020*	−54.670***	−22.820***
	[0.054]	[0.002]	[0.002]
R^2	0.020	0.145	0.046

This table reports the regression results of Model [3] in the trading volume groups based on the first-half hour trading volume for all the markets. All trading days in the sample are sorted into terciles based on the first half-hour trading volume year by year, and we then combine each volume tercile across all years to form three volume groups. In all models, r_n is the dependent variable. r_1 is the first half-hour return and r_{n-1} is the second-to-last half-hour return. The intercepts are annualized and in percentage, and the slope coefficients are scaled by 100. The p-values are in parentheses, with ***, **, and * indicating the statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period for each market is as indicated in Table 1. The *p*-values are generated after correcting for Newey and West (1987) standard errors.

Table 4
IMOM and volatility.

Panel A: US				Panel B: China				Panel C: Hong Kong SAR			
	Low	Medium	High		Low	Medium	High		Low	Medium	High
Intercept	−2.859*	−2.396	0.501	Intercept	−0.573	−5.091	−7.319	Intercept	3.665**	−0.275	−4.544
	[0.052]	[0.244]	[0.890]		[0.816]	[0.104]	[0.162]		[0.023]	[0.914]	[0.171]
r_1	6.090***	5.440**	7.830***	r_1	8.240***	6.160***	7.090***	r_1	−2.890*	−1.760*	1.290
	[0.000]	[0.015]	[0.001]		[0.000]	[0.004]	[0.006]		[0.099]	[0.098]	[0.251]
r_{n-1}	3.450	−0.926	16.490**	r_{n-1}	1.740	14.540**	25.410***	r_{n-1}	−16.530***	−14.490***	−20.630***
	[0.156]	[0.842]	[0.011]		[0.722]	[0.013]	[0.008]		[0.000]	[0.000]	[0.000]
R^2	0.017	0.01	0.041	R^2	0.027	0.048	0.073	R^2	0.042	0.029	0.048
Panel D: Japan				**Panel E: South Korea**				**Panel F: Singapore**			
	Low	Medium	High		Low	Medium	High		Low	Medium	High
Intercept	−0.573	2.737	0.791	Intercept	0.393	−0.995	−0.072	Intercept	1.015	−0.598	1.167
	[0.690]	[0.130]	[0.753]		[0.631]	[0.362]	[0.960]		[0.469]	[0.660]	[0.672]
r_1	1.590	1.610	2.200***	r_1	0.568	0.707	2.630*	r_1	−1.430	−1.840	−0.595
	[0.182]	[0.102]	[0.003]		[0.747]	[0.705]	[0.074]		[0.344]	[0.110]	[0.290]
r_{n-1}	0.746	5.630	10.740*	r_{n-1}	4.270	0.423	14.740**	r_{n-1}	−14.350***	−41.440**	−33.020***
	[0.889]	[0.262]	[0.059]		[0.101]	[0.484]	[0.017]		[0.005]	[0.045]	[0.000]
R^2	0.002	0.007	0.024	R^2	0.005	0.001	0.062	R^2	0.011	0.115	0.055

This table reports the regression results of Model [3] in the volatility groups based on the first-half hour volatility for all the markets. The first half−hour volatility is estimated using one-minute returns, and then all the trading days are divided into terciles (low, medium, and high) by their first half-hour volatility. In all models, r_n is the dependent variable. r_1 is the first half-hour return and r_{n-1} is the second-to-last half-hour return. The intercepts are annualized and in percentage, and the slope coefficients are scaled by 100. The p-values are in parentheses, with ***, **, and * indicating the statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period for each market is as indicated in Table 1. The *p*-values are generated after correcting for Newey and West (1987) standard errors.

for the US market. These results, together with the results from the trading volume partitions, confirm the success of our replication.

For the APAC markets, as with the results in Table 4, the signs of the coefficients are largely consistent with the main results across the volatility groups. In China, both r_1 and r_{n-1} remain important in predicting r_n in the medium- and high-volatility groups. Given that R^2 is the highest in the high-volatility group, this result suggests that the IMOM effect is associated with the first half-hour volatility in the Chinese market. For the other markets, r_1 and r_{n-1} are observed to be significant in different volatility groups. For example, in both Japan and South Korea, both r_1 and r_{n-1} are significantly positive in the high-volatility group. Except where r_1 is positive in Hong Kong SAR in the high-volatility group, negative coefficients are observed in Hong Kong SAR and Singapore across all the volatility groups. Overall, the results suggest that the first half-hour volatility tend to have a stronger influence on IMOM than the first half-hour trading volume in the APAC markets. The results also suggest that intraday momentum is stronger with higher first half-hour volatility in the APAC markets.

E. *COVID-19 Crisis Analysis*

To complete the analysis, we rerun Models (1) to (3) during the COVID-19 crisis period. It is important to note that there is no exact and universal definition for the period of the crisis. In this paper, the COVID-19 crisis is defined as when the majority of the markets crashed soon after the COVID-19 outbreak, from February 14 to March 31, 2020. Table 5 show the first half-hour summary statistics and the average numbers of daily trades over this period. The summary statistics over the COVID-19 period indicate that the mean first half-hour trading volume is higher than for the whole period across all the markets, except for Japan. The average trade size and volatility tend to be lower, and the daily number of trades is considerably higher across the markets during the COVID-19 period. However, these results should be interpreted with caution, since we are comparing a very short sample period to a much longer one.

Table 5
Summary statistics during the COVID-19 crisis.

Panel A: Summary statistics on first half-hour trading volume					
Market	N	MIN	MAX	MEAN	STD
US	32	4.96	60.01	30.10	13.96
China	33	39.21	386.02	147.65	92.97
Japan	31	0.01	0.08	0.03	0.02
Hong Kong SAR	33	4.57	28.31	14.11	6.13
South Korea	33	0.11	2.10	0.74	0.49
Singapore	33	0.02	2.34	0.67	0.54
Panel B: Summary statistics on first half-hour average trade size					
Market	N	MIN	MAX	MEAN	STD
US	32	1.79	2.78	2.20	0.26
China	33	93.17	330.67	167.47	58.40
Japan	31	0.70	4.98	1.83	0.95
Hong Kong SAR	33	38.08	1154.76	306.35	259.16
South Korea	33	1.85	8.15	4.48	1.69
Singapore	33	14.29	66.94	32.88	12.37
Panel C: Summary statistics on first half-hour volatility					
Market	N	MIN	MAX	MEAN	STD
US	32	0.00	8.02	1.22	1.67
China	33	0.01	2.30	0.36	0.48
Japan	31	0.00	9.73	1.26	1.95
Hong Kong SAR	33	0.03	2.67	0.49	0.62
South Korea	33	0.00	7.49	1.15	1.77
Singapore	33	0.00	2.88	0.65	0.79
Panel D: Summary statistics on the average daily number of trades					
Market	N	MIN	MAX	MEAN	STD
US	32	134.54	1667.87	873.49	384.00
China	33	16.17	95.38	38.91	17.75
Japan	31	0.25	2.08	0.84	0.40
Hong Kong SAR	33	0.91	13.20	4.84	3.75
South Korea	33	3.03	20.64	9.77	5.45
Singapore	33	0.08	4.10	1.45	1.05

This table reports the summary statistics of the ETFs during the COVID-19 crisis period. Panels A, B, C, and D report the summary statistics on trading volume (in millions), trade size (in hundreds) and volatility (multiplied by 1000) of the first half trading hour, and daily number of trades (in thousands) for all the ETFs, respectively.

Table 6
IMOM during the COVID-19 crisis.

Panel A: US	[1]	[2]	[3]
Intercept	221.561	74.914	225.749
	[0.181]	[0.344]	[0.219]
r_1	21.050**		29.310***
	[0.033]		[0.010]
r_{n-1}		−27.190	−83.640*
		[0.628]	[0.095]
R^2	0.126	0.011	0.209

Panel B: China	[1]	[2]	[3]
Intercept	−15.173	−17.020	−15.807
	[0.225]	[0.201]	[0.245]
r_1	3.490		2.930
	[0.367]		[0.472]
r_{n-1}		9.440	6.120
		[0.308]	[0.563]
R^2	0.023	0.014	0.028

Panel C: Hong Kong SAR	[1]	[2]	[3]
Intercept	47.138**	47.616**	45.567***
	[0.012]	[0.036]	[0.010]
r_1	−0.879		−1.320
	[0.851]		[0.820]
r_{n-1}		−30.520	−30.910
		[0.208]	[0.194]
R^2	0.001	0.086	0.090

Panel D: Japan	[1]	[2]	[3]
Intercept	10.598	−5.636	10.129
	[0.629]	[0.853]	[0.636]
r_1	12.120**		12.040**
	[0.030]		[0.039]
r_{n-1}		−10.170	−2.460
		[0.718]	[0.930]
R^2	0.200	0.007	0.200

Panel E: South Korea	[1]	[2]	[3]
Intercept	5.311	−2.615	0.536
	[0.829]	[0.904]	[0.978]
r_1	8.140*		3.050
	[0.054]		[0.510]
r_{n-1}		64.730***	61.750***
		[0.000]	[0.001]
R^2	0.065	0.327	0.314

Panel F: Singapore	[1]	[2]	[3]
Intercept	−5.423	−13.068	−5.612
	[0.777]	[0.533]	[0.763]
r_1	8.900***		8.860***
	[0.000]		[0.000]
r_{n-1}		11.480	2.150
		[0.708]	[0.933]
R^2	0.166	0.005	0.166

This table reports the regression results of Model [3] during the COVID-19 crisis, defined as the period from 14FEB2020 to 31MAR2020, for all the markets. In all models, r_n is the dependent variable. r_1 is the first half-hour return and r_{n-1} is the second-to-last half-hour return. The intercepts are annualized and in percentage, and the slope coefficients are scaled by 100. The p-values are in parentheses, with ***, **, and * indicating the statistical significance at the 1%, 5%, and 10% levels, respectively. The *p*-values are generated after correcting for Newey and West (1987) standard errors.

Table 6 shows the performance of Model (3) during the COVID-19 crisis.[9] While the IMOM effect in the US market persists in the crisis period, $r_{n\text{-}1}$ becomes negative in the combined model. The magnitudes of r_1 and $r_{n\text{-}1}$ and the levels of their significance change considerably in the APAC markets. For example, both r_1 and $r_{n\text{-}1}$ completely lose their predictive power in China, indicating the absence of the IMOM effect during the crisis. The predictive power holds in Japan for the first half-hour return, and in South Korea only for the model where r_1 is the sole variable. Interestingly, the first half-hour return positively predicts the last half-hour return in Singapore in the crisis period. Since the crisis first started in China and then spread to other markets, this could explain why the Chinese market exhibits a significant change. In summary, for the APAC markets that exhibit intraday momentum, the effect tends to be weaker in the COVID-19 crisis period, especially for the Chinese market. The results should be interpreted with caution, since the COVID-19 crisis period is rather short, with the markets rebounding quickly in the second quarter of 2020.[10]

5. Conclusions

This study examines the IMOM effect in the selected APAC markets. The study first confirms the IMOM effect in the US market, as documented by Gao et al. (2018). This validates our empirical methodology, which is then carried out for other markets. The main results show that the IMOM effect exists mainly in China and Japan, while a week IMOM effect is observed in South Korea. There is no evidence of the IMOM effect in Hong Kong SAR and Singapore. Generally, the first half-hour volatility is found to have a stronger influence on the IMOM effect than the first half-hour trading volume in the APAC markets. Finally, for the APAC markets that exhibit intraday momentum, the effect is weaker during the COVID-19 crisis period. The absence of the IMOM effect in Hong Kong SAR and Singapore could be explained by the low levels of trading in ETFs and deserves future research.

Author statement

Manapon Limkriangkrai: Conceptualization; Methodology; Software; Major empirical analysis; Investigation; Data Cleansing; Writing - Original Draft, Review & Editing; Visualization; Project administration

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Appendix A

Pre-Registration Study (Pitch)

PBFJ Replication Study Master Pitch Template (with Cues)

Pitcher Team Name	JEL code G1, G11, G12 Date Completed 7 May 2021
(A) Working Title	Market Intraday Momentum: Asia-Pacific Markets Evidence
(B) Basic Research Question	Does the intraday momentum exist in the Asia-Pacific markets?
(C) Key paper(s)	**Target replication paper:** Gao, L, Han Y., Li, S.Z. and Zhou, G., 2018, Market Intraday Momentum, *Journal of Financial Economics*, 129, 394–414. Other key papers Li, Z, A Sakkas, A., and Urquhart, A., 2021, Intraday Time Series Momentum: Global Evidence and Links to Market Characteristics, *Journal of Financial Markets* 57, 100,619. Ho, T., J.R. Lv, & E. Schultz, 2021, Market Intraday Momentum in Australia, *Pacific-Basin Finance Journal 65*, 101,499.
(D) Motivation/Puzzle	**Motivation:** The Efficient Market Hypothesis (EMH, Fama, 1970) advocates that an efficient market is one whereby current security prices fully reflect all available information. In particular, the market is expected to be at least weak-form efficient as the past (price) information is readily available. However, a recent study by Gao et al. (2018) documents that there is a market intraday momentum (IMOM) in the US market from 1993 to 2013 based on the S&P500 exchange-traded fund (ETF) data. Specifically, the market IMOM effect indicates that the market's first half-hour return from the close of the previous trading day predicts the last half-hour return in the current trading day – and that this predictability is significant both statistically and economically. Furthermore, they find that the effect is stronger when the market is more volatile, when the trading volume is high, and when financial crisis is excluded. Hence, the IMOM effect is another evidence of the well documented price momentum, and consequently motivates us to carry out the analyses for the major Asia-Pacific (APAC) markets. We choose APAC markets because the majority are categorized as emerging

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[9] It should be noted that we do not examine the globe financial crisis, given that not all market index data started before 2008.

[10] The mostly likely explanation to our findings of the weakened IMOM effect in the APAC markets is the short sample period employed. This is because we do not observe that the trading is noticeably weakened in the defined COVID-19 period (see Table 5).

(*continued*)

PBFJ Replication Study Master Pitch Template (with Cues)	
Pitcher Team Name	JEL code G1, G11, G12 Date Completed 7 May 2021
	markets and prior research show that emerging markets are characterized by low correlations with returns on other emerging markets and with developed markets (Harvey, 1995). Thus, evidence from APAC markets provides a validation test on a sample that is not highly correlated with data used in prior research. In addition, a number of recent studies show that the Covid-19 crisis has a negative impact on stock returns and a positive impact on market volatility. As momentum strategies are known to have performed poorly during the crisis period, the inclusion of the Covid-19 crisis period in our analysis will provide further insights to the IMOM effect. **Puzzle:** Does the market intraday momentum (IMOM) exist in the Asia-Pacific (APAC) markets? **Chosen Asian-Pacific markets:** This project is a cross-market study on intraday momentum based on selected APAC markets. Most APAC markets are smaller in size and are categorized as emerging markets. Thus, we only consider APAC markets that are representative of the region and also have the required data available. The markets considered in this study include: China, Hong Kong SAR, South Korea, Singapore, Taiwan, Thailand and Malaysia. [Note: In certain classifications, Hong Kong SAR and Singapore are considered to be the 'top' emerging markets in the region.] **Expected outcome:** There are possibilities that the IMOM may only exist in specific markets. Regardless of what the finding is, it will contribute to the evidence related to the Market IMOM.
THREE	**Three** core aspects of any empirical research project i.e. the "**ID**io**T**s" guide
(E) Idea?	**Core idea:** The central purpose of the replication study is to examine whether the IMOM also exist in the APAC markets. In addition, we have a timely 2020 data to examine how the IMOM effect might be different during the COVID crisis. **Central hypothesis:** The IMOM effect exists in APAC markets.
(F) Data?	**Data source:** The ETFs intraday data for the selected APAC markets are sourced from Datascope. The starting years of the different ETFs for the selected markets vary between 1999 and 2001, hence we will choose a uniform starting year of 2000, while the ending year for all ETFs is 2020. **Sample size:** We will select one ETF that tracks the major market index for each market over the sample period. Intraday data for the ETFs are used in the analysis. **Data issues:** The data issue is minimum as the members in this project have experience with this type of data. **Quality of the data:** The data sources are reliable and have been used extensively in prior studies.
(G) Tools?	**Empirical framework:** Following Gao et al. (2018), in the examination of the intraday return predictability, on a trading day *t*, the first half-hour returns based on the previous day's ETF close price, and then the price every 30-min from the market open to market close. These result in the total of 13 half-hour observations per trading day: $r_{j,t} = \frac{p_{j,t}}{p_{j-1,t}} - 1, j = 1, \dots, 13$ [1] **IMOM Predictive Regression Analysis** The first predictive regression of the last half-hour return on the first half-hour return is specified as: $r_{13,t} = \alpha + \beta r_{1,t} + \varepsilon_t, t = 1, \dots, T$ [2] Where $r_{1,t}$ and $r_{13,t}$ are the first and last half-hour returns on day *t*, and *T* is the total trading days. Gao et al. (2018) also document that the 12th half-hour (i.e. the second-to-last half hour), r_{12}, potentially can affect the last half hour return provided there is a strong momentum during the day. Hence, we will also rerun [2] with r_{12} replacing r_1. We will also combine the two predictors and specify the regression as: $r_{13,t} = \alpha + \beta_{r1} r_{1,t} + \beta_{r12} r_{12,t} + \varepsilon_t, t = 1, \dots, T$ [3] **Out-of-Sample Predictability** The out-of-sample R^2 is specified as: $R^2_{OS} = 1 - \frac{\sum_{t=1}^{T} (r_{13,t} - \widehat{r}_{13,t})^2}{\sum_{t=1}^{T} (r_{13,t} - \overline{r}_{13,t})^2}$ [4] As defined in Gao et al. (2018, p.397) "where $\widehat{r}_{13,t}$ is the forecasted last half-hour return from the predictive regression estimated through period t – 1 and $\overline{r}_{13,t}$ is the historical average forecast estimated from the sample mean through period t – 1. A positive R^2_{OS} indicates that the predictive regression forecast beast the simple historical average." The additional analyses will also include Crisis Periods: the GFC crisis and the COVID crisis – with the main analyse re-run during and outside the crisis, and before and after the crisis. Volatility and Volume: We will examine the predictability in the sub-samples in Low / Medium / High volatility and trading volume. **Software for research:** Our analysis will be mainly based on SAS. The team members have experiences in using the programs to perform statistical/econometric tests in this study.
TWO	**Two** key questions
(H) What's New?	In this replication study, we offer out-of-sample evidence on the IMOM effect. We do so by examining ETFs in a group of emerging Asia-Pacific stock markets. We choose these markets because, although there are relevant studies that uses data from developed markets, little is known about the predictability of intraday returns in emerging markets. In addition, our extended sample period covers the recent COVID crisis in 2020. We are able to compare whether the COVID crisis and the 2008 financial crisis have the same effect on IMOM.
(I) So What?	As implied by the EMH, the market should at least be weak-form efficient, the simple past return data should not have any predictive power even at the intraday level. If momentum profits really are due to the slow reaction of prices to information contained in past returns, we should be able to find similar evidence in other markets. As emerging markets are more volatile than developed markets and also have low correlations with returns on other emerging markets and with developed markets, our analysis provides valid out-of-sample test on the IMOM effect.
ONE	**One** bottom line
(J) Contribution?	Our study will provide the strong out-of-sample IMOM evidence using seven emerging APAC markets, and also a timely examination of the impact of the COVID crisis on the IMOM effect. In contrast to the voluminous research in the U.S. and Japan

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PBFJ Replication Study Master Pitch Template (with Cues)				
Pitcher Team Name	JEL code	G1, G11, G12	Date Completed	7 May 2021
	relating to the cross-sectional behavior of stock returns to market risk and firm characteristics, there has been very limited research relating to the emerging markets. However, the extraordinary growth of the emerging stock markets, especially in the APAC region, during the last decade has already attracted a lot of attention from investors around the world. Research on the emerging stock markets in the APAC region will definitely provide academics and practitioners a better understanding on the cross-sectional behavior of stock returns in this region.			
(K) Other Considerations				The research team is familiar with the anomalies / asset-pricing work and the relevant AUS literature. The risk of this project is low.

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