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Intraday Momentum In the Korean stock market

한국 주식시장에서의 일중 모멘텀

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Abstract

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Is buying winners and selling losers on an intraday basis an effective investment strategy? To shed light on this question, this paper presents whether the return from the previous closing price to the first 30-min price predicts the last half-hour return on the Korean stock market. This study asks two specific related questions: Does intraday momentum exist in the Korean stock market? In which situation does the momentum effect become stronger?

Keyword: Intraday, Momentum, Intraday Momentum

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1. Introduction

Is buying winners and selling losers on an intraday basis an effective investment strategy? To shed light on this question, this paper presents whether the return from the previous closing price to the first 30-min price predicts the last half-hour return on the Korean stock market.

Contrary to the second-to-last half-hour return, the first half-hour return and the last half-hour return are not consecutive periods. Nevertheless, if a momentum pattern exists, it could be applied as a useful investment strategy on an intraday basis.

This study asks two specific related questions: Does intraday momentum exist in the Korean stock market? In which situation does the momentum effect become stronger?

2. Related Papers

Many studies on the momentum effect have been conducted since Jegadeesh and Titman (1993). Rouwenhorst at al. (1998) and Moskowitz at al. (2013) examined the international momentum effect, while Jostova at al. (2013) reported on the bond momentum effect. More recent studies investigated intraday momentum in the U.S. (Gao at al., 2018) and China (Chu et al., 2019; Zhang at al., 2019).

Studies on momentum strategies have also been conducted in the context of South Korea. Kho (1997) pointed out that the momentum strategies in South Korea show insignificant negative monthly returns. However, Kim (2012) and Eom (2013) documented that momentum strategies had been effective since the 1997 Asian financial crisis. However, no paper to date focuses on momentum on an intraday basis.

Several studies have been conducted on return patterns during intraday trading in the Korean stock market. Jang (1993) showed a V-shaped pattern of returns from 1998 to 1990. Soh (2011) and Kim at al. (2012) investigated half-hour returns within five trading days in series, and found that although a strong negative correlation existed in the first few intervals, the trend weakened with time.

3. Data and Identification of Returns and Volatility

3.1. Data

To explore the intraday return predictability in South Korea, I use the KODEX200 (069500.KS). Since going public in 2002, the KODEX200 has been one of the oldest and the most popular exchange-traded funds (ETFs) in Korea. It is designed to track the Korea Composite Stock Price Index 200 (KOSPI200), which is a capitalization-weighted index of 200 Korean stocks. The intraday trading data of the KODEX200 are sourced from the Korean

Exchange (KRX). The daily data for the KODEX200 and KOSPI200 are sourced from FnGuide's DataGuide platform. I use the price of the first trade of each minute as the price per minute.

The sample period runs from 2006 to 2018. I exclude the first trading day of the New Year and the Korean College Scholastic Ability Test day (*Su-neung*) per year because the KRX adjusted the trading hours on these days. I also exclude the day when the *Su-neung* was delayed due to the earthquake for the same reason.

The data summary is shown in Table 1.

3.2. Identifying Returns and Volatility

I calculate the first half-hour return from the previous closing price to the first 30-min price (9:30 am), and thereafter, I also calculate the returns at 30-min intervals until the closing time. In total, 13 half-hour returns exist per day because the KRX opens at precisely 9:00 am and closes at 3:30 pm (Korean Time).

However, note that the regular trading hours of the KRX were extended on August 1, 2016, and therefore, the closing time was pushed back by 30 min to 3:30 pm from 3:00 pm. In other words, only 12 half-hour returns existed per day before the extension of the trading hours.

$$r_{i,t} = \frac{p_{i,t}}{p_{i-1,t}} - 1,$$

$$i = \begin{cases} 1, \cdots, 13, \ after\ the\ extension\ of\ trading\ hours, \\ 1, \cdots, 12, \ before\ the\ extension\ of\ trading\ hours, \end{cases} \tag{1}$$

where $p_{i,t}$ is the price at the i-th half hour, and $p_{i-1,t}$ is the price at the previous half hour on each trading day t. Note that $p_{0,t}$ is the previous closing price (and not the opening price) to capture the overnight information.

Motivated by Goyal and Welch (2008) and Gao et al. (2018), the first half-hour volatility is calculated using the 1-min returns to analyze the impact of volatility on the returns predictability. In detail, I first calculate the returns minute by minute within the first half hour and then sum the squared 1-min returns.

4. U-shaped Trading Volume

Trading volume is a remarkable indicator for market participants. If strong confidence exists in the stock market's direction, then the volume will be raised. This phenomenon will accelerate especially in the case of ETFs because of the liquidity provider.

As explained above, the trading hours in the Korean stock market can be regarded as a series of twelve or thirteen intervals for every half hour. Figure 1 shows the trend of the trading volumes for the intervals, and a U-shaped pattern is evident. In detail, the trading volume surges at the opening and closing of the market, and is lower at midday compared to at other times.

In that case, why are transactions concentrated at specific times of the day, such as opening and closing? There may be many explanations. First, investors tend to make transactions at favorable times, namely when the market liquidity is high enough to reduce their transaction costs. Therefore, not only the informed investors, but also their uninformed counterparts want to trade at the opening and closing of the market. Second, some market participants want to hedge the overnight risk, driven by the overnight earning release or news from abroad. For example, institutional traders and passive funds mostly review their exposure daily and monitor their risk strictly. Therefore, they close out their positions immediately before the end of the trading hours and buy shares again next morning.

5. Empirical Results

5.1. Predictive Regression Analysis

In this section, I examine whether the first half-hour return and the second-to-last half-hour return together or separately exert predictability on the last half-hour return in the Korean stock over the whole sample period. Motivated by the findings of Gao et al. (2018) and Zhang et al. (2019), I exploit the following three predictive regressions and present the results in Panel A of Table 2.

$$r_{Last,t} = \alpha + \beta_{First} r_{First,t} + \epsilon_t, \qquad t = 1, \dots, T, \tag{2}$$

$$r_{Last,t} = \alpha + \beta_{STL} r_{STL,t} + \epsilon_t, \qquad t = 1, \dots, T, \text{ and} \tag{3}$$

$$r_{Last,t} = \alpha + \beta_{Firs} r_{First,t} + \beta_{STL} r_{STL,t} + \epsilon_t, \qquad t = 1, \dots, T, \tag{4}$$

where $r_{Last,t}$, $r_{First,t}$, and $r_{STL,t}$ are the last, the first, and the second-to-last half-hour return on day t, respectively. T is the total number of trading days during the sample period.

First, I investigate the predictability of the last half-hour return on the first half-hour return using Eq. (2). The first column in Panel A of Table 2 shows that the first half-hour return is a positive predictor of the last half-hour return. The slope is 2.09 (scaled by 100), R^2 is 0.45%, and the result is statistically significant at the 1% level.

Second, consider the predictive regression of the last half-hour return on the second-to-last half-hour return in Eq. (3). Notably, $r_{STL,t}$ and $r_{Last,t}$ are consecutive time periods. Therefore, if a strong price persistence exists during the day, $r_{STL,t}$ and $r_{Last,t}$ may move in the same direction. The second column in Panel A of Table 2 reports a positive slope of 8.68 (scaled by 100), significant t-statistics, and an R^2 value of 0.54%.

In addition, I run the multivariable regression model in Eq. (4) to investigate whether both the first half-hour return and the second-to-last half-hour return simultaneously predict the last half-hour return. The result in the third column in Panel A of Table 2 indicates that despite their combination, the two predictors remain significantly positive, and R^2 is 0.95%.

5.2. Financial Crisis

To obtain more insight, I break down the whole sample period further into two sub-periods: the sub-period of the financial crisis and the sub-period excluding the financial crisis. The financial crisis spans from December 2007 through June 2009, and the non-financial crisis period covers the periods before and after the financial crisis. The forecasting models are as expressed in Eqs. (2), (3), and (4).

In Panel B, during the financial crisis sub-period, the coefficient of $r_{First,t}$ is 6.87 (scaled by 100) and significant at the 1% level. The predictability of $r_{First,t}$ is stronger as it shows a larger slope and a much higher R^2 value during the financial crisis sub-period than during the whole sample period. Moreover, the predictability of $r_{STL,t}$ becomes insignificant.

In Panel C, during the sub-period that excluded the financial crisis sub-period, on the other hand, the coefficient of $r_{First,t}$ is even negative at the 10% significance level, whereas the coefficient of $r_{STL,t}$ is positive, displays highly significant *t*-statistics, and has an R^2 value of 1.62%.

The above results mark the biggest difference between the findings of this study and those of Gao et al. (2018). According to the latter, the predictability of $r_{First,t}$ and $r_{STL,t}$ became stronger during the financial crisis sub-period in comparison with the sub-period excluding it, but they still reported positively significant results for the U.S.

5.3. Out-of-sample Forecasting

The base regression coefficients are estimated using ordinary least squares (OLS). In addition, following Goyal and Welch (2008), Neely et al. (2014), Gao et al. (2018), and Zhang et al. (2019), I explore out-of-sample (OOS) forecasting statistics as a robustness check in this section.

The OOS estimation is computed as

$$\bar{r}_{Last,m+1} = \left(\frac{1}{m}\right)\sum_{j=1}^{m} r_j \quad , \tag{5}$$

$$\hat{r}_{Last,m+1} = \hat{\alpha}_m + \hat{\beta}_{First,m} * r_{First,m+1}, \text{ and} \tag{6}$$

$$R_{oos}^2 = 1 - \frac{\sum_{t=m+1}^{T}(r_{Last,t} - \hat{r}_{Last,t})^2}{\sum_{t=m+1}^{T}(r_{Last,t} - \bar{r}_{Last,t})^2}, \quad (7)$$

where $r_{Last,t}$, $\bar{r}_{Last,t}$, and $\hat{r}_{Last,t}$ are the actual return, historical average forecast, and predictive regression forecast for the last half-hour return, respectively. The OOS only uses the data available up to the day on which the forecast is made. I use the year 2006 as the initial estimation period, and add one month of returns at a time in sequence. Therefore, the forecast evaluation period spans from 2007 to 2018.

The OOS measures the proportional reduction in the mean squared forecast error for the predictive regression forecast in comparison with the historical average. Therefore, a positive R_{oos}^2 means that the predictive regression forecast outperforms the historical average. In addition, Goyal and Welch (2008) asserted that the historical average forecast is a very rigorous OOS benchmark, and therefore, predictive regression forecasts typically fail to meet or outperform the historical average.

Table 3 displays the relevant coefficients: R^2 from OLS and R_{oos}^2 from OOS. Panels A and B of Table 3 show the results during the whole sample period and the financial crisis sub-period, respectively. Note that the whole sample period in this table refers to the forecast evaluation period (2007 to 2018), not the initial estimation period.

As shown in Table 3, only the R_{oos}^2 forecasting statistics in the first column of Panel B are positive. In other words, only the predictability of $r_{First,t}$ outperforms the historical average during the financial crisis on an OOS basis. The finding is similar to the above in panel A.

6. External Factors

Do any other factors affect the predictability of the sub-period excluding the financial crisis sub-period? To answer this question, I conducted additional research on the business cycle and market illiquidity.

6.1. Business Cycle

To analyze factors influencing the predictability, I divided the whole sample period into two parts depending on the business cycle: expansion days and recession days. The National Statistics Committee of Korea (Statistics Korea) discloses data on the business cycle. In detail, the peaks of the cycle occurred in January 2008, August 2011, and September 2017, whereas the valleys of the cycle occurred in April 2005, February 2009, and March 2013.

As Table 4 shows, during the expansion days, only the second-to-last half-hour return displayed a powerful predictive ability. On the other hand, the predictability of the first half-hour return is evident during the recession days.

In detail, Panel B of Table 4 reports the coefficient of $r_{First,t}$ as 3.59 and a t-statistic of 3.73.

6.2. Market Illiquidity

To investigate the impact of market illiquidity, I measure the illiquidity of the KOSPI200, which is tracked by the KODEX200. According to Amihud (2002), as the proxy of illiquidity, I first calculate the average daily ratio of the absolute KOSPI200 return to the dollar trading volume over the previous five days. Then, I divide the trading days into two groups, high Amihud (low liquidity) and low Amihud (high liquidity), and run regressions for each group.

The first column of Panel B in Table 5 shows that $r_{First,t}$ has a slope coefficient of 2.40 and a t-statistic of 3.12 at the significant level. Thus, with regard to illiquidity, the direction of the first half-hour return remains unchanged.

On the other hand, on the days showing high liquidity, the predictive ability of $r_{First,t}$ weakens, and strong price persistence is noted between $r_{STL,t}$ and $r_{Last,t}$.

7. Characteristics of the First Half-hour Return

To obtain more insights into the predictability, I analyze it depending on the characters of the first half-hour return as well as the external factors. Notably, because the trading volume and volatility of the KODEX200 rise every year, I follow the methodology below to control this bias.

7.1. Volatility

I calculate the volatility of the first half-hour return and then sort all the trading days into three groups year by year, namely low, medium, and high volatility days. Next, I regress the last half-hour return on the first half-hour return and the second-to-last half-hour return together by group during the sample period.

Panel A of Table 6 shows the result. The predictability of the first half-hour return is significant for the high volatility group. On the other hand, the predictive power of the second-to-last half-hour return is significant for the low and medium volatility groups.

7.2. Trading Volume

In the case of the trading volume for the first half hour also, I sort the whole sample trading days of the year into three groups and run the regression in the same way as described above.

As shown in Panel B of Table 6, the predictability of $r_{First,t}$ is relatively strong for high trading volume days. However, for low and medium volume days, I find no statistically significant predictive power of the first half-hour return. Only the second-to-last half-our return remains a statistically significant predictor of the last half-hour return for the low volume group.

7.3. Investor Trading

Compared with Gao et al. (2018), who studied the U.S. stock market, and Zhang et al. (2019), who focused on the Chinese stock market, I extended my study to the entities. The Korean stock market involves four major entities that trade stocks and ETFs: individuals, institutions, foreign investors, and others. Moreover, the data on the trading activities among these entities are available in Korea. Therefore, I investigate the impact of the entities' behaviors on the first half-hour return.

First, I calculate the net volume by subtracting the sell volume from the buy volume for each entity over the first half hour. Then, the net volume is divided by a given daily trading volume. This is called the net buying ratio. Depending on the net buying ratio, I split all the trading days into three parts for each entity: high, medium, and low. Then, I run the regression in Eq. (4)

for each entity.

In Panel A of Table 7, the predictive ability of $r_{First,t}$ is significantly stronger for the high and medium institutional investors' net buying ratio. In Panel B, on the other hand, the predictive ability of $r_{First,t}$ appears to be significant for the low and medium individual investors' net buying ratio. In Panel C, the predictability of the last half-hour return is significantly strong for almost every group.

8. Conclusion

In this study, I investigate whether the intraday momentum is effective in the Korean stock market and whether the pattern of the trading volume is U-shaped.

The main finding of the study is that the first half-hour return is a statistically important predictor of the last half-hour return, especially during the financial crisis. As a robustness check, I run the OSS regression as well. In addition, this study shows that not only the financial crisis, but also other factors affect the predictability of the last half hour. With regard to the external factors, predictability becomes stronger during the recession days and days when the market is illiquid. My analysis on the characteristics of the first half-hour return shows that the higher the volatility, volume, and institutional net buying ratio for the first half hour, the stronger the predictability.

Thus, this study not only investigated the momentum of the Korean stock market on an intraday basis, but also provided an explanation from the point of view of the traders for this momentum, unlike previous studies on this topic in the U.S. and Chinese markets.

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Figure 1. Trading volume on every half-hour according to period

Average 30-min trading volume of the KODEX200. Panel A spans from January 2, 2006 to July 29, 2016 (Period A, after the trading hours were extended). Panel B spans from August 1, 2016 to December 31, 2018 (Period B, before the trading hours were extended). Panel C spans from December 1, 2007 to June 1, 2009 (the financial crisis sub-period).

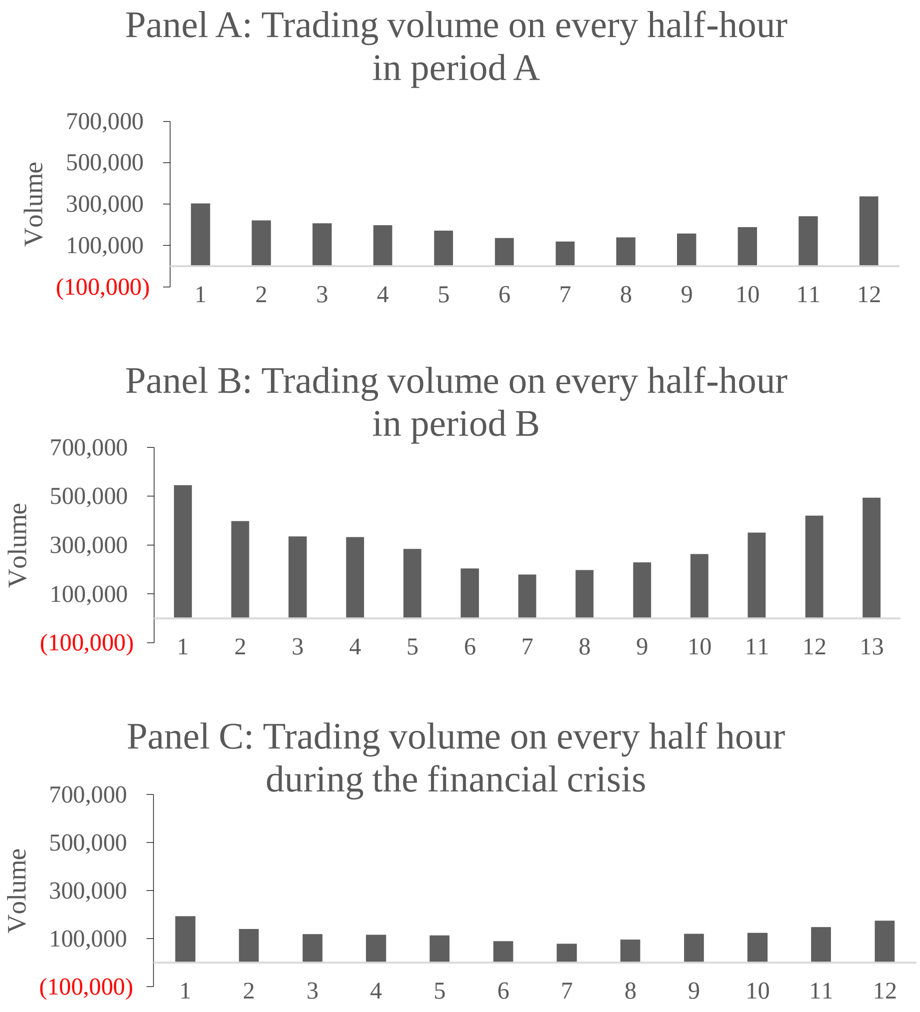


Table 1. Data summary

Table 1 shows the summary of the data. The samples are the daily levels of the trading data from 2006 to 2018. The sample period contains 3,187 trading days, trading volumes of approximately 14,542 million, and approximately 390,732 million shares.

Period	Trading Days	Trading Volume (in million)	Number of Shares (in million)
2006	245	159	9,240
2007	244	342	11,405
2008	246	668	14,540
2009	251	914	17,012
2010	249	356	17,579
2011	246	776	23,872
2012	246	962	34,200
2013	245	1,830	43,349
2014	243	1,905	41,202
2015	246	1,735	44,213
2016	244	1,430	45,942
2017	240	1,675	38,966
2018	242	1,791	49,211
2006–2018	**3,187**	**14,542**	**390,732**

Table 2. Predictive regressions: whole period, financial crisis sub-period, or excluding financial crisis sub-period

Table 2 shows the predictive regression results of the last half-hour return, r_{Last}, on the first half-hour return, r_{First}, and the second-to-last half-hour return, r_{STL}. Note that r_{First} is the return from the previous closing price to the first 30-min price. Panel A of Table 2 reports the regression results during the whole sample period. Panels B and C of Table 2 report the same results as Panel A, but the sample periods differ. Panels B and C show the results for the sub-period of the financial crisis and the sub-period excluding it, respectively. The returns in percentage and the slope coefficients are scaled by 100. Coefficients labeled "$***$", "$**$", and "$*$" are significant at the 1%, 5%, and 10% levels, respectively. The whole sample period spans from February 2006 to December 2018, and the financial crisis sub-period spans from December 2007 through June 2009.

	r_{First}	r_{STL}	r_{First} and r_{STL}	r_{First}	r_{STL}	r_{First} and r_{STL}	r_{First}	r_{STL}	r_{First} and r_{STL}
	Panel A (Whole period)			Panel B (Financial crisis sub-period)			Panel C (Excluding financial crisis sub-period)		
α	0.01 (1.38)	0.01 (1.57)	0.01 (1.44)	0.03 (0.98)	0.02 (0.89)	0.03 (0.98)	0.01 (1.32)	0.01 (1.32)	0.01 (1.42)
β_{First}	2.09*** (3.79)		2.00*** (3.62)	6.87*** (4.25)		6.90*** (4.26)	-0.97* (-1.69)		-1.07* (-1.88)
β_{STL}		8.68*** (4.16)	8.35*** (4.01)		-0.01 (0.00)	-1.75 (-0.30)		14.99*** (6.79)	15.10*** (6.84)
R^2(%)	0.45	0.54	0.95	4.49	0.00	4.51	0.10	1.62	1.75

Table 3. Out-of-sample predictability

Table 3 reports the result of the ordinary least squares (OLS) and out-of-sample (OOS) forecasting statistics.

$$R^2{}_{oos} = 1 - \frac{\sum_{t=1}^{T}(r_{Last,t} - \hat{r}_{Last,t})^2}{\sum_{t=1}^{T}(r_{Last,t} - \bar{r}_{Last,t})^2}$$

where $r_{Last,t}$, $\bar{r}_{Last,t}$, and $\hat{r}_{Last,t}$ are the actual return, historical average forecast, and predictive regression forecast for the last half-hour return, respectively. I use the year 2006 as the initial estimation period and add one month of returns at a time in sequence. Therefore, the whole forecast evaluation period spans from 2007 to 2018, and the financial crisis sub-period spans from December 2007 through June 2009. The returns in percentage and the slope coefficients are scaled by 100. Coefficients labeled "$***$", "$**$", and "$*$" are significant at the 1%, 5%, and 10% levels, respectively.

	r_{First}	r_{STL}	r_{First} and r_{STL}	r_{First}	r_{STL}	r_{First} and r_{STL}
	Panel A (Whole period)			Panel B (Financial crisis sub-period)		
α	0.00 (0.60)	0.00 (0.74)	0.00 (0.62)	0.03 (0.98)	0.02 (0.89)	0.03 (0.98)
β_{First}	2.19*** (3.89)		2.11*** (3.75)	6.87*** (4.25)		6.90*** (4.26)
β_{STL}		7.70*** (3.53)	7.36*** (3.38)		-0.01 (0.00)	-1.75 (-0.30)
R^2(%)	0.51	0.42	0.90	4.49	0.00	4.51
R^2_{oos}(%)	-0.53	-0.77	-1.40	1.60	-3.15	-1.77

Table 4. Business cycle

Table 4 shows the predictive regression results depending on the business cycle. According to the National Statistics Committee of Korea (Statistics Korea), I split the whole sample period into two parts: expansion days and recession days. According to Statistics Korea, the peaks of the cycle occurred in January 2008, August 2011, and September 2017, and the valleys of the cycle occurred in April 2005, February 2009, and March 2013. The returns in percentage and the slope coefficients are scaled by 100. Coefficients labeled "$***$", "$**$", and "$*$" are significant at the 1%, 5%, and 10% levels, respectively.

	r_{First}	r_{STL}	r_{First} and r_{STL}	r_{First}	r_{STL}	r_{First} and r_{STL}
	Panel A (Expansion days)			Panel B (Recession days)		
A	0.01***	0.01***	0.01***	-0.01	-0.01	-0.01
	(2.84)	(2.87)	(2.85)	(-0.57)	(-0.66)	(-0.58)
β_{First}	0.12		0.21	3.59***		3.62***
	(0.19)		(0.10)	(3.73)		(3.74)
β_{STL}		16.76***	16.76***		-0.13	-1.30
		(6.98)	(6.98)		(-0.03)	(-0.32)
R^2(%)	0.00	2.16	2.16	1.41	0.00	1.42

Table 5. Market illiquidity

Table 5 demonstrates the results of the predictive regression according to the market illiquidity. According to Amihud (2002), I first calculate the average daily ratio of the absolute KOSPI200 return to the dollar trading volume over the previous five days. Then, I split the trading days into two groups, high Amihud (low liquidity) and low Amihud (high liquidity), and run regressions for each group. The returns in percentage and the slope coefficients are scaled by 100. Coefficients labeled "∗∗∗", "∗∗", and "∗" are significant at the 1%, 5%, and 10% levels, respectively.

	r_{First}	r_{STL}	r_{First} and r_{STL}	r_{First}	r_{STL}	r_{First} and r_{STL}
	Panel A Low Amihud (High liquidity)			Panel B High Amihud (Low liquidity)		
A	0.00	0.00	0.00	0.02**	0.02**	0.02**
	(-0.67)	(-0.55)	(-0.56)	(1.99)	(2.16)	(2.01)
β_{First}	0.96		0.89	2.40***		2.34***
	(1.17)		(1.11)	(3.12)		(3.04)
β_{STL}		22.07***	22.03***		4.84*	4.37
		(7.07)	(7.06)		(1.67)	(1.51)
R^2(%)	0.09	3.05	3.12	0.61	0.18	0.75

Table 6. Volatility and trading volume of the first half hour

Table 6 reports the impact of the volatility and trading volume for the first half hour on the predictability.I calculate the volatility and volume of the first half hour return and then sort all the trading days of the year into three groups: low, medium, and high volatility days. Then, I regress the last half-hour return on the first half-hour return and the second-to-last half-hour return together by group during the sample period. The returns in percentage and the slope coefficients are scaled by 100. Coefficients labeled "∗∗∗", "∗∗", and "∗" are significant at the 1%, 5%, and 10% levels, respectively.

	Panel A (Volatility)			Panel B (Trading Volume)		
	Low	Medium	High	Low	Medium	High
α	0.01**	0.01	0.01	0.02	0.01	-0.01
	(2.02)	(0.96)	(0.99)	(2.57)	(1.63)	(-0.58)
β_{First}	-1.39	0.13	3.02***	-1.02	-1.13	3.39***
	(-1.29)	(0.14)	(3.17)	(-0.69)	(-1.10)	(4.03)
β_{STL}	18.40***	21.14***	2.73	15.48***	3.45	8.33**
	(5.14)	(5.99)	(0.75)	(4.39)	(1.06)	(2.16)
R^2(%)	2.62	3.30	1.02	1.82	0.21	2.03

Table 7. Investors' trading for the first half-hour return

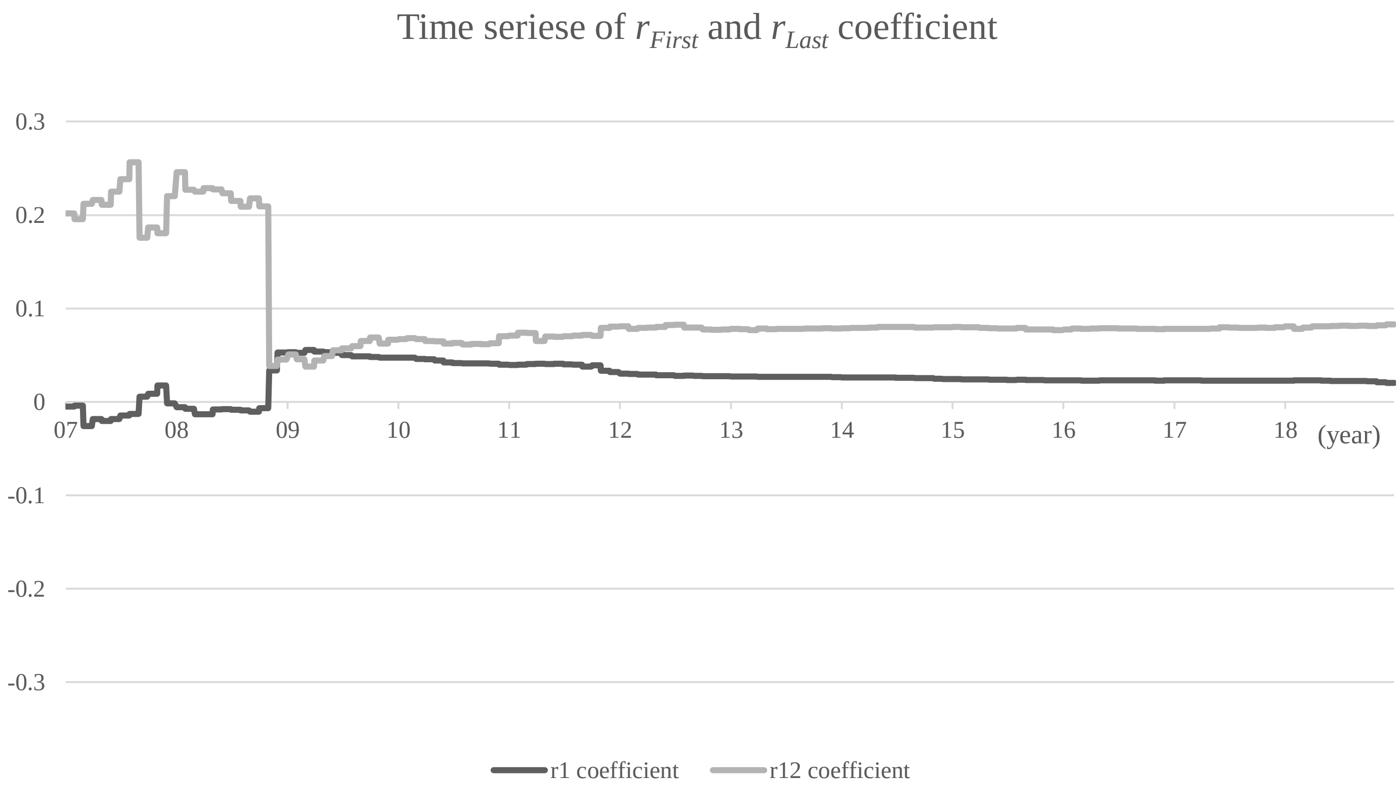
Table 7 reports the impact of the investors' trading for the first half hour on the predictability. There are four major trading entities in Korea: individual investors, institutional investors, foreign investors, and others. I calculate the net volume by subtracting the sell volume from the buy volume for each entity over the first half hour. Then, the net volume is divided by a given daily trading volume. This is called the net buying ratio. Depending on the net buying ratio, I split all the trading days into high, medium, and low for each entity. Then, I run the regression in Eq. (4) for each. The returns in percentage and the slope coefficients are scaled by 100. Coefficients labeled "∗∗∗", "∗∗", and "∗" are significant at the 1%, 5%, and 10% levels, respectively.

	Panel A (Institutional investors)			Panel B (Individual investors)		
	Low	Medium	High	Low	Medium	High
α	0.00	0.02**	-0.01	0.00	0.00	0.02
	(0.32)	(2.53)	(-1.52)	(0.00)	(-0.16)	(1.63)
β_{First}	0.16	3.24***	4.12***	2.47**	5.50***	1.29
	(0.17)	(2.80)	(4.19)	(2.31)	(3.99)	(1.30)
β_{STL}	6.45*	11.31***	7.91**	2.07	4.76	14.65***
	(1.89)	(3.24)	(1.98)	(0.51)	(1.29)	(4.54)
R^2(%)	0.34	1.71	2.10	0.54	1.64	2.09

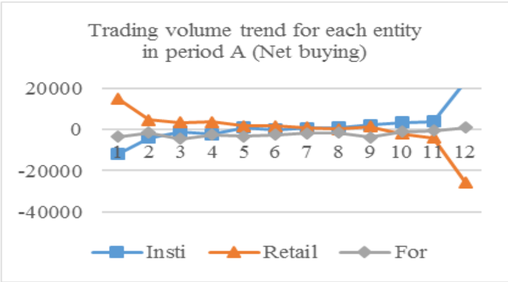
	Panel C (Foreign investors)			Panel D (Others)		
	Low	Medium	High	Low	Medium	High
α	-0.01	0.02***	0.01	0.00	0.01	0.02*
	(-0.83)	(3.37)	(0.72)	(-0.13)	(0.71)	(1.91)
β_{First}	2.81***	-2.07**	2.64***	2.73***	-1.23	3.12***
	(2.95)	(-1.97)	(2.69)	(2.96)	(-1.12)	(3.41)
β_{STL}	9.43***	13.72***	1.00	6.56*	20.50***	1.77
	(2.87)	(4.23)	(0.23)	(1.88)	(5.57)	(0.49)
R^2(%)	1.70	1.86	0.71	1.22	2.85	1.13

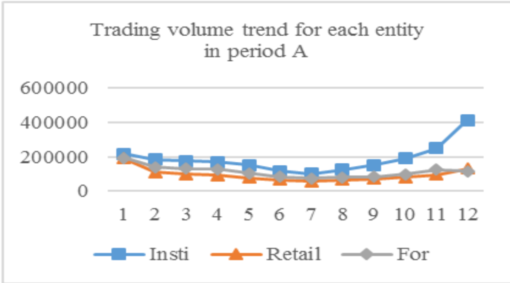
Appendix A. Time series of coefficient

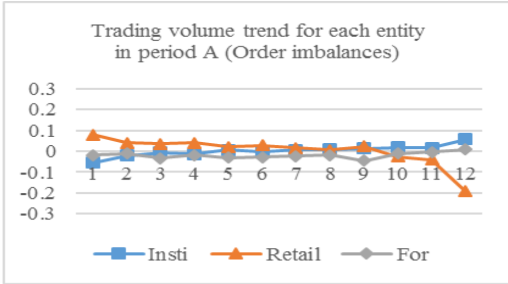
It plots the slopes of r_{First} and r_{STL}, estimated recursively over time. The methodology follows the OSS regression above. Especially during the financial crisis there are a lot of variation in both r_{First} and r_{STL}

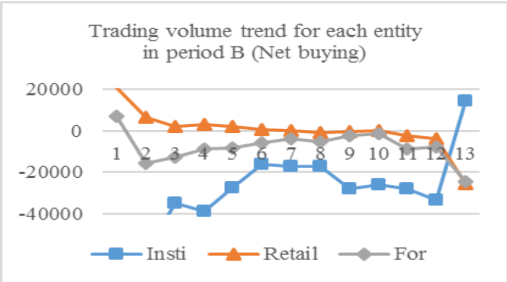


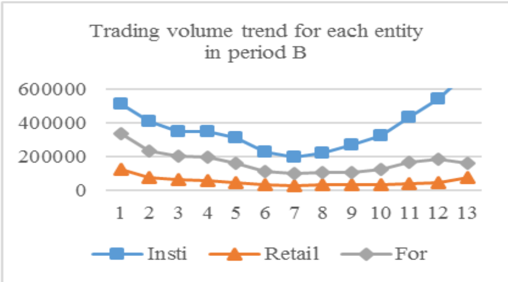
Appendix B. Trading Volume trend by entities

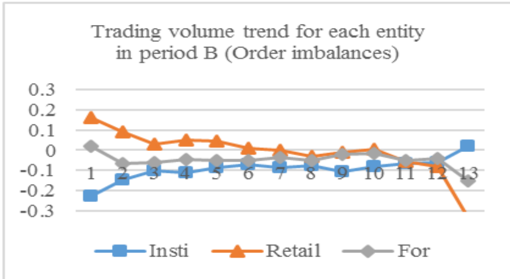


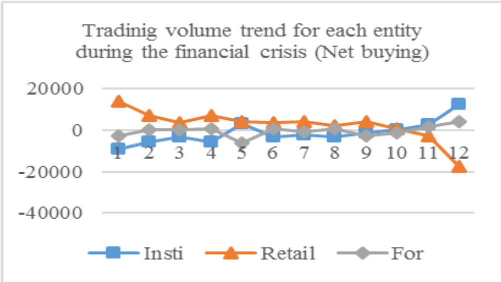


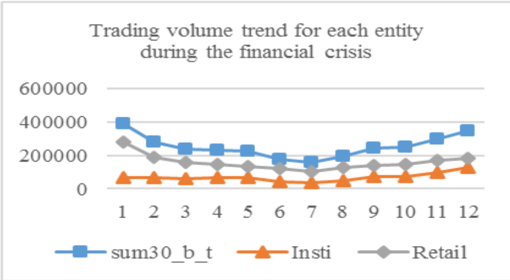


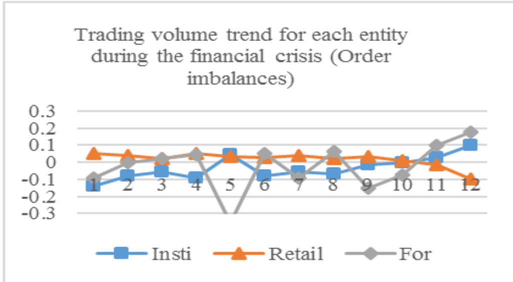












국 문 초 록

본 논문은 한국 주식시장에서 일중 모멘텀이 나타나며, 이는 특히 2008년 금융위기에 두드러진 점을 확인하였다. 한국거래소 시장에 상장되어있는 ETF 중 대표성을 가지는 KODEX 200을 대상으로, 전일 종가부터 거래일 첫 30분까지의 수익률로 거래일 마지막 30분 수익률에 대한 예측력을 검증하였으며, 강건성 확인을 위하여 Out-of-sample forecasting 방법론을 추가로 활용하였다. 상기 일중 모멘텀에 영향을 주는 요인은 외부적 요인과, 거래일 첫 30분간의 특성으로 크게 두 가지로 나누어 살펴볼 수 있다. 전자의 경우 경기 수축기일수록, 시장의 유동성이 부족할수록 일중 모멘텀이 두드러진 것을 확인할 수 있었다. 후자의 경우 첫 30분간 변동성과 거래량, 기관의 순 매수 비율이 높을수록 일중 모멘텀이 뚜렷하게 나타남을 확인하였다. 본 논문의 연구 결과는 투자 관점에서 한국 시장의 모멘텀 현상을 일중 단위로 검증한 점에서 의의를 가지며, 미국과 중국에서 확인한 일중 모멘텀에 관한 선행 연구에 추가적으로 주체별 영향을 확인했다는 점에서 의의를 가진다. 다만, 연구 대상을 확대하여 검증하는 추가적인 숙제를 남긴다.

주요어: 일중 모멘텀, 모멘텀

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