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Delta-hedging demand and intraday momentum: Evidence from China

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ABSTRACT

This paper reveals that the rest-of-day return has positively significant prediction on the last 30-min return in the Chinese SSE 50 exchange-traded fund market. Its predictive power is economically significant and will decay in the next three days. Moreover, it reveals the relationship between intraday return prediction and short gamma hedging demand from option market makers, demonstrating that intraday hedging could be postponed till the end of a trading day. Intraday momentum caused by rebalancing traders and information investors cannot be completely offset by option market makers on days with positive net gamma exposure. Our results are robust to alternative exchange-traded fund index option and its underlying asset.

1. Introduction

There is substantial evidence that the efficient market hypothesis has been challenged essentially and that returns are predictable. Stock market is investigated to gain potential benefits of the investment (Carmen and Michael [1]). Dai et al. [2] statistically and economically improve the accuracy of stock return forecasts by combining new technical indicators and a new two-step economic constraint forecasting model from both in-sample and out-of-sample perspective. Xu et al. [3] constructs three monthly sentiment indices to forecast the excess stock index returns both in- and out-of-sample in China and find that the proposed sentiment indices have different predictive powers. Yu et al. [4] utilize the least squares estimator weighted by a combination of lagged realized semi-variances related to positive and negative returns to forecast return significantly in both statistical and economic evaluation frameworks. However, a critical trade-off in the financial market is risk–return trade-off which indicates a rise in potential return with respect to an increase of risk. In other words, the higher expected returns are associated with the higher levels of risk; such trade-off is considered to be a fundamental aspect in finance (Christian [5]). Though some investors may choose to keep a safe trading and therefore, accept lower return on behalf of low risk, investors having risk-averse nature may desire higher return and hence, take high risk with the trading. Thus stock return volatility forecasting also plays an important role in financial markets, such as portfolio allocation and risk management. Liu and Pan [6] use a variety of technical indicators to forecast stock return volatility and produce significantly more out-of-sample performance accuracy. Yu and Huang [7] find that economic policy uncertainty index has the significant improvement of the forecast performance of stock index volatility by using the GARCH–MIDAS model. Dai et al. [8] employs that the prevailing shrinkage approaches can effectively improve stock return volatility forecasting in a data-rich environment. Moreover, Dai and Zhu [9] document the return volatility spillover effects and the dynamic relationships among energy commodities and the Chinese stock markets related to Belt and Road initiative and find there exists a high interdependence among all analyzed assets, and the total volatility spillover

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has a sharp increase under the major crisis events. Besides, they achieve effective hedging strategy based on hedge ratios and the optimal portfolio weights. In short, these findings are beneficial for both investors and policy makers.

With the increasing discovery of financial market anomalies, asset price momentum has always been a hot research topic of behavioral finance and asset pricing (Andrei and Cujean [10]). In this ground-breaking work, Jegadeesh and Titman [11] discover that the famous momentum strategy of buying past winners portfolios and selling past losers portfolios in equity markets can provide significant positive returns within the holding period of three to twelve months, which is called the cross-sectional momentum. In addition, cross-sectional momentum is found to prevail in the global commodity futures markets in the research of Kang and Kwon [12]. Moreover, past returns of individual asset has been the focus of time-series momentum strategies, which is quite different from that of cross-sectional momentum strategies. Moskowitz et al. [13] raised the concept of time-series momentum pattern that the past return of a security can be predictive of its future performance by examining the persistency of returns. The time-series momentum is popular among a large amount of asset classes (Georgopoulou and Wang [14]). A time-series momentum strategy using a longer sample period is applied to global markets, with the conclusion that it has been effective over the past 137 years (Hurst et al. [15]). Koijen et al. [16] analyze carry trades, in which time-series momentum returns is utilized as a risk factor.

However, the previous literatures on time-series momentum concentrates on low-frequency data instead of high-frequency (intraday) one. More recently, Gao et al. [17] concluded that the last half-hour returns can be predicted by the first half-hour returns or the second to last half-hour return in the U.S. stock market.[1] In addition, Coleman and Milanova [19] use the two predictors at the same time to predict accurate 30-min return, which yields a much more significant effect in the US stock markets than that of other stock markets all over the world. Likewise, Elaut et al. [20] explores the effect of trading volume and return volatility on intraday momentum of stock markets. Given the volatility and trading volume analysis of the first half-hour, they divide the given trading days into lower, medium, and higher terciles, and then compute the statistics for each tercile. They find that compared with mid-volume trading days and low-liquidity trading days, intraday momentum is more significant during the high volatility trading days. Along the same lines, Zhang et al. [21] conducted both in- and out-of-sample analysis and he found that intraday momentum appears in the stock market of China. Chu et al. [22] observed remarkable intraday momentum and reversal effect of the Chinese stock market by taking the first half-hour return as a trading signal, even with the consideration of overnight return and the day-of-the-week effect. Researchers introduce new technical models to forecast the last 30-min return better and provide the evidence about the advantage of proposed models (Li et al. [23]). They show that intraday momentum indexes help investors make better trading decisions in the stock markets. What is more, in terms of mean–variance investor allocation among risk-free bills and equities, the last half-hour predictions of the current intraday momentum can achieve remarkable economic results (Eross et al. [24]).

Generally speaking, study from Gao et al. [17] provides two prevailing explanations to be the driver force behind this phenomenon in financial markets, which are infrequent portfolio rebalancing and late informed trading. Bogousslavsky [25] theoretically illustrates that infrequent rebalancing of portfolios results in intraday momentum. The rebalancing trading is postponed to the market shutdown probably for the slow movement of capital. Intuitively speaking, the last 30-min return positively correlates with the first 30-min return because the trading of the two are in the same trading direction, hence conducting the intraday pattern. The intraday return prediction can be motivated by the activities of late-informed investors as well. To avoid overnight risk and utilize high liquidity, investors who get or process information behind time prefer to choose the last half-hour exchange. In this way, late investors in the last 30-min can be in the same direction with those of the first 30-min of the day, thus resulting in intraday momentum. Apart from statistical significance, both the explanations are of economic benefits to existing intraday momentum.

A recent study by Baltussen et al. [26] discovers that hedging short gamma exposure creates intraday momentum across all major asset classes. If products (options, for example) are with gamma exposure, market makers under most circumstances would net short such products. Market participants in markets have shown that the derivative trading with short gamma positions have influence on volatility of underlying assets (Bessembinder and Seguin [27]; Robbani and Bhuyan [28]). Bollen and Whaley [29] point out that for portfolio insurance, institutional traders tends to buy in index puts. To ensure positions delta-neutral, a common strategy for market makers is to purchase extra securities when prices rise and sell these securities when prices fall. Market swings would therefore be exacerbated by such trading influenced by market price movement, resulting in market intraday momentum. In contrast, if option market makers are net long gamma (for example, with net short put and long call positions and markets drifting up), they may actually need to trade towards the opposite direction of the market. Therefore, effects of the above trade activities could be set off with such trading strategy, and possibly lead to no intraday momentum or even intraday reversals. Hence, if market intraday momentum is strongly effected by hedging demand, it could disappear when option market makers are not net short gamma, and become salient as option market makers short more gamma. The current study probes into the driver force of the intraday momentum for the Chinese SSE exchange-traded fund (50ETF) market from the perspective of hedging demand of option market makers. As SSE 50ETF option is the first option listed in China (on February 9th, 2015), we choose the corresponding underlying asset to obtain enough sample data to investigate.

[1] Heston et al. [18] divide daily trading time into thirteen half-hour intervals to test whether there is regularity in a certain period of the day in the U.S. stock market. They have investigated whether stock price fluctuation, turnover situation, return rate and other stock indexes in a certain period of the trading day occur periodically in a certain period of trading day.

Table 1
The time intervals.

Parts	Label	Time interval
Overnight	ON	from close on day $t-1$ to open on day t
First half an hour	FH	the first 30-min after the market open on day t
Middle of the day	M	from the end of FH to an hour before the market close on day t
Second-to-last half an hour	SLH	the second-to-last 30-min before the market close on day t
Last half an hour	LH	the last 30-min before the market close on day t
Combination of the first two partitions	ONFH	from close to the first 30-min after the market open on day t
Combination of the first four partitions	ROD	from close on day $t-1$ to the last 30-min before the market close on day t

Contributions of this research can be concluded in three perspectives. First, we verify the intraday momentum in the Chinese exchange-traded fund market. Different from Chu et al. [21] and Zhang et al. [20] who construct the return at the 30 min level, our research discovers that the rest-of-day return ($\boldsymbol{r_{ROD}}$, defined from Table 1), compared with the first 30-min return ($\boldsymbol{r_{ONFH}}$, defined from Table 1), is a more suitable signal to predict more significantly and positively the last half-hour return ($\boldsymbol{r_{LH}}$, defined from Table 1) from perspectives of in-sample and out-of-sample. Second, unlike Zhang et al. [20] and Xu et al. [30] who provide similar theoretical explanations with that of Gao et al. [17], we attempt to understand the driver force of intraday momentum in the Chinese market from the perspective of hedging demand of option market makers. Consistent with the hedging demand hypothesis, our results show that intraday momentum effect is more significant during days of net gamma positions in China. Last but not least, we construct a trading strategy based on the intraday momentum and find that the proposed strategy can generate better performance than benchmark strategy.

The rest of the paper is structured as follows. The sampling data is described in Section 2. The market intraday momentum pattern is quantitatively analyzed in Section 3. The gamma hedging demand channel is proved in Section 4. Section 5 provides robustness results. Section 6 offers conclusions from our analysis.

2. Data

In this paper, SSE 50 ETF data is used to investigate the intraday momentum in stock market of China. The SSE 50 ETF option data is also obtained to calculate the proxy of net gamma exposure (NGE) of option market makers. Our sample is from 21st April 2015 to 31st December 2020, collected from the Wind database. To analyze intraday return prediction, we divide the trading day into five intervals seen from Table 1 and Fig. 1.

In order to test the intraday return predictability on each trading day t, we compute the return of buying closing price (c) the day before ($t-1$) and selling 30-min opening price (o) the next day (t), which is shown in Eq. (1). The last 30-min return for SSE 50 ETF is predicted as Eq. (2).

$$\boldsymbol{r_{ONFH,t}} = \frac{\boldsymbol{P_{o+30,t}}}{\boldsymbol{P_{c,t-1}}} - 1 \tag{1}$$

$$\boldsymbol{r_{LH,t}} = \frac{\boldsymbol{P_{c,t}}}{\boldsymbol{P_{c-30,t}}} - 1 \tag{2}$$

Where $\boldsymbol{P_{o+30,t}}$ is the price at 30-min after the current day's (t) open (o); $\boldsymbol{P_{c,t-1}}$ is the price at previous day's ($t-1$) close (c); $\boldsymbol{P_{c-30,t}}$ is the price at 30-min before the current day's (t) close (c); and $\boldsymbol{P_{c,t}}$ is the price at the current day's (t) close (c).

The return until the last 30-min, the return of buying closing price the day before and selling 30-min opening price the next day for SSE 50 ETF is calculated as Eq. (3)

$$\boldsymbol{r_{ROD,t}} = \frac{\boldsymbol{P_{c-30,t}}}{\boldsymbol{P}_{\mathrm{c},\boldsymbol{t-1}}} - 1 \tag{3}$$

Where $\boldsymbol{P}_{\mathrm{c}-30,\boldsymbol{t}}$ is the price at 30-min after today's (t) close (c).

We also calculate the return between the end of the first 30-min and the last hour and the second-to-last half hour, which is shown by Eqs. (4) and (5) respectively.

$$\boldsymbol{r_{M,t}} = \frac{\boldsymbol{P}_{\mathrm{c}-60,\boldsymbol{t}}}{\boldsymbol{P}_{\mathrm{o}+30,\boldsymbol{t}}} - 1 \tag{4}$$

$$\boldsymbol{r_{SLH,t}} = \frac{\boldsymbol{P_{c-30,t}}}{\boldsymbol{P}_{\mathrm{c}-60,\boldsymbol{t}}} - 1 \tag{5}$$

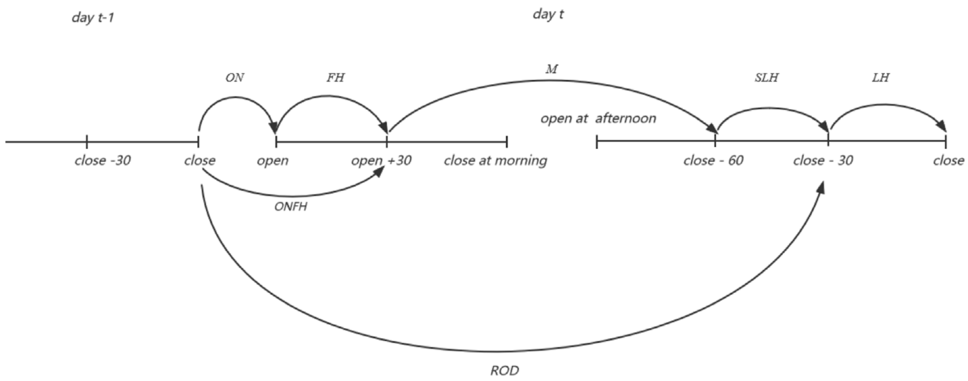

Fig. 1. The time intervals.

Where $\boldsymbol{P}_{\mathrm{c}-60,\boldsymbol{t}}$ is the price at 60 min after today's (t) close (c), $\boldsymbol{P}_{\mathrm{o}+30,\boldsymbol{t}}$ is the price at 30-min after today's (t) opening (o).$\boldsymbol{P}_{\mathrm{c}-30,\boldsymbol{t}}$ is the price at 30-min after today's (t) close (c).

3. Empirical findings

In this paper, the several regression specifications are considered to investigate intraday momentum. In the first specification, we use $\boldsymbol{r}_{\boldsymbol{ONFH}}$ to predict the last half-an-hour return ($\boldsymbol{r}_{\boldsymbol{LH}}$), which is similar with approach of Gao et al. [17], that is, the first half-hour return predicts the last half-hour period return. This study makes use of the single predictor, which is computed as Eq. (6).

$$\boldsymbol{r}_{\boldsymbol{LH},\boldsymbol{t}} = \alpha + \beta_{\boldsymbol{ONFH}} \times \boldsymbol{r}_{\boldsymbol{ONFH},\boldsymbol{t}} + \varepsilon_{\boldsymbol{t}} \tag{6}$$

Moreover, on account of the return during the mid-day ($\boldsymbol{r}_{\boldsymbol{M}}$) and the return in the penultimate 30-min ($\boldsymbol{r}_{\boldsymbol{SLH}}$), the second specification is proposed as Eq. (7).

$$\boldsymbol{r}_{\boldsymbol{LH},\boldsymbol{t}} = \alpha + \beta_{\boldsymbol{ONFH}} \times \boldsymbol{r}_{\boldsymbol{ONFH},\boldsymbol{t}} + \beta_{\boldsymbol{M}} \times \boldsymbol{r}_{\boldsymbol{M},\boldsymbol{t}} + \beta_{\boldsymbol{SLH}} \times \boldsymbol{r}_{\boldsymbol{SLH},\boldsymbol{t}} + \varepsilon_{\boldsymbol{t}} \tag{7}$$

All the above three periods returns are merged into the return during the rest of the day ($\boldsymbol{r}_{\boldsymbol{ROD}}$), which is calculated by Eq. (8).

$$\boldsymbol{r}_{\boldsymbol{LH},\boldsymbol{t}} = \alpha + \beta_{\mathrm{ROD}} \times \boldsymbol{r}_{\boldsymbol{ROD},\boldsymbol{t}} + \varepsilon_{\boldsymbol{t}} \tag{8}$$

According to Welch and Goyal [31], in-sample predictability does not necessarily imply out-of-sample predictability. Based on this, out-of-sample forecasting is considered to be more stringent for return forecasting. Given this, the out-of-sample (OOS)$\boldsymbol{R}^2_{\boldsymbol{OS}}$ is computed to evaluate the out-of-sample predictability in the following empirical analysis. Following the convention in return forecasting (see, e.g., Rapach et al. [32]; Zhu & Zhu [33]; Neely et al. [34]; Huang et al. [35]; Jiang et al. [36]; Wang et al. [37]; Zhang et al. [38]), out-of-sample $\boldsymbol{R}^2_{\boldsymbol{OS}}$ statistic is used to assess the out-of-sample predictability of the proposed model relative to the well accepted historical average model, which is calculated as $\overline{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}+1} = 1/\mathrm{t}\sum_{\boldsymbol{k}=1}^{\boldsymbol{t}} \boldsymbol{r}_{\boldsymbol{LH},\boldsymbol{t}}$. The out-of-sample $\boldsymbol{R}^2_{\boldsymbol{OS}}$ statistic is given by Eq. (9).

$$\boldsymbol{R}^2_{\boldsymbol{OS}} = 1 - \frac{\sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} (\boldsymbol{r}_{\boldsymbol{LH},\boldsymbol{t}} - \hat{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}})^2}{\sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} (\boldsymbol{r}_{\boldsymbol{LH},\boldsymbol{t}} - \overline{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}})^2} \tag{9}$$

Where $\hat{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}}$ is the last 30-min return calculated by the proposed model, and $\overline{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}}$ is the historical average of the last 30-min return till period $t-1$. If $\boldsymbol{R}^2_{\boldsymbol{OS}}$ is positive, $\hat{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}}$ outperforms the historical mean. Then, we run a Clark and West (2007) test to examine the loss function of proposed model and benchmark model.

The reduction in MSFE (mean squared forecast error) is counted by $\boldsymbol{R}^2_{\boldsymbol{OS}}$ statistic to predict the return based on the prevailing historical average. The Clark and West [39] statistic is adopted to further test whether a forecasting model can be significantly improved in MSFE. The null hypothesis of the Clark and West [39] statistic is that the MSFE of the benchmark model is less than or equal to the MSFE of the proposed forecasting model. Mathematically, the Clark and West [39] statistic is computed as Eq. (10).

$$\boldsymbol{f}_{\boldsymbol{t}} = (\boldsymbol{r}_{\boldsymbol{LH},\boldsymbol{t}} - \overline{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}})^2 - (\boldsymbol{r}_{\boldsymbol{LH},\boldsymbol{t}} - \widehat{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}})^2 + (\overline{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}} - \widehat{\boldsymbol{r}}_{\boldsymbol{LH},\boldsymbol{t}})^2 \tag{10}$$

Table 2
Market intraday momentum regressions.

β_{ONFH}	β_M	β_{SLH}	β_{ROD}	R^2 (%)	R^2_{os} (%)
0.0499*				0.79	1.03*
(1.815)					
0.0410	0.0169	0.2077***		4.65	3.71*
(1.561)	(0.654)	(3.137)			
			0.0532***	2.48	5.26***
			(3.298)		

In this table, regression analysis of the intraday return prediction for SSE 50 ETF is reported. Present robust t-statistics is calculated by the Newey and West [40] method, which is in parentheses. *Adjusted* R^2 is expressed as percentage and significance level at 1%, 5%, and 10% is presented by ***, **, and * respectively. The intercept is not reported.

and the test statistic follows from regressing $\boldsymbol{f_t}$ on a constant. A significant positive result indicates that in comparison with $\bar{\boldsymbol{r}}_{\boldsymbol{LH},t}$, the recursive historical mean, predictor $\hat{\boldsymbol{r}}_{\boldsymbol{LH},t}$ yields a significantly lower MSPE.

3.1. Baseline results

In our analysis, we first report the in-sample results and out-of-sample results provided in Table 2. The table reports the estimated coefficients and Newey and West [40] robust t-statistics. Column (1) of the table shows that the results of Eq. (6) indicates a strong correlation between $\boldsymbol{r_{ONFH}}$ and $\boldsymbol{r_{LH}}$, the $\beta_{\boldsymbol{ONFH}}$ is positive (0.0499), which is significant at the 10% level. Column (2) of the table shows the results of Eq. (7): The predictive power of $\boldsymbol{r_{SLH}}$ (t-value $= 3.137$) is significantly positive while that of $\boldsymbol{r_{ONFH}}$ (t-value $= 1.561$) is positive but insignificant. However, $\boldsymbol{r_M}$ has insignificant prediction of $\boldsymbol{r_{LH}}$(t-value $= 0.654$).

In column (3) of the table, the results of Eq. (8) show that the most significant prediction on $\boldsymbol{r_{LH}}$ can be found on $\boldsymbol{r_{ROD}}$, which is obtained by adding up all returns before the last half an hour. First, $\boldsymbol{r_{ROD}}$ has the highest t-value of 3.298 and the highest out-of-sample $\boldsymbol{R-squared}$($\boldsymbol{R^2_{oos}}$) of 5.26%. Interestingly, even if $\boldsymbol{r_{ONFH}}$, $\boldsymbol{r_M}$ and $\boldsymbol{r_{SLH}}$ are jointly used, the $\boldsymbol{R^2_{oos}}$ of $\boldsymbol{r_{ROD}}$ is also higher than that of the former circumstance. Overall, these results indicate $\boldsymbol{r_{ROD}}$ can most significantly predict $\boldsymbol{r_{LH}}$ in the Chinese ETF index market.

3.2. Horse race between $\boldsymbol{r_{ONFH}}$ and $\boldsymbol{r_{ROD}}$

Under the hedge-based explanation from the prior paper, we also verify the hypothesis that market makers want to buy spots so as to make $\boldsymbol{r_{LH}}$ change in the same way as $\boldsymbol{r_{ROD}}$, leading to the market intraday momentum. To confirm the hypothesis, Eq. (11) is estimated respectively for conditions in which the signs of $\boldsymbol{r_{ONFH}}$ and $\boldsymbol{r_{ROD}}$ are the same or different.

$$\boldsymbol{r}_{\boldsymbol{LH},t} = \alpha + \beta_{\boldsymbol{ONFH}} \times \boldsymbol{r}_{\boldsymbol{ONFH},t} + \beta_{\boldsymbol{ROD}} \times \boldsymbol{r}_{\boldsymbol{ROD},t} + \varepsilon_t \tag{11}$$

Table 3 presents the results of our analysis. The evidence from Table 3 clearly shows that When $\boldsymbol{r_{ROD}}$ and $\boldsymbol{r_{ONFH}}$ have the same sign, $\boldsymbol{r_{ROD}}$ tend to have the better prediction on $\boldsymbol{r_{LH}}$, depending on the t-value and $\boldsymbol{R-squared}$. When $\boldsymbol{r_{ROD}}$ and $\boldsymbol{r_{ONFH}}$ have opposite signs, $\boldsymbol{r_{ROD}}$ also has better prediction on $\boldsymbol{r_{LH}}$, and the coefficient for $\boldsymbol{r_{ONFH}}$ is positive but insignificant. Without conditioning, we see clearly that $\boldsymbol{r_{ROD}}$ is a significant predictor for $\boldsymbol{r_{LH}}$ while $\boldsymbol{r_{ONFH}}$ tends to be an insignificant one. In general, the results support the hypothesis that $\boldsymbol{r_{ROD}}$ should be more relevant than $\boldsymbol{r_{ONFH}}$ in identifying the hedging demand before market close.

3.3. Economic significance

In this section, to evaluate the economic significance, we assess the performance of intraday return prediction in ETF market. Similar to Gao et al. [17], we construct a market-timing strategy as Eq. (12).

$$\eta(\boldsymbol{r}) = \begin{cases} \boldsymbol{r_{LH}}, & \boldsymbol{if}\ \boldsymbol{r} > 0. \\ -\boldsymbol{r_{LH}}, & \boldsymbol{otherwise}. \end{cases} \tag{12}$$

For this strategy, $\boldsymbol{r_{ONFH}}$ and $\boldsymbol{r_{ROD}}$ are used as predictors, with their trading profits evaluated. At the same time, we use Always long as benchmark to compare the timing strategy. The trading strategy performance is presented in Table 4. In general, we find that the success rates are over 0.50 among the timing strategies. Furthermore, $\boldsymbol{r_{ROD}}$ generates higher profits than $\boldsymbol{r_{ONFH}}$, as well as Sharpe ratios. What is more, the strategies on the basis of $\boldsymbol{r_{ROD}}$ outperform benchmark strategy depending on Sharpe ratios. Fig. 2 plots the cumulative return of the intraday timing strategy on the basis of $\boldsymbol{r_{ROD}}$(solid line) and the benchmark Always Long strategy (dashed line). Obviously, strategy based on $\boldsymbol{r_{ROD}}$ outperforms a passive Always Long strategy over the time.

Table 3
Horse race analysis of the intraday momentum.

	β_{ONFH}	R^2 (%)	β_{ROD}	R^2 (%)	β_{ONFH}	β_{ROD}	R^2 (%)
Equal sign	0.0435	0.69	0.0553***	3.24	−0.0774	0.0939***	4.05
	(1.469)		(2.743)		(−1.604)	(2.775)	
Different sign	0.1248	1.68	0.0169	0.02	0.1898	0.0746**	2.89
	(1.510)		(0.289)		(1.054)	(2.099)	
Full sample	0.0499	0.79	0.0532***	2.48	−0.0165	0.0602**	2.46
	(1.415)		(2.798)		(−0.448)	(2.313)	

The regression analysis for Eq. (1) (first two columns), Eq. (3) (middle columns), or Eq. (5) (last three columns) is reported in this table, including conditions in which signs of $\boldsymbol{r_{ROD}}$ and $\boldsymbol{r_{ONFH}}$ are (i) the same, (ii) different, or (iii) without conditioning. Present robust t-statistics is calculated by the Newey and West [40] method, which is in parentheses.*Adjusted* R^2 is expressed as percentage and significance level at 1%, 5%, and 10% is presented by ***, **, and * respectively. The intercept is not reported.

Table 4
Market intraday momentum: Economic significance.

	Avg ret (%)	Std dev (%)	SR	Success
$\eta(\boldsymbol{r_{ONFH}})$	8.27	7.29	1.13	0.50
$\eta(\boldsymbol{r_{ONFH}}, \boldsymbol{r_{ROD}})$	9.58	6.32	1.52	0.52
$\eta(\boldsymbol{r_{ROD}})$	10.75	7.25	1.48	0.52
AlwaysLong	1.60	7.28	0.22	0.50

In this table, performances of the three timing strategies (based on $\eta(\boldsymbol{r_{ONFH}})$, $\eta(\boldsymbol{r_{ONFH}}, \boldsymbol{r_{ROD}})$, $\eta(\boldsymbol{r_{ROD}})$ and one benchmark strategy – Always Long – respectively) are shown. The sample period is April 21st, 2015 through December 31st, 2020.

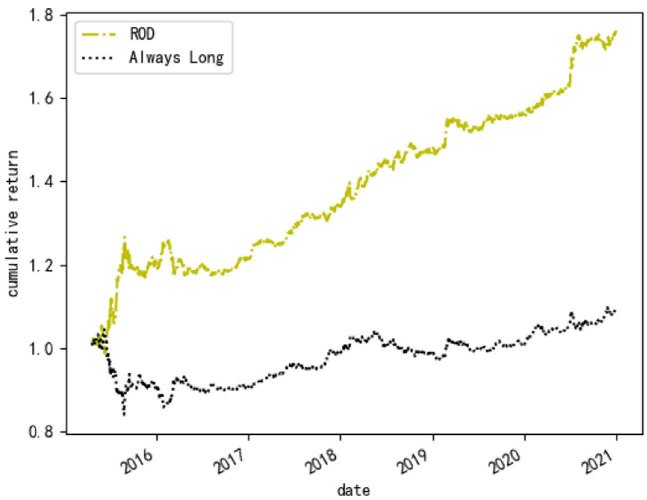

Fig. 2. Economic significance based on intraday momentum. The cumulative returns of the $\eta(\boldsymbol{r_{ROD}})$ timing strategy and the Always Long benchmark strategy are presented in the plot.

4. Intraday return prediction based on delta-hedging demand

According to Baltussen et al. [26], intraday momentum is generated by the market makers with negative NGE due to Delta-hedging demand. Specifically, gamma measures how much the price of a derivative accelerates when the underlying security price moves. The declarers in markets generally grapple with products with gamma exposure via net short sale. Consequently, to ensure positions delta-neutral, a common strategy for market makers is to purchase extra securities when prices rise and sell these securities when prices fall. Market swings would therefore be exacerbated by such trading influenced by market price movement, resulting in market intraday momentum. We hypothesize that option market makers who are on average net negative gamma trade in the direction of the market, hence their delta hedges are rebalanced. How does this mechanism perform in the Chinese market? Therefore, we conduct two tests—the first test directly proves the existence of the hedging channel, and the second test successfully differentiates hedging traders from late informed traders.

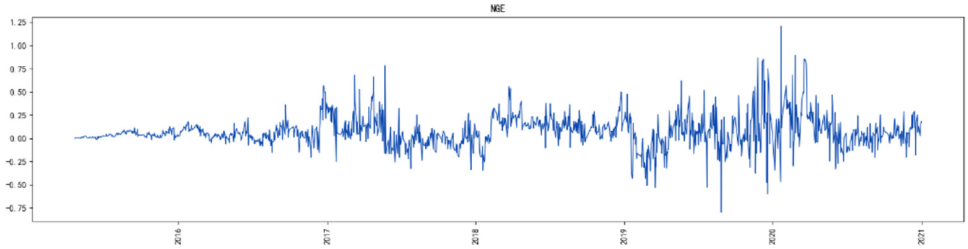

Fig. 3. Net gamma positioning for the SSE 50 ETF between April 2015 and December 2020.

4.1. Delta-hedging demand from option market makers

Before the analysis, we construct proxy of the net gamma exposure as follows, which is the same with the measure obtained from Baltussen et al. [26].

In terms of a call (C) option on day t with strike price $\boldsymbol{s} \in \boldsymbol{S}_t^c$ and maturity $\boldsymbol{m} \in \boldsymbol{M}_t^c$, the net gamma exposure (NGE) is given by Eq. (13).

$$\boldsymbol{NGE}_{s,m,t}^{C} = \Gamma_{s,m,t}^{C} \times \boldsymbol{OI}_{s,m,t}^{C} \times 100 \times \boldsymbol{P}_t \tag{13}$$

Where $\Gamma_{s,m}^{C}$ is the option's gamma, $\boldsymbol{OI}_{s,m}^{C}$ is the option's open interest, and 100 is the adjustment from option contracts to shares of the underlying. $\boldsymbol{P}_t$ represents the SSE 50 ETF index level on day t.

Considering a put (P) option on day t which has strike price $\boldsymbol{s} \in \boldsymbol{S}_t^P$ and maturity $\boldsymbol{m} \in \boldsymbol{M}_t^P$, the net gamma exposure (NGE) is shown in Eq. (14).

$$\boldsymbol{NGE}_{s,m,t}^{P} = \Gamma_{s,m,t}^{P} \times \boldsymbol{OI}_{s,m,t}^{P} \times (-100) \times \boldsymbol{P}_t \tag{14}$$

Where we use the adjustment of -100 as this represents short gamma for option market makers and $\boldsymbol{P}_t$ represents the SSE 50 ETF index level on day t.

The NGE of the SSE 50 ETF index is then presented by Eq. (15).

$$\boldsymbol{NGE}_{\mathrm{t}} = \frac{\sum \boldsymbol{s} \in \boldsymbol{S}^{C} \sum \boldsymbol{m} \in \boldsymbol{M}^{C} \boldsymbol{NGE}_{s,m}^{C} + \sum \boldsymbol{s} \in \boldsymbol{S}^{P} \sum \boldsymbol{m} \in \boldsymbol{M}^{P} \boldsymbol{NGE}_{s,m}^{P}}{\boldsymbol{MV}_t} \tag{15}$$

Where $\boldsymbol{MV}_t$ is the market value of the SSE 50 ETF index.

We use option data to calculate the NGE variable following the Eq. (15) from April, 2015 to December, 2020. Fig. 3 shows fluctuations of the NGE for the SSE 50 ETF index in the 5 years. To do our analysis, we regress the $\boldsymbol{r}_{LH}$ on $\boldsymbol{r}_{ROD}$ for different circumstances with various signs of the NGE under the assumption that option market makers will buy spots to make the delta stay neutral when NGE is negative. Table 5 reports the evidences that the intraday return prediction is more significant during the days with negative NGE compared with those with a positive NGE in term of T-value. This supports the claim that option hedging demand is one of the factors influencing the intraday momentum. However, the intraday momentum is also significant at 10% level on days with positive NGE, which is different from the results of Baltussen et al. [26]. Theoretically, rebalancing traders and informed investors could also trigger intraday momentum. When option market makers are net long gamma, they would sell spots for the delta to stay neutral. Thus, they trade against the market and effects of intraday momentum caused by former traders could be set off. We find the reversals generated by option market makers with net long gamma are not enough to set off intraday momentum by rebalancing traders and informed investors, generating significant intraday momentum on days with positive NGE.

Furthermore, we consider effect of the interaction term $\boldsymbol{NGE}_t * \boldsymbol{ROD}_t$, which is presented in Eq. (8), as well as $\boldsymbol{NGE}_t$. Table 6 reports the results, showing that intraday momentum is more significant under the condition of negative net gamma exposure. From the last two columns, it is shown that our results have no causal link with the time trend common for intraday return prediction and net gamma exposure by conducting a difference-in-difference analysis. Therefore, it can be confirmed that our results have no relation with a time trend common for intraday return prediction and NGE.

4.2. Delta-hedging: analysis for intraday and end-of-day

According to Leland [41], under the circumstance of complete hedging, return after the hedge is unpredictable based on return before the hedge, for the reason that the delta tends to be neutral at the end of each discrete interval (due to transaction costs). Based on the above mentioned explanation, our supposition is that, considering the cost for transaction, large price movements would probably lead to hedging, while small price jumps would not. If the gamma is negative, when large price jumps take place, hedging will cause the price to change in the same way as the jumps does. As a result, when hedging happens, the return after the jump may be positively forecasted by cumulative return up to and including

Table 5
Intraday return prediction conditioned by net gamma exposure.

	Intercept	β_{ROD}	R^2 (%)
$NGE_{t-1} >= 0$	−0.0001 (−0.106)	0.0372* (1.743)	1.13
$NGE_{t-1} < 0$	0.0003 (1.621)	0.1365*** (4.735)	17.04

Table 5 shows the regression of r_{LH} on r_{ROD}, under conditions for different signs of the net gamma exposure (NGE) for SSE 50 ETF option. Present robust t-statistics is calculated by the Newey and West [40] method, which is in parentheses. *Adjusted* R^2 is expressed as percentage and significance level at 1%, 5%, and 10% is presented by ***, **, and * respectively. The intercept is not reported.

Table 6
Intraday return prediction and net gamma exposure: further analysis.

	r_{LH}			Δr_{LH}	
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0001 (0.580)	0.0001 (0.538)	0.0001 (0.116)	−0.0001 (−0.051)	−0.0001 (−0.051)
$r_{ROD,t}$	0.0531*** (2.792)	0.0367* (1.748)	0.0657*** (3.105)		
$I_{NGE\leq 0} * r_{ROD,t}$		0.1002*** (2.834)			
$NGE * r_{ROD,t}$			−0.1568** (−2.297)		
NGE_t			0.0001 (0.157)		
$\Delta r_{ROD,t}$				0.0464** (2.305)	0.0551** (2.413)
$\Delta NGE * r_{ROD,t}$					−0.0952 (−1.399)
ΔNGE_t					0.0011* (1.662)
R^2 (%)	2.47	3.64	2.95	1.71	1.89

This table shows the regression of r_{LH} on a constant, r_{ROD}, $I_{NGE\leq 0} * r_{ROD,t}$, NGE_t, $NGE * r_{ROD,t}$ for SSE 50 ETF index. Present robust t-statistics is calculated by the Newey and West [40] method, which is in parentheses. *Adjusted* R^2 is expressed as percentage and significance level at 1%, 5%, and 10% is presented by ***, **, and * respectively. The intercept is not reported.

the jump. Specifically, if the jump is detected while the hedge is not timely and incomplete, the last 30-min return could be predicted by the cumulative jump return.

Table 7 provides the results. The evidences show that returns after jump ($r_{post\ jump}$) can be positively predicted by cumulative jump returns.[2] Next, we divide $r_{post\ jump}$ into two sections: the return from post-jump to the end of SLH ($r_{post\ jump\ to\ SLH}$) and the return in the last 30-min (r_{LH}). From evidences of Table 7, $r_{post\ jump\ to\ SLH}$ can be predicted positively by the cumulative jump returns, manifesting that there is intraday hedging after large jumps. More importantly, r_{LH} can be positively and significantly forecasted by the cumulative jump returns, indicating that intraday hedging is only partially completed, while additional significant hedging is postponed till the very end of the day. It is meaningful to investigate the driver forces behind this phenomenon. Therefore, we offer explanation from liquidity. Fig. 4 plots U-shape intraday volume pattern, which confirms that liquidity peaks after the opening and right before closing, while spreads tend to be lower with a higher market depth before the close of trading. Therefore, traders might not hedge their positions completely right after a jump is spotted. They will probably hedge most of their positions in the last half hour. In addition, Brock and Kleidon [42] and Hong and Wang [43] report the best strategy for market makers is to push the delta to neutral before market close, so as to avoid low liquidity and overnight price risk.

4.3. Price pressure vs. informed trading

This section proves the difference between the hedging traders and late informed traders. Under different price pressure, hedging will make price revert to the mean in the near future, while the permanent price impact will be induced by fundamental information under the informed trading explanation.

In the study, to explore the persistence of the intraday return prediction, we extend the last half hour with five time spans (see Fig. 5). This study starts from the standard setting of regressing $r_{LH,t}$ on $r_{ROD,t}$, then progressively adding the

2 Here, we define a jump following the definition of Baltussen et al. [26].

Table 7
Intraday return prediction and jumps.

$r_{post\ jump}$	R^2 (%)	$r_{post\ jump\ of\ SLH}$	R^2 (%)	r_{LH}	R^2 (%)
0.1191**	1.73	0.0623	0.44	0.0569**	2.02

Table 7 shows regression results of the cumulative jump returns to returns after jump. The intercept is not reported. Present robust t-statistics is calculated by the Newey and West [40] method, which is in parentheses. *Adjusted* R^2 is expressed as percentage and significance level at 1%, 5%, and 10% is presented by ***, **, and * respectively.

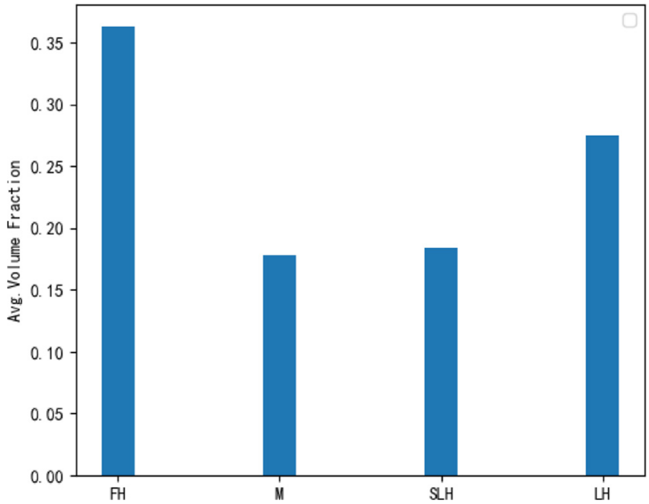

Fig. 4. Trading volume distribution of the trading day. The average trading volume for every time span is shown in this figure.

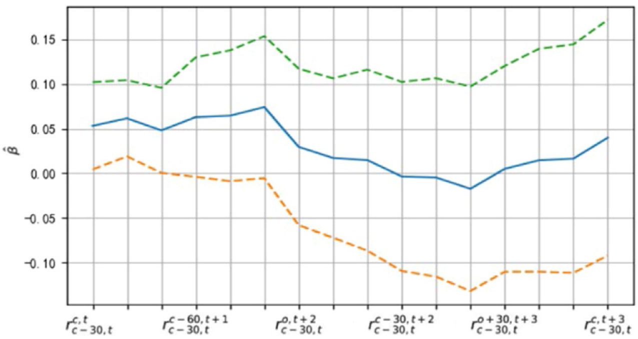

Fig. 5. Market intraday momentum and reversals. The regression coefficients and corresponding confidence bounds (at 1% level) of using $\boldsymbol{r_{ROD}}$ to predict $\boldsymbol{r_{LH}}$ and progressively adding time spans: overnight, first 30-min return, middle of day, penultimate 30-min return, and last 30-min return, until market close after three days ($\boldsymbol{r^{c,t+3}_{c-30,t}}$) .

mentioned time spans until a regression of the return from 30-min before market close of the present day until market close after three days ($\boldsymbol{r^{c,t+3}_{c-30,t}}$) on the return until 30-min before market close of the present day ($\boldsymbol{r_{ROD,t}}$) is completed.

Fig. 5 demonstrates that the intraday momentum is not persistent, the forecasting power of $\boldsymbol{r_{ROD}}$ will arise until 60 min before close next day and then decay in three days. In other words, we confirm mean-reversion in the near future under the hedging explanation.

5. Robustness test

In this section, CSI 300 ETF options and its underlying asset are chosen for further investigation and validation of the main findings discussed in Sections 3 and 4. The entire sample period is from December 23rd, 2019 through February 28th, 2022. The out-of-sample period is from July 7th, 2022 through February 28th, 2022

Table 8 reports the empirical results for CSI 300 ETF, where the regression models are identical with the above analysis. In a nutshell, a robust result is found, which demonstrates that statistically and economically speaking, considerable

Table 8
Market intraday momentum regressions.

β_{ONFH}	β_{M}	β_{SLH}	β_{ROD}	R^2 (%)	R^2_{os} (%)
0.0532**				1.89	0.65**
(2.500)					
0.0491**	0.0637***	0.0312		4.61	−1.27**
(2.510)	(3.050)	(0.460)			
			0.0544***	4.84	2.87***
			(3.593)		

In this table, regression analysis of the intraday return prediction for CSI 300 ETF is reported. Present robust t-statistics is calculated by the Newey and West [40] method, which is in parentheses. *Adjusted* R^2 is expressed as percentage and significance level at 1%, 5%, and 10% is presented by ***, **, and * respectively. The intercept is not reported.

Table 9
Market intraday momentum: Economic significance.

	Avg ret (%)	Std dev (%)	SR	Success
$\eta(\boldsymbol{r_{ONFH}})$	2.35	4.71	0.50	0.49
$\eta(\boldsymbol{r_{ONFH}}, \boldsymbol{r_{ROD}})$	7.16	3.95	1.81	0.51
$\eta(\boldsymbol{r_{ROD}})$	12.13	4.65	2.61	0.52
AlwaysLong	8.44	4.68	1.80	0.55

In this table, performances of the three timing strategies (based on $\eta(\boldsymbol{r_{ONFH}})$, $\eta(\boldsymbol{r_{ONFH}}, \boldsymbol{r_{ROD}})$, $\eta(\boldsymbol{r_{ROD}})$ and one benchmark strategy – Always Long – respectively) are shown. The sample period is April 21st, 2015 through December 31st, 2020.

Table 10
Intraday return prediction conditioned by net gamma exposure.

	Intercept	β_{ROD}	R^2 (%)
$\boldsymbol{NGE_{t-1}} >= 0$	0.0003*	0.0393**	2.65
	(1.771)	(2.069)	
$\boldsymbol{NGE_{t-1}} < 0$	0.0003	0.0674***	6.53
	(0.980)	(2.281)	

Table 10 shows the regression of $\boldsymbol{r_{LH}}$ on $\boldsymbol{r_{ROD}}$, under conditions for different signs of the net gamma exposure (NGE) for SSE 50 ETF. option. Present robust t-statistics is calculated by the Newey and West [40] method, which is in parentheses. *Adjusted* R^2 is expressed as percentage and significance level at 1%, 5%, and 10% is presented by ***, **, and * respectively. The intercept is not reported.

forecasting gains is generated by our intraday momentum. That $\boldsymbol{r_{ROD}}$ has the strongest predicting capacity on the last 30-min return. First, $\boldsymbol{r_{ROD}}$ has the highest t-value of 3.593 and the highest out-of-sample $\boldsymbol{R} - \boldsymbol{squared}$ ($\boldsymbol{R^2_{oos}}$) of 2.87%. Moreover, when $\boldsymbol{r_{ONFH}}, \boldsymbol{r_{M}}$ and $\boldsymbol{r_{SLH}}$ are jointly used, they have a negative $\boldsymbol{R^2_{oos}}$, −1.27%. Particularly, compared with using $\boldsymbol{r_{ONFH}}$ from the in-sample analysis and out-of-sample analysis, using $\boldsymbol{r_{ROD}}$ to predict the last 30-min return shows higher accuracy in predictions. In short, these results support the above analysis that $\boldsymbol{r_{ROD}}$ can most significantly predict $\boldsymbol{r_{LH}}$ in the Chinese ETF index market.

The economic significance outcomes are shown in Table 9. For the benchmark strategies, we found that economic values are relatively low compared with market timing strategy based on $\boldsymbol{r_{ROD}}$. Specifically, the prevailing Always long strategy conducts the smaller average return of 8.44% and the slight greater standard deviation of 4.68%, leading to the lower Sharpe ratio of 0.95. Conversely, timing strategy based on $\boldsymbol{r_{ROD}}$ yields considerably higher economic values. Particularly speaking, the strategy has the highest Sharpe ratio of 1.75. The findings support the previous proposition from the market timing perspective. Fig. 6 also plots the cumulative return of the intraday timing strategy on the basis of $\boldsymbol{r_{ROD}}$(solid line) and the benchmark Always Long strategy (dashed line).

A negative $\boldsymbol{NGE_t}$ suggests that option market makers will delta hedge in the same direction as the market has moved, which is consistent with market intraday return prediction. Therefore, we make conditional regressions of the $\boldsymbol{r_{LH}}$ on $\boldsymbol{r_{ROD}}$ based on the sign of the ***NGE***. Table 10 indicates that indeed intraday return prediction is more significant during days with negative ***NGE***. Meanwhile, during positive ***NGE*** days, less significant intraday momentum is detected, which strongly supports our hedging demand hypothesis, i.e., that option hedging demand is part of the driving force of intraday momentum. In addition, traders might not hedge their positions completely right after a jump is spotted. They will probably hedge most of their positions in the last half hour. The evidence is shown in Table 11. Fig. 7 also provides explanation from liquidity, which confirms that liquidity peaks after the opening and right before closing, while spreads tend to be lower with a higher market depth before the close of trading.

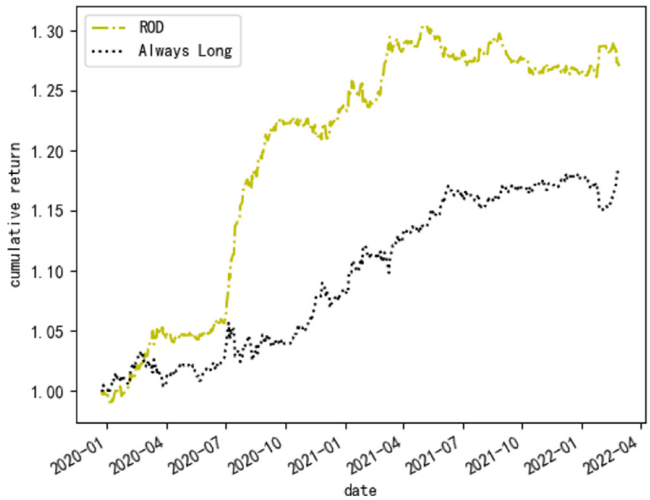

Fig. 6. Strategy performance of intraday return prediction. In this figure, the cumulative returns of the $\eta(\boldsymbol{r_{ROD}})$ timing strategy and the Always Long benchmark strategy are shown. The sample period is April 21st, 2015 through December 31st, 2020.

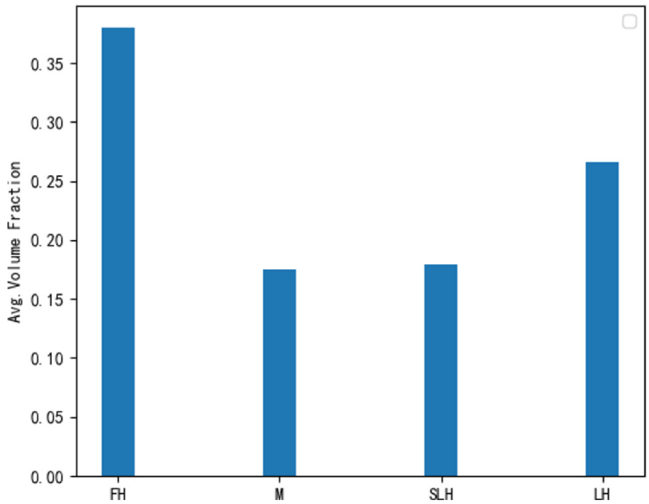

Fig. 7. Trading volume distribution of the trading day. The average trading volume for every time span is shown in this figure.

Table 11
Intraday return prediction and jumps.

$\boldsymbol{r_{post\ jump}}$	$\boldsymbol{R}^2$ (%)	$\boldsymbol{r_{post\ jump\ of\ SLH}}$	$\boldsymbol{R}^2$ (%)	$\boldsymbol{r_{LH}}$	$\boldsymbol{R}^2$ (%)
0.1136**	3.25	0.0563	0.60	0.0573***	7.34

Table 11 shows regression results of the cumulative jump returns to returns after jump. The intercept is not reported. Present robust t-statistics is calculated by the Newey and West [40] method, which is in parentheses. *Adjusted* R^2 is expressed as percentage and significance level at 1%, 5%, and 10% is presented by ***, **, and * respectively.

6. Conclusions

This study investigates intraday time-series momentum in the Chinese SSE 50 ETF market. After in-sample and out-of-sample tests, it can be seen that the rest-of-day return have more significant information to predict the last 30-min return, compared with the first 30-min return. Moreover, the strategy based on the rest-of-day return can generate substantial profits and higher Sharpe ratios. Also, our results indicate that the momentum generated by the rest-of-day returns will decay in the next three days. More importantly, we provide the evidence that intraday returns predictability is driven by short gamma hedging demand from option market makers, and find the intraday hedging may be postponed till the end of a trading day. At the same time, intraday momentum caused by rebalancing traders and information investors could not be completely set off by option market makers on days with positive net gamma exposure. The results are robust to alternative index option and its underlying asset.

CRediT authorship contribution statement

Xianghui Yuan: Conceptualization, Formal analysis, Investigation, Writing – original draft, Supervision, Funding acquisition. **Xiang Li:** Methodology, Investigation, Software, Writing – review & editing, Visualization, Data curation, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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