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Cross-sectional reversal of intraday returns and investor heterogeneity in an emerging market

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Abstract

In this paper, we confirm cross-sectional reversals in intraday returns in China's A-share market. Intraday reversals are shown to be robust with respect to seasonality, alternative samples, and the daily price-limit rule. To investigate the potential drivers, trade volumes and order imbalances of different sizes are used to identify investors. We find that large trades account for the highest proportion, and the large order imbalances reach a peak in the first half-hour of trading on a day. When we link intraday reversals to heterogeneous investors, we find that reversal strategies of traders with early information are responsible for intraday cross-sectional reversals.

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1. Introduction

The reversal effect of stock returns shows that stocks with lower returns in the previous period have higher returns in the future, and stocks that performed poorly in the past tend to perform better in the future. The reversal effect in stock returns has been a topic of great interest in financial economics ever since the anomaly was discovered by DeBondt and Thaler (1985). The reversal effect not only forms the basis of investment strategy but is also related to the debate over market efficiency (Fama, 1998). Returns reversal can be not only yearly and monthly (long-term; Chopra, Lakonishok, & Ritter, 1992; DeBondt & Thaler, 1985; Jegadeesh, 1990) but also weekly, daily, and even intraday (short-term; Bremer & Sweeney, 1991; Cox & Peterson, 1994; Grant, Wolf, & Yu, 2005; Lou, Polk, & Skouras, 2019). Two possible explanations, rational and behavioral, have been proposed in the

literature to explain the reversal effect (Barberis, Shleifer, & Vishny, 1998; Da, Liu, & Schaumburg, 2014; Daniel, Hirshleifer, & Subrahmanyam, 1998; Fama & French, 1996; Hong and Stein, 1999; Kelly, Moskowitz, & Pruitt, 2021; Pástor & Stambaugh, 2003). The first explanation is based on traditional finance theory. For example, Fama and French (1996) use the market capitalization factor (SMB) and the book-to-market ratio factor (HML) to explain the reversal effect, and Pástor and Stambaugh (2003) explain returns reversal with the liquidity factor. The second explanation is based on behavioral finance theory, which argues that returns reversal is a result of investor overreaction to information (Barberis et al., 1998). The two explanations can coexist. For example, Da et al. (2014) show that liquidity and sentiment can both explain returns reversal. Although these studies have made some progress in terms of explanations, little research has explored which kinds of investors drive the reversal effect. One important exception is Lou et al. (2019), who link the reversal effect between overnight and intraday returns to the tug of war between individual traders at the opening and institutions trading during the rest of the day.

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In this paper, we explore intraday returns reversal in China's A-share market. The extant literature on the reversal effect is based mostly on stock markets in developed countries, such as US, but cross-sectional intraday returns reversal in emerging markets has been less studied. Unlike markets in developed countries, which are dominated by institutional investors, China's stock market is dominated by individual investors, who lack professional investment knowledge. And the role of institutional investors in the A-share market at this stage is still subject to debate. For example, on January 31, 2015, the China Securities Regulatory Commission (CSRC) released a report after the inspection of mutual fund companies, suspecting that 11 had engaged in insider trading. This A-share market environment has been complicated by institutional investors because they often obtain important information on listed companies in advance to earn profits through unconventional means, such as collusion with firm management. It is unclear whether the driving force of intraday returns reversal in China's stock market is individual or institutional investors.

Lou et al. (2019) attribute intraday reversals to heterogeneous investors with different trading preferences and show that individuals prefer to trade at the opening, but institutions prefer to trade over the course of the day. However, this might not be true in China, where the A-share markets open by call auction. If investors participate in the opening call auction, they must be able not only to take the initiative to search for information during the previous night but also to process the relative information. This is very difficult for Chinese individual traders because most of them possess only rudimentary stock knowledge (Kang, Liu, & Ni, 2002). Individual investors do not have an informational advantage. Only investors who both have an informational advantage and the ability to process information can trade at the opening (Gao, Han, Li, & Xiong, 2019). Individual investors are generally regarded as engaging in late-informed trading, hence, we call them late-informed traders (Barber, Odean, & Zhu, 2009). Furthermore, more information asymmetry might arise in the opening session (Kalay, Wei, & Wohl, 2002). Gerace, Liu, Tian, and Zheng (2015) confirm that in the Chinese market the opening spread is about 1.7 times that of the rest of the day. To protect themselves, uninformed individual traders try their best to avoid trading at the call auction. For example, with the help of investor account data, Gao et al. (2019) indicate that individuals seldom trade in call auctions. Individual traders prefer continuous trading (Kalay et al., 2002). Institutional investors are more aggressive in the opening hour of the trading day (Duong, Kalev, & Krishnamurti, 2009). If they are correct, then, the explanation of the tug of war between individual and institutional traders as described by Lou et al. (2019) does not fit the A-share market.

Whether a return's predictability can be seen at the intraday level is crucial for detecting financial market efficiency (Gao, Han, Li, & Zhou, 2018). Lou et al. (2019) study the reversal between overnight and intraday returns, whereas we focus on the reversal between the first half-hour returns and later returns. The first half-hour of a trading day is distinctive because of many information announcements released between the closing

of prior trading day and the opening of new trading (Gao et al., 2018). New information might not be captured by overnight returns, and it usually takes about 30 min to digest (Gao et al., 2018). Although the intraday time-series momentum using the first half-hour returns to predict the last half-hour returns in the Chinese stock markets has been investigated (Chu, Gu, & Zhou, 2019; Zhang, Ma, & Zhu, 2019), it is not clear whether the first half-hour returns have cross-sectional predictability to the returns for the rest of the day.

In this paper, we use the first half-hour returns to confirm the existence of intraday returns cross-sectional reversals in China's A-share market. To link the reversal effects to heterogeneous investors, we use trade volume and order imbalance of different sizes to identify investors. The results indicate that large traders reverse their position by trading against the first half-hour. Larger orders are more likely to be made by investors who obtained information before the opening of trade. Therefore, we conclude that reversals by these investors are responsible for intraday returns cross-sectional reversals.

Our contribution to the literature is as follows. First, we provide fresh empirical evidence on intraday returns cross-sectional reversals in emerging markets. We confirm that the first half-hour returns can negatively predict the rest of the day's returns in the cross section. Intraday returns reversal is robust to both seasonality and alternative sample periods. Furthermore, intraday returns cross-sectional reversal is not affected by daily price-limit rules. Second, our research contributes to the theory of investor heterogeneity. Most of the prior research on investor heterogeneity comes from low-frequency data, more than that for either intraday trades or settings outside emerging markets. Using intraday high-frequency data, we provide evidence of intraday behavior by heterogeneous investors in an emerging market, in this case, China. We find that, throughout the day, small (individual) traders tend to trade more whereas large traders tend to trade less. More important, small trade size order imbalances (OIBs) are positive throughout the day, but large order imbalances reach a maximum in the first half-hour and, thereafter, become negative for the rest of the day. The evidence is not consistent with the current literature, which indicates that large trades are highly persistent because large traders tend to buy or sell the same stocks in multiple subsequent half-hours. Third, we link intraday returns cross-sectional reversals to investors with early information. We show that changes in small OIBs do not affect the reversal effect, but changes in large OIBs significantly do. The literature on informed trading shows that informed investors prefer both early trading and large trades (Easley & O'Hara, 1987; Ibikunle, 2015). We, therefore, conclude that the role of investors with early information is a prominent driver of intraday return cross-sectional reversals. It is these investors' reversal in positions against their early trades that is responsible for intraday reversals. Fourth, our results explain why emerging markets such as those in China have no cross-sectional momentum effect (Cheema & Nartea, 2014; Wu, 2011). The first half-hour returns and the rest of the day's returns are strongly negatively correlated. This result shows that stocks that rise in price during the first half-hour tend to

have a drop in price during the rest of the day, and vice versa. The reversal of intraday returns is the reason that low-frequency returns have no momentum effect.

The structure of our paper is as follows. Section 2 is the literature review. Section 3 describes the context of the Chinese stock market and sample. The empirical methodology and results are presented in Section 4. Section 5 discusses the potential drivers of intraday return reversals. Section 6 summarizes our findings and discussion. Section 7 is the conclusion, with policy implications.

2. Literature review

Momentum and reversal effects are important topics in finance. Lehmann (1990) and Lo and MacKinlay (1990) find that short-term stock returns are negatively auto-correlated. Berkman, Koch, Tuttle, and Zhang (2012) detect a strong reversal tendency between overnight returns and daytime returns in the US market, with such intraday reversals more striking for stocks that attract more attention by individual investors. Jegadeesh and Titman (1993), however, confirm the existence of a momentum effect in the US market. They show that the strategies of buying winner stocks and selling loser stocks obtain significant excess returns. Rouwenhorst (1998) identify returns persistence characteristics in 12 international stock markets, with an average duration of one year. Griffin, Ji, and Martin (2003) indicate that momentum profit is significant not only statistically but also economically, in both good and bad economic conditions. Additionally, the momentum effect exists not only in the cross section but also in time series. In recent years, scholars have begun to pay special attention to the time-series momentum effect. For example, Moskowitz, Ooi, and Pedersen (2012), He and Li (2015), Hong and Satchell (2015), and Andrei and Cujean (2017) find that past returns on securities can significantly predict their future returns. Although the momentum trading strategy has significant statistical and economic significance, it has higher negative skewness and kurtosis, which means a higher crash risk (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016).

In addition to the low-frequency momentum and reversals based on weekly, monthly, and yearly time dimensions, many papers also report high-frequency momentum and reversals. For example, Heston, Korajczyk, and Sadka (2010) and Murphy and Thirumalai (2017) examine intraday return cross-sectional momentum in US securities markets. Gao et al. (2018) discuss the intraday return time-series momentum in the S&P 500 ETF (Exchange Traded Fund) market. Zhang et al. (2019) and Chu et al. (2019) show similar intraday returns time-series momentum in the A-share market. The reversal of intraday returns is also confirmed as significant in developed securities markets. For example, Berkman et al. (2012) and Lou et al. (2019) find reversal between overnight returns and daytime returns in US markets. A growing literature covers intraday predictability in other financial markets, such as commodities (Xu, Bouri, Saeed, & Wen, 2020) and cryptocurrency markets (Wen, Bouri, Xu, & Zhao, 2022). To the best of our knowledge, the cross-sectional reversal of

intraday returns in China's A-share market has been studied less. It is unclear whether intraday returns cross-sectional reversal is unique to developed markets.

Two main explanations have been given for momentum and reversal effects: the first relies on traditional finance and the second on behavioral finance. Basing their reasoning on traditional finance, Jegadeesh and Titman (1993) explain the momentum effect using the CAPM (Capital Asset Pricing Model), whereas Fama and French (1996) use a three-factor model. Andrei and Cujean (2017) propose a rational expectation model, which states that a necessary condition for the momentum effect is greater information flow. The most representative theoretical models based on behavioral finance theory are by Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999). These theories propose behavioral biases to interpret the effects of momentum and reversal. For example, Daniel et al. (1998) believe that, because of the combined effect of overconfidence and attribution bias, stock prices display short-term momentum and long-term reversals. Hong and Stein (1999) argue that momentum traders generate momentum effects, and news watchers generate reversal effects. The model proposed by Barberis et al. (1998) shows that investors overreact or underreact to market information, thus causing momentum or reversal effects. Lou et al. (2019) link investor heterogeneity to intraday returns reversal effects and argue that the reversal effects are the result of a tug of war between individuals and institutions.

The literature on trading behavior by heterogeneous investors is growing.

First, heterogeneous investors have various information and analytical skills. For example, institutional investors may be better informed than individual investors (Chakravarty, 2001). Chiang, Qian, and Sherman (2010) suggest that institutions trade based on information, but individual investors are uninformed, and the trades by individual investors show return-chasing behavior. Cai, He, and He (2010) maintain that trades initiated by institutional investors can be regarded as informed trades. Yan and Zhang (2009) find that institutions are better informed and trade actively to exploit their informational advantage.

Second, heterogeneous investors have different trading time preferences. Griffin, Harris, and Topaloglu (2003) and Dasgupta, Prat, and Verardo (2011) show that, to collect information, individual investors are active at nighttime, and institutional investors trade more frequently during the day. Lou et al. (2019) find that institutional investors tend to trade throughout the day, especially at the close, whereas individual investors prefer to trade near or at the open.

Third, heterogeneous investors have different trading pattern preferences. The literature suggests that the individual investor is a contrarian trader, but the institutional investor is a momentum trader. For example, Grinblatt and Keloharju (2001) suggest that institutional investors tend to be momentum investors, buying winner stocks and shorting loser stocks. In contrast, Choe, Kho, and Stulz (1999) and Grinblatt and Keloharju (2001) find that individual investors demonstrate short-term reversal trading patterns. Bertsimas and Lo (1998)

show that institutional investors split parent orders into child orders and execute these orders at even intervals to minimize transaction costs. Breen, Hodrick, and Korajczyk (2002) find that more than 90 percent of institutional orders are completed on the same day that they are initiated. Campbell, Ramadorai, and Schwartz (2009) illustrate that institutional traders are highly persistent and are more likely to buy or sell the same stocks in multiple subsequent half-hours.

Most of the prior research on investor heterogeneity, however, comes from lower-frequency data than that provided by intraday trades and in settings other than emerging markets. The evidence from Chinese markets is not consistent with that in this prior literature. For example, Gao et al. (2019) find that, in the Chinese stock market, individuals seldom trade at the opening call auction or even in the subsequent half-hour. Duxbury and Yao (2017) and Wen, Zou, and Wang (2021) report that, in the A-share market, institutions are contrarian traders. This evidence shows that trading behavior by heterogeneous investors in developed markets might not apply to emerging markets, such as China. Hence, we investigate the intraday trading behavior of heterogeneous investors in the Chinese market.

The literature on informed trading offers us a motivation for studying the role of investor heterogeneity in intraday reversals. In theoretical models, Hirshleifer, Subrahmanyam, and Titman (1994) and Brunnermeier (2005) both indicate that informed investors obtain information on a stock earlier than other traders and that they trade based on their private information at the outset. Afterward, late-informed traders learn the information and trade on it. Informed traders face competition from other informed traders, and their information advantage may be short-lived; informed traders thus prefer early trades (Easley & O'Hara, 1987; Karpoff, 1987). Barclay and Hendershott (2003) suggest more informed trading takes place early in the day. Anand, Chakravarty, and Martell (2005) find that informed investors are most aggressive early in the day. The trading volume in the first half-hour accounts for the highest share of trading volume for the day. For those who receive information early, trading in the first half-hour is desirable in order to take advantage of high liquidity (Jin, Kearney, Li, & Yang, 2020). Late-informed investors do not trade early but, instead, trade when information becomes available (Kadan, Michaely, & Moulton, 2018).

Hence, in this paper, we divide investors into two groups: early-informed traders and late-informed traders. Following the literature, we assume that the early-informed trading takes place in the first half-hour but late-informed investors trade the rest of the day.

3. The context of the Chinese stock market and the sample

In March 1990, the Chinese government allowed Shanghai and Shenzhen to pilot public offerings. The Shanghai Stock Exchange (SSE) was established on November 26, 1990, and Shenzhen Stock Exchange (SZSE) on December 1, 1990, as a trial. Two categories of shares are traded on the China's stock market: A-shares and B-shares. B-shares are particular shares

listed on China's stock exchanges, marked at par value in RMB and traded in foreign currencies. The official name of A-shares is RMB common stock, that is, shares issued by a Chinese company, listed in China, marked at par value in RMB, and traded in RMB. The trading volume of A-shares and B-shares greatly differs. For example, on November 11, 2022, the value of A-shares traded was RMB 513.4 billion, whereas that of the B-shares traded was only RMB 200 million. The biggest obstacle to the development of the B-share market is a lack of liquidity, but the A-share market has become China's most important stock market.

As of December 31, 2019, 3757 companies were listed on the A-share market, with a total market value of about RMB 59 trillion. Since June and September 2018, respectively, A-shares have been included in the MSCI and FTSE Russell indexes, which gives more international investors more access to them. Given the importance of A-shares to global investors, it is particularly important to study the predictability of A-shares.

China's A-share market differs from the US stock market. First, the A-share market is dominated by individual investors, who comprise more than 95 percent of investors, and account for more than 80 percent of the value of trade. Second, unlike the trading system in the US stock market, the A-share market uses pure order-driven trading, a daily price-limit rule, and a T + 1 settlement system. Third, China's A-share market has a high degree of information asymmetry, which is not alleviated by institutional investors because of their frequent collusion with insiders to earn profits.

We use the 180 constituent stocks on the SSE as our sample. These stocks have large market capitalization, good liquidity, and strong industry representation. According to SSE statistics, the outstanding market value of these stocks comprise at least 70 percent of the total outstanding market value of the SSE and 70 percent of the transaction value. Individual investors in China's A-share market have larger positions and trading volumes in large-cap stocks than in small-cap stocks. For example, Hu and Wang (2013) show that small-cap and large-cap stocks held by individual investors accounted for 10 percent and 40 percent of the total portfolio, respectively, whereas the trading volume accounted for 15 percent and 30 percent of total transactions, respectively. Moreover, a high proportion of the 180 constituent shares on the SSE are held by institutions. Therefore, this sample enables us to analyze the role of institutional and individual investors at the same time.

Every six months, the SSE adjusts the 180 constituents based on the principle of sample stability and dynamic tracking, in general, by no more than 10 percent. Our sample period is from January 6, 2015, to October 31, 2019, and the 180 constituents are based on the SSE adjustment announced on December 1, 2014. The 180 stock intraday prices are collected from the CSMAR (China Stock Market & Accounting Research) database.

The A-share market operates from 9:30 am to 11:30 am and from 1:00 pm to 3:00 pm. The first half-hour has some particularities. First, news is usually released during the overnight non-trading period. The market takes about a half-hour to digest new information (Gao et al., 2018). Agarwalla, Jacob,

Table 1
Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
$r_{1,t}$	−0.03%	1.69%	−10.05%	10.04%
$r_{2to8,t}^i$	0.04%	2.01%	−18.18%	19.22%
r_t	0.02%	2.72%	−10.18%	10.19%

Notes: This table reports summary statistics. $r_{1,t}$ is the first half-hour returns on day t , and $r_{2to8,t}^i$ is the cumulative return from the second to eighth half-hour on day t . r_t is the daily return on day t . The sample period is January 6, 2015, to October 31, 2019.

and Pandey (2015) state that market volatility and trading volume take about 30 min to stabilize. Ibikunle (2015) argues that a large part of price discovery takes place in the first trading hour because a lot of new information is released to the market early. Second, as discussed in the literature review, we believe that informed investors trade earlier in the day (hereafter, early-informed investors). With the progress of trading and the passage of time, uninformed traders gradually obtain information, so they usually trade later in the day (hereafter, late-informed investors). The first half-hour is usually viewed as the period with a high incidence of informed trading. Therefore, a trading day is divided between the first half-hour (from 9:30 am to 10:00 am) and the rest of the day (from 10:00 am to 3:00 pm, i.e., from the second to the eighth half-hour). The return from the first half-hour is defined as the percentage change in price at 10:00 am compared with the previous day's closing price,

$$r_{1,t}^i = (P_{1,t}^i - P_{c,t-1}^i) / P_{c,t-1}^i$$

where $r_{1,t}^i$ represents the first half-hour returns of firm i on day t . $P_{c,t-1}^i$ is the closing price on day $t - 1$. $P_{1,t}^i$ is the first half-hour closing price on day t . $r_{2to8,t}^i$ is firm i 's cumulative return from 10:00 am to 3:00 pm, which is defined as follows,

$$r_{2to8,t}^i = (P_{c,t}^i - P_{1,t}^i) / P_{1,t}^i$$

where $P_{c,t}^i$ is the firm i 's closing price on day t .

Table 1 lists the descriptive statistics of these variables. The maximum and minimum of the first half-hour returns ($r_{1,t}$) in Table 1 are 10.04 percent and −10.05 percent, respectively, which are the results of the daily price limit of 10 percent on Chinese stock markets.¹ The mean $r_{1,t}$ is −0.03 percent, with a standard deviation of 1.69 percent. Note that mean $r_{2to8,t}^i$ is positive. Table 1 shows that mean $r_{2to8,t}^i$ is 0.04 percent, and its standard deviation is 2.01 percent. On June 30, 2015, the stock for Beijing Tongrentang (Code 600085) gradually rose from the lower price limit at 10:30 am to the upper price limit at closing. As a result, the maximum $r_{2to8,t}^i$ is 19.22 percent. On May 5, 2015, the stock for Greenland Holdings (Code 600606) gradually fell from the upper price limit hit at opening to the lower price limit at closing. Consequently, the minimum $r_{2to8,t}^i$ is −18.18 percent. This is evidence that the sample period has individual intraday return reversals.

Table 2
Basic regressions.

Variables	(1)	(2)
	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	−0.073*** (−11.66)	−0.100*** (−10.25)
$Volatility_{1,t}^i (\times 10^{-3})$		9.67 (0.89)
$\ln Volume_{1,t}^i (\times 10^{-5})$		−1.73 (−0.18)
$\ln Size_{1,t}^i (\times 10^{-4})$		2.12 (1.57)
$r_{2to8,t-1}^i (\times 10^{-2})$		−2.95*** (−5.88)
$\beta_0 (\times 10^{-3})$	0.490 (1.20)	−2.58 (−1.39)
R^2	0.040	0.162

Notes: This table reports the results of univariate regression and multiple regressions. Column (1) gives the results of $r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \epsilon_{2to8,t}^i$ and Column (2) lists the results of $r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 Volatility_{1,t}^i + \beta_3 \ln Volume_{1,t}^i + \beta_4 \ln Size_{1,t}^i + \beta_5 r_{2to8,t-1}^i + \epsilon_{2to8,t}^i$. $r_{1,t}^i$ represents the first half-hour returns of firm i on day t , and $r_{2to8,t}^i$ is firm i 's cumulative returns from 10:00 am to 3:00 pm. $Volatility_{1,t}^i$ is the volatility measured in terms of absolute value of the first half-hour returns. $\ln Volume_{1,t}^i$ is the logarithm of firm i 's trading volume in the first half-hour on day t . $\ln Size_{1,t}^i$ is the logarithm of firm i 's size measured by stock market value. $r_{2to8,t-1}^i$ is the lagged dependent variable. Each model is estimated based on Fama-MacBeth two-step regression with Newey-West robust standard errors, and the corresponding t -statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

4. Empirical methodology and results

4.1. Univariate regression

We first analyze intraday returns reversals following the Fama-McBeth two-step approach and using the following univariate cross-sectional regression.

$$r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \epsilon_{2to8,t}^i \quad (1)$$

Column (1) in Table 2 reports the Fama-MacBeth regression results, along with the Newey-West robust standard errors. Column (1) shows that the returns from the second half-hour to the eighth half-hour demonstrate a reversal of the first half-hour returns. The coefficients of $r_{2to8,t}^i$ are negative and statistically significant at the 1 percent level. The coefficient of −0.073 suggests that a one-standard-deviation increase in the first half-hour returns lead to a 308 percent decline in the returns for the rest of the day compared with the mean. R^2 is 4 percent, which is rather high. The same R^2 at intraday frequency is better than at low frequency (Gao et al., 2018). Moreover, it is higher than that of the intraday momentum effect. For example, the R^2 of the intraday momentum effect reported in US markets is 1.1 percent (Gao et al., 2018), and the R^2 of the intraday momentum effect in Chinese markets is 1.9 percent (Zhang et al., 2019). In summary, Table 2 indicates that the returns from the second half-hour to the eighth half-hour are significantly and negatively related to the first half-hour returns in the cross section.

¹ The values in Table 1 differ slightly from $\pm 10\%$, as a result of rounding.

Table 3
Weekly effect.

Variables	Monday	Tuesday	Wednesday	Thursday	Friday
	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	-0.0982*** (-5.68)	-0.119*** (-7.53)	-0.122*** (-3.58)	-0.0769*** (-4.10)	-0.0835*** (-4.58)
$Volatility_{1,t}^i (\times 10^{-3})$	-13.0 (-0.61)	9.46 (0.50)	42.1 (1.19)	-7.44 (-0.38)	16.1 (0.75)
$\ln Volume_{1,t}^i (\times 10^{-5})$	1.20 (0.05)	28.1 (1.32)	-12.2 (-0.55)	-22.0 (-1.15)	-3.54 (-0.18)
$\ln Size_{1,t}^i (\times 10^{-4})$	0.81 (0.23)	-2.60 (-0.83)	1.99 (0.69)	5.11** (2.07)	5.30** (2.15)
$r_{2to8,t-1}^i (\times 10^{-2})$	-1.26 (-0.98)	-4.21*** (-3.87)	-3.50*** (-3.14)	-3.03*** (-2.94)	-2.69** (-2.34)
$\beta_0 (\times 10^{-3})$	0.03 (0.01)	2.11 (0.55)	-1.03 (-0.24)	-5.55 (-1.48)	-8.51** (-2.36)
R^2	0.190	0.165	0.150	0.155	0.153

Notes: This table reports the results on weekday seasonality. The regression model is $r_{2to8,w}^i = \beta_0 + \beta_1 r_{1,w}^i + \beta_2 Volatility_{1,w}^i + \beta_3 \ln Volume_{1,w}^i + \beta_4 \ln Size_{1,w}^i + \beta_5 r_{2to8,w-1}^i + \varepsilon_{2to8,w}^i$, where $w = \text{Monday, Tuesday, ..., Friday}$. $r_{2to8,w}^i$ is cumulative returns from the second to the eighth half-hour on day w . $Volatility_{1,w}^i$ is measured in terms of absolute value of the first half-hour returns for firm i . $\ln Volume_{1,w}^i$ is the logarithm of firm i 's trading volume at the first half-hour on day w . $\ln Size_{1,w}^i$ is the logarithm of firm i 's size measured by outstanding stock market value at the first half-hour on day w . $r_{2to8,w-1}^i$ is the lagged dependent variable. Each model is estimated based on Fama-MacBeth two-step regression with Newey-West robust standard errors, and the corresponding t -statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

4.2. Multiple regression

We note that some concern might arise that the predictive power of the first half-hour returns is mainly a manifestation of a firm's fundamentals, trading activity, or other factors. To alleviate this concern, we employ control variables, including the firm's size, trading volume, volatility, and lagged dependent variable,

$$r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 Volatility_{1,t}^i + \beta_3 \ln Volume_{1,t}^i + \beta_4 \ln Size_{1,t}^i + \beta_5 r_{2to8,t-1}^i + \varepsilon_{2to8,t}^i \quad (2)$$

where $Volatility_{1,t}^i$ is the volatility measured in terms of the absolute value of the first half-hour returns. $\ln Volume_{1,t}^i$ is the logarithm of firm i 's trading volume in the first half-hour on day t . $\ln Size_{1,t}^i$ is the logarithm of firm i 's size measured by the stock market value. The inclusion of the lagged dependent variable $r_{2to8,t-1}^i$ is inspired by Heston et al. (2010), which shows that intraday returns persists during the same time interval on the following days.

Column (2) in Table 2 reports the Fama-MacBeth results of multiple regressions. β_1 is -0.1, which is larger in Table 2 than in the univariate regressions. The t value is -10.25, which indicates that β_1 is significant at the 1 percent level. Thus, we conclude that the predictive power of the first half-hour returns is robust to firm size, volatility, trading volume, and lagged returns over the same period.

4.3. Robustness tests

4.3.1. Seasonality

In this section, we check the robustness of the reversal effect by testing both its weekday seasonality and monthly

seasonality. We report the regression results of the weekly effect in Table 3. We find that the reversal effect is pervasive. The coefficient β_1 is significant at the 1 percent level on all weekdays (i.e., from Monday to Friday).

Table 4 lists the monthly results. We find that the coefficient β_1 is also significant in all months, except October. Therefore, the reversal effect is a prevalent phenomenon that is robust to seasonality.

4.3.2. Subsample analysis

In order to observe whether the reversal effect exists in alternative samples, we divide the sample into five yearly subsamples to represent different market states. In 2015, a highly volatile trading year, the Chinese stock market experienced a crash. In 2016 and 2018, A-shares fell by 12 percent and 25 percent, respectively, but in 2017 and 2019, A-shares rose by 6 percent and 22 percent, respectively. Table 5 lists the subsample results. β_1 is statistically significant at the 1 percent level in all years. This result illustrates that the reversal effect is not affected by market states.

4.3.3. The daily price-limit rule

Our full sample includes all 180 constituent stocks of the SSE, among which some stocks hit their daily price limits; however, after a stock hits its daily price limit, the stock price cannot continue to rise or fall. Therefore, it is doubtful that the reversal effect is the result of the daily price limit. In order to eliminate this concern, in the following robustness test, we omit stocks that hit the daily price limit on day t . Table 6 reports the results, showing that the reversal effect is still significant at the 1 percent level, even after the omission of stocks that reach the daily price limit. Therefore, the reversal effect is not the result of the daily price-limit rule.

Table 4
Monthly effect.

Variables	January	February	March	April	May	June
	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	−0.0918*** (−4.00)	−0.136*** (−3.99)	−0.190*** (−2.78)	−0.0836*** (−3.73)	−0.124*** (−5.45)	−0.0740*** (−3.21)
$Volatility_{1,t}^i (\times 10^{-3})$	23.2 (0.92)	−4.61 (−0.12)	38.8 (0.57)	−31.5 (−1.12)	73.0** (2.53)	−3.49 (−0.13)
$\ln Volume_{1,t}^i (\times 10^{-5})$	−6.10 (−0.21)	57.1* (1.74)	22.9 (0.78)	8.77 (0.28)	−16.2 (−0.53)	−42.7 (−1.53)
$\ln Size_{1,t}^i (\times 10^{-4})$	3.82 (1.03)	−4.59 (−1.01)	−2.53 (−0.66)	2.79 (0.86)	1.87 (0.47)	4.29 (1.12)
$r_{2to8,t-1}^i (\times 10^{-2})$	−4.14** (−2.39)	−2.49 (−1.28)	−4.71*** (−3.11)	−3.72** (−2.16)	−4.17** (−2.43)	−1.57 (−0.88)
$\beta_0 (\times 10^{-3})$	−7.28 (−1.27)	0.37 (0.05)	3.47 (0.65)	−5.37 (−0.84)	0.27 (0.04)	0.86 (0.14)
R^2	0.155	0.151	0.160	0.136	0.178	0.174
Variables	July	August	September	October	November	December
	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	−0.0704*** (−2.77)	−0.0966*** (−4.28)	−0.131*** (−3.67)	−0.0300 (−0.73)	−0.115*** (−5.04)	−0.0479* (−1.87)
$Volatility_{1,t}^i (\times 10^{-3})$	8.06 (0.24)	7.33 (0.25)	67.5* (1.71)	−62.4 (−1.38)	−4.11 (−0.16)	−20.2 (−0.65)
$\ln Volume_{1,t}^i (\times 10^{-5})$	−16.4 (−0.45)	−18.1 (−0.44)	−41.4 (−1.16)	35.1 (1.13)	27.3 (0.75)	−7.24 (−0.23)
$\ln Size_{1,t}^i (\times 10^{-4})$	5.02 (0.74)	2.82 (0.61)	5.06 (0.95)	−0.71 (−0.16)	1.26 (0.33)	4.73 (1.20)
$r_{2to8,t-1}^i (\times 10^{-2})$	−14.0 (−0.74)	−6.38*** (−3.94)	−1.97 (−1.28)	1.07 (0.57)	−3.76* (−1.95)	−0.91 (−0.50)
$\beta_0 (\times 10^{-3})$	−5.17 (−0.60)	−1.87 (−0.38)	−0.98 (−0.16)	−3.68 (−0.60)	−5.82 (−1.02)	−6.99 (−1.41)
R^2	0.174	0.181	0.163	0.156	0.167	0.141

Notes: This table reports the results on monthly seasonality. The regression model is $r_{2to8,m,t}^i = \beta_0 + \beta_1 r_{1,m,t}^i + \beta_2 Volatility_{1,m,t}^i + \beta_3 \ln Volume_{1,m,t}^i + \beta_4 \ln Size_{1,m,t}^i + \beta_5 r_{2to8,m,t-1}^i + \varepsilon_{2to8,m,t}^i$, where $m = \text{January, February, ..., December}$. $r_{2to8,m,t}^i$ is cumulative returns from the second to eighth half-hour on day t of month m . $Volatility_{1,m,t}^i$ is measured in terms of absolute value of the first half-hour returns. $\ln Volume_{1,m,t}^i$ is the logarithm of trading volume at the first half-hour. $\ln Size_{1,m,t}^i$ is the logarithm of firm's size measured by outstanding stock market value at the first half-hour. $r_{2to8,m,t-1}^i$ is firm i 's cumulative returns from the second to the eighth half-hour on the previous day. Each model is estimated based on Fama-MacBeth two-step regression with Newey-West robust standard errors, and the corresponding t -statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

Table 5
Alternative sample.

Variables	2015	2016	2017	2018	2019
	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	−0.124*** (−5.97)	−0.147*** (−4.39)	−0.0929*** (−7.08)	−0.0689*** (−4.17)	−0.0618*** (−3.63)
$Volatility_{1,t}^i (\times 10^{-3})$	−1.57 (−0.06)	19.4 (0.56)	−22.1 (−1.25)	9.74 (0.53)	50.3** (2.53)
$\ln Volume_{1,t}^i (\times 10^{-5})$	−66.1* (−1.95)	8.97 (0.52)	36.1** (2.40)	0.05 (0.00)	14.5 (0.78)
$\ln Size_{1,t}^i (\times 10^{-4})$	4.92 (1.00)	1.04 (0.44)	−0.55 (−0.25)	3.98* (1.95)	1.04 (0.44)
$r_{2to8,t-1}^i (\times 10^{-2})$	−3.38*** (−3.06)	−2.94*** (−2.60)	−3.60*** (−2.98)	−1.64 (−1.59)	−3.26*** (−2.93)
$\beta_0 (\times 10^{-3})$	5.40 (0.81)	−3.03 (−0.96)	−4.00 (−1.31)	−7.35** (−2.17)	−4.10 (−1.62)
R^2	0.199	0.170	0.160	0.144	0.134

Notes: This table reports the regression results for different years. The regression model is $r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 Volatility_{1,t}^i + \beta_3 \ln Volume_{1,t}^i + \beta_4 \ln Size_{1,t}^i + \beta_5 r_{2to8,t-1}^i + \varepsilon_{2to8,t}^i$, where $r_{1,t}^i$ represents the first half-hour returns of firm i on day t , and $r_{2to8,t}^i$ is cumulative returns from the second to the eighth half-hour. $Volatility_{1,t}^i$ is measured in terms of absolute value of the first half-hour returns. $\ln Volume_{1,t}^i$ is the logarithm of trading volume at the first half-hour. $\ln Size_{1,t}^i$ is the logarithm of firm's size measured by outstanding stock market value at the first half-hour. $r_{2to8,t-1}^i$ is firm i 's cumulative returns from the second to the eighth half-hour on day $t - 1$. Each model is estimated based on Fama-MacBeth two-step regression with Newey-West robust standard errors, and the corresponding t -statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

Table 6
Excluding stocks that reach the daily price limit.

Variables	(1)	(2)
	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	-0.0868*** (-13.52)	-0.112*** (-11.52)
$Volatility_{1,t}^i (\times 10^{-3})$		1.83 (0.17)
$\ln Volume_{1,t}^i (\times 10^{-5})$		-5.42 (-0.57)
$\ln Size_{1,t}^i (\times 10^{-4})$		2.18 (1.63)
$r_{2to8,t-1}^i (\times 10^{-2})$		-3.04*** (-6.12)
$\beta_0 (\times 10^{-3})$	0.41 (1.02)	-1.98 (-1.09)
R^2	0.043	0.165

Notes: This table reports the results without stocks that reach their daily price limits. If a stock reached the daily price limit on day t , then the stock is omitted from the sample. Column (1) gives the results of $r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \epsilon_{2to8,t}^i$, and Column (2) lists the results of $r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 Volatility_{1,t}^i + \beta_3 \ln Volume_{1,t}^i + \beta_4 \ln Size_{1,t}^i + \beta_5 r_{2to8,t-1}^i + \epsilon_{2to8,t}^i$. $r_{1,t}^i$ represents the first half-hour returns of firm i on day t , and $r_{2to8,t}^i$ is firm i 's cumulative returns from 10:00 am to 3:00 pm. $Volatility_{1,t}^i$ is the volatility measured in terms of absolute value of the first half-hour returns. $\ln Volume_{1,t}^i$ is the logarithm of firm i 's trading volume in the first half-hour on day t . $\ln Size_{1,t}^i$ is the logarithm of firm i 's size measured by the stock market value. $r_{2to8,t-1}^i$ is the lagged dependent variable. Each model is estimated based on Fama-MacBeth two-step regression with Newey-West robust standard errors, and the corresponding t -statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

5. Potential drivers

5.1. Intraday returns reversal and investor heterogeneity

According to the literature discussed above, investors in the stock market can be divided into two groups: early-informed investors and late-informed investors. How do early-informed investors benefit from their short-lived private information? Brunnermeier (2005) and Kadan et al. (2018) show that it is optimal for early-informed investors to trade early if they obtain private information. If this private information becomes public information, risk aversion drives these early-informed investors to reverse their position by trading against their early trades (Kadan et al., 2018). Therefore, we hypothesize that early-informed investors' reversal trades are responsible for intraday return cross-sectional reversal.

Because of data limitations, we do not know which transactions are initiated by early-informed investors, but they often initiate relatively large transactions (Blau, Van Ness, & Van Ness, 2009; Easley & O'Hara, 1987; Karpoff, 1987; Sun & Ibikunle, 2017). This is due to competition from other informed investors whose private information may be short-lived (Easley & O'Hara, 1987; Karpoff, 1987). Easley and O'Hara (1987) and Karpoff (1987) suggest that informed investors are much more likely to actively trade with their private information rather than use it in degrees. Blau et al. (2009) hold that informed investors prefer block trading when they make

informed trades. Institutional investors are widely considered to have information advantages over individual investors and, therefore, are regarded as early-informed investors. Chakravarty (2001) finds that larger orders are more likely to be from institutions than individuals. Small orders correlate well with late-informed retail investors (Barber et al., 2009). Lou et al. (2019) suggest that institutions are linked to large trades and individuals to small trades. Barclay and Warner (1993) argue that if informed investors break up their orders into smaller trade orders, most orders would be medium in size, rather than small, based on cost considerations. Therefore, we use the size of each trade in high-frequency trading data to identify investors.

There is no conclusive definition of large and small trades (Chan & Fong, 2000). Following Easley, Kiefer, and O'Hara (1997), we employ two thresholds for dividing trade into small and large trades: those below RMB 10,000 or less than 1000 shares are small trades; those over RMB 100,000 or more than 10,000 shares are large trades. Table 7 reports the proportion of small or large trades in each half-hour out of total small or large trades in a day. Table 7 shows that when investors are identified based on these thresholds, the proportion of large and small order trades differs. However, small trades account for the lowest proportion in the first half-hour of a day, and large trades account for the highest proportion in the first half-hour of a day. For example, Column (1) in Table 7 shows that large trade orders comprise 28.73 percent in the first half-hour of a day, and small trade orders comprise only 7.68 percent in the first half-hour of a day. This finding is not consistent with Lou et al. (2019), who assume that individuals are likely to trade at or near the market open whereas institutions trade during the remainder of the day. Our result is consistent with the findings by Gao et al. (2019), which indicate that individuals seldom trade in either the opening call auction or the subsequent half-hour. Due to their lack of investment experience and information-gathering ability, individuals in the Chinese market are unlikely to obtain early information. This higher information asymmetry between the two types of investors at or near the market open also

Table 7
Intraday distribution of the volume of large and small trades (%).

Half-hour	(1)		(2)	
	Large trades ≥10,000 shares	Small trades ≤1000 shares	Large trades (%) ≥RMB 100,000	Small trades (%) ≤RMB 10,000
1	28.73	7.68	33.80	3.62
2	11.25	10.14	10.83	11.09
3	9.39	12.19	8.42	15.43
4	8.07	16.12	6.67	15.34
5	9.51	13.33	9.22	18.28
6	7.74	13.51	6.24	15.66
7	8.30	16.58	6.91	12.53
8	17.01	10.45	17.90	8.05
2 to 8	71.27	92.32	66.20	96.38

Notes: This table reports the results for the intraday distribution of large and small trades. We use two thresholds for dividing trade into small and large trades: those below RMB 10,000 or less than 1000 shares are small trades; those over RMB 100,000 or more than 10,000 shares are large trades.

Table 8
Intraday distribution of large and small OIB.

Half-hour	Large OIBs ≥10,000 shares	Small OIBs ≤1000 shares	Large OIBs ≥ RMB 100,000	Small OIBs ≤ RMB 10,000
1	2,708,794	32,126	2,738,750	19,749
2	322,616	14,203	335,844	9761
3	−332,149	14,681	−325,876	7895
4	−341,974	15,049	−345,351	8571
5	152,154	7904	138,566	4336
6	−374,116	7001	−384,687	2482
7	−335,989	8067	−330,339	3799
8	−839,623	11,402	−815,409	8306
2–8	−1,749,081	78,307	−1,727,252	45,150

Notes: This table reports the results for the intraday distribution of large and small OIBs. We use two thresholds for dividing trade into small and large trades: those below RMB 10,000 or less than 1000 shares are small trades; those over RMB 100,000 or more than 10,000 shares are large trades.

discourages individual investors from trading. In contrast, large traders are more focused on trading in the first half-hour, probably because of their information advantage.

The trading volumes in Table 7 do not identify the direction of trades. Chordia and Subrahmanyam (2004) suggest that order imbalances can provide additional power beyond volume in explaining stock returns. Thus, order imbalances of different sizes are used in this section to further investigate the potential drivers of reversal effects. We calculate two proxies for order imbalances: the number of shares of buyer-initiated trades minus the number of shares of seller-initiated trades (*OIB-Shares*); and the value of buyer-initiated trades minus the value of seller-initiated trades (*OIBRMB*). Table 8 lists the distribution of large OIBs and small OIBs in a day, and, for the sake of brevity, reports only the results for *OIBRMB*.² The table shows that the small OIBs are always positive throughout the day, but the large OIBs reach a peak in the first half-hour, then drops sharply, and is even negative for the rest of the day. This result indicates that large traders reverse their position by trading against the first half-hour. The evidence is not consistent with that of Campbell et al. (2009), who indicate that large trades are highly persistent because large traders tend to buy or sell the same stocks in multiple subsequent half-hours. This result also shows that large informed investors in the Chinese stock market are not momentum traders at the intraday level. Large trades usually come from informed traders, such as institutions. However, Chinese institutional investors often exhibit the characteristics of short-term traders. For example, Wu Xiaoling, the vice chairman of the Financial and Economic Committee of the National People's Congress, said that short-term trades by institutional investor were excessive in the A-share market (Tencent Finance Annual Meeting in 2015). Lou Jiwei, the director of the Foreign Affairs Committee and a former minister of finance, said that the accounts of Chinese institutional investors demonstrate high turnover rates (China Wealth Management 50 forum in 2019).

² The unreported results divided by *OIBShares* are similar to those in Table 8.

In summary, Tables 7 and 8 show that large and small traders have different trading behaviors over the course of the day. To test the role of large and small orders in intraday reversals, we run the following regression:

$$r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 RS_t^i + \beta_3 RL_t^i + \beta_4 (r_{1,t}^i \times RS_t^i) + \beta_5 (r_{1,t}^i \times RL_t^i) + \beta_6 Volatility_{1,t}^i + \beta_7 \ln Volume_{1,t}^i + \beta_8 \ln Size_{1,t}^i + \beta_9 r_{2to8,t-1}^i + \epsilon_{2to8,t}^i \quad (3)$$

$$RS_t^i = SmallOIB_{2to8,t}^i / SmallOIB_{1,t}^i, RL_t^i = LargeOIB_{2to8,t}^i / LargeOIB_{1,t}^i$$

where RS_t^i (RL_t^i) is the ratio of the rest of the day's small (large) OIB to that of the first half-hour for firm i on day t . $SmallOIB_{1,t}^i$ is the order imbalance of small trades in first half-hour. $SmallOIB_{2to8,t}^i$ is the order imbalance of small trades from the second half-hour to the eighth half-hour. $LargeOIB_{1,t}^i$ is the order imbalance of large trades in the first half-hour. $LargeOIB_{2to8,t}^i$ is order imbalance of large trades from the second half-hour to the eighth half-hour. Because OIBs can explain returns (Chordia & Subrahmanyam, 2004), the purpose of Equation (3) is to test whether the intraday reversal effect is caused by the changes in small or large OIBs.

Table 9 lists the regression results. Table 9 shows that the coefficients of $r_{1,t}^i \times RL_t^i$ are significantly positive at the 1 percent level in all cases. However, the coefficients of $r_{1,t}^i \times RS_t^i$ are not significant except for Column (2). This result indicates that intraday reversals are weakly related to changes in small OIBs, but strongly positively correlated with changes in large OIBs. Table 8 shows that large order OIBs are positive in the first half-hour, but negative from the second to the eighth half-hour. We thus conclude that the decline of large OIBs from the second to the eighth half-hour lead to the intraday reversal effect.

To further test the relationship between intraday return cross-sectional reversals and large order reversals, we also run the following equation:

$$r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 D_t^i + \beta_3 (r_{1,t}^i \times D_t^i) + \beta_4 Volatility_{1,t}^i + \beta_5 \ln Volume_{1,t}^i + \beta_6 \ln Size_{1,t}^i + \beta_7 r_{j,t-1}^i + \epsilon_{2to8,t}^i \quad (4)$$

where D_t^i is a dummy variable. If $LargeOIB_{2to8,t}^i$ is negative and $LargeOIB_{1,t}^i$ is positive, D_t^i is set at 1; otherwise, it is 0. Therefore, D_t^i represents large order reversals. Table 10 lists the results of Equation (4). In Table 10, the coefficients of $r_{1,t}^i$ are not significant, but the coefficients of $r_{1,t}^i \times D_t^i$ are significantly negative at the 1 percent level. This result shows that if a large trade is not reversed (i.e., $D_t^i = 0$), the intraday cross-sectional reversal effect disappears. As mentioned above, large orders are generally considered to come from informed traders with information advantages. In order to make use of their information advantages, these informed traders trade early in the trading day. Over time, information is gradually made public. In order to earn a profit, early-informed traders engage in reversal trading. Therefore, we conclude that the reversal of

Table 9
Intraday returns reversal and relative change of order flow.

Variables	(1)	(2)	(3)	(4)
	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	-0.0421 (-0.58)	-0.0545 (-0.88)	-0.0311 (-0.41)	-0.0260 (-0.32)
$RS_t^i (\times 10^{-6})$	-1.65** (-2.50)	-1.20 (-1.08)	-0.89 (-1.00)	-2.15** (-2.11)
$RL_t^i (\times 10^{-6})$	-7.41* (-1.84)	-6.55* (-1.88)	-4.34 (-0.98)	-4.59 (-1.07)
$r_{1,t}^i \times RS_t^i (\times 10^{-5})$	-0.51 (-0.08)	18.4* (1.96)	-4.19 (-0.63)	5.10 (0.60)
$r_{1,t}^i \times RL_t^i (\times 10^{-3})$	6.49*** (13.01)	6.71*** (13.29)	6.59*** (12.28)	6.72*** (12.25)
$Volatility_{1,t}^i (\times 10^{-2})$	-5.99 (-0.82)	-5.51 (-0.88)	-7.35 (-0.96)	-7.82 (-0.96)
$\ln Volume_{1,t}^i (\times 10^{-5})$	-0.32 (-0.03)	-0.30 (-0.03)	-3.25 (-0.34)	-3.21 (-0.33)
$\ln Size_{1,t}^i (\times 10^{-4})$	2.55* (1.84)	2.51* (1.81)	2.27* (1.67)	2.25* (1.67)
$r_{2to8,t-1}^i (\times 10^{-2})$	-2.98*** (-5.82)	-2.93*** (-5.71)	-2.84*** (-5.57)	-2.81*** (-5.50)
$\beta_0 (\times 10^{-3})$	-3.48* (-1.82)	-3.37* (-1.76)	-2.47 (-1.30)	-2.43 (-1.28)
R^2	0.201	0.202	0.203	0.203

Notes: This table reports the results of $r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 RS_t^i + \beta_3 RL_t^i + \beta_4 (r_{1,t}^i \times RS_t^i) + \beta_5 (r_{1,t}^i \times RL_t^i) + \beta_6 Volatility_{1,t}^i + \beta_7 \ln Volume_{1,t}^i + \beta_8 \ln Size_{1,t}^i + \beta_9 r_{2to8,t-1}^i + \varepsilon_{2to8,t}^i$. $RS_t^i (RL_t^i)$ is the ratio of the rest of a day's small (large) OIB to that of the first half-hour for firm i on day t . We use two thresholds for dividing trade into small and large trades: those below RMB 10,000 or less than 1000 shares are small trades; those over RMB 100,000 or more than 10,000 shares are large trades. OIB is measured by the value of (or the number of shares) buyer-initiated trades less than that of seller-initiated trades. In Column (1), small trades are those less than 10,000 RMB, large trades are those more than 100,000 RMB, and OIB is the value of buyer-initiated trades minus that of seller-initiated trades. In Column (2), small trades are those less than 10,000 RMB, large trades are those more than 100,000 RMB, and OIB is the shares of buyer-initiated trades minus that of seller-initiated trades. In Column (3), small trades are those less than 1000 shares, large trades are those more than 10,000 shares, and OIB is the value of buyer-initiated trades minus that of seller-initiated trades. In Column (4), small trades are those less than 1000 shares, large trades are those more than 10,000 shares, and OIB is the shares of buyer-initiated trades minus that of seller-initiated trades. Each model is estimated based on Fama-MacBeth two-step regression with Newey-West robust standard errors, and the corresponding t -statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

large trades is responsible for intraday return cross-sectional reversals.

5.2. The role of macroeconomic news

The information advantage of informed traders should be reflected in the important information window period. Because macroeconomic news is an important information source for informed traders, it is interesting to study the impact of news releases on intraday reversals. We therefore focus on the regular 10:00 am news releases from China's National Bureau of Statistics (NBS). Every month (except February), the NBS releases important economic information, such as national economic conditions and the consumer price index (CPI). These news releases provide us with an excellent sample with which to test the

Table 10
Reversal of intraday returns and large orders.

Variables	(1)	(2)	(3)	(4)
	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	0.00495 (0.48)	0.00604 (0.59)	0.00358 (0.35)	0.00462 (0.45)
$D_t^i (\times 10^{-3})$	-5.74*** (-33.34)	-5.75*** (-33.26)	-5.80*** (-34.16)	-5.81*** (-34.30)
$r_{1,t}^i \times D_t^i$	-0.246*** (-24.28)	-0.249*** (-24.88)	-0.246*** (-24.69)	-0.248*** (-25.14)
$Volatility_{1,t}^i (\times 10^{-2})$	3.70*** (3.34)	3.80*** (3.44)	3.48*** (3.14)	3.58*** (3.24)
$\ln Volume_{1,t}^i (\times 10^{-5})$	4.61 (0.47)	4.55 (0.47)	5.19 (0.53)	5.18 (0.53)
$\ln Size_{1,t}^i (\times 10^{-4})$	1.75 (1.32)	1.73 (1.31)	1.70 (1.27)	1.68 (1.26)
$r_{2to8,t-1}^i (\times 10^{-2})$	-2.40*** (-4.89)	-2.39*** (-4.88)	-2.44*** (-4.99)	-2.43*** (-4.97)
$\beta_0 (\times 10^{-3})$	-1.73 (-0.95)	-1.70 (-0.94)	-1.73 (-0.95)	-1.71 (-0.94)
R^2	0.225	0.226	0.226	0.226

Notes: This table reports the results of $r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 D_t^i + \beta_3 (r_{1,t}^i \times D_t^i) + \beta_4 Volatility_{1,t}^i + \beta_5 \ln Volume_{1,t}^i + \beta_6 \ln Size_{1,t}^i + \beta_7 r_{2to8,t-1}^i + \varepsilon_{2to8,t}^i$. D_t^i is set at 1 if the OIB of large trades from the second half-hour to the eighth half-hour is negative and those in first half-hour are positive; otherwise 0. We use two thresholds for dividing trade into small and large trades: those over RMB 100,000 or more than 10,000 shares are large trades. OIB is measured by the value of (or the number of shares) buyer-initiated trades less than that of seller-initiated trades. In Column (1), large trades are those more than 100,000 RMB, and OIB is the value of buyer-initiated trades minus that of seller-initiated trades. In Column (2), large trades are those more than 100,000 RMB, and OIB is the shares of buyer-initiated trades minus that of seller-initiated trades. In Column (3), large trades are those more than 10,000 shares, and OIB is the value of buyer-initiated trades minus that of seller-initiated trades. In Column (4), large trades are those more than 10,000 shares, and OIB is the shares of buyer-initiated trades minus that of seller-initiated trades. Each model is estimated based on Fama-MacBeth two-step regression with Newey-West robust standard errors, and the corresponding t -statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

effect of information because the information is not fully available until 10:00 am. However, as early-informed investors, such as institutions, can predict information before the market opens through their ability to obtain that information themselves, it is possible for informed investors to drive the market up or down before any news is released. Other investors obtain the news later (after 10:00 am) and, so, cannot react before the news is released. Late-informed investors, such as individuals, might follow an investment strategy in which they trade in the same direction as shown in the first half-hour. As late-informed investors chase returns, early-informed investors reverse their position by trading against their early information to earn profits. As a result, we expect the intraday return reversals to be more significant on macro news-release dates. We run the following equation to test the role of information.

$$r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 MA_t + \beta_3 (r_{1,t}^i \times MA_t) + \beta_4 Volatility_{1,t}^i + \beta_5 \ln Volume_{1,t}^i + \beta_6 \ln Size_{1,t}^i + \beta_7 r_{2to8,t-1}^i + \varepsilon_{2to8,t}^i \quad (5)$$

Table 11
The role of information announcements.

Variables	(1) News-release days	(2) Non-news-release days	(3) Full sample
	$r_{2to8,t}^i$	$r_{2to8,t}^i$	$r_{2to8,t}^i$
$r_{1,t}^i$	-0.081*** (-11.66)	-0.117*** (-7.28)	-0.110*** (-11.39)
$Volatility_{1,t}^i (\times 10^{-3})$			1.83 (0.17)
$\ln Volume_{1,t}^i (\times 10^{-5})$			-5.42 (-0.57)
$\ln Size_{1,t}^i (\times 10^{-4})$			2.18 (1.63)
$r_{2to8,t-1}^i (\times 10^{-2})$			-3.04*** (-6.12)
$MA_t (\times 10^{-4})$			-7.60 (-0.89)
$r_{1,t}^i \times MA_t (\times 10^{-3})$			-2.63* (-1.77)
$\beta_0 (\times 10^{-3})$	0.51 (1.21)	-0.12 (-0.11)	-1.22 (-0.77)
R^2	0.036	0.047	0.165

Notes: Columns (1) and (2) report the grouped regression results for “news-release days” and “non-news-release days.” Column (3) reports the results of $r_{2to8,t}^i = \beta_0 + \beta_1 r_{1,t}^i + \beta_2 MA_t + \beta_3 (r_{1,t}^i \times MA_t) + \beta_4 Volatility_{1,t}^i + \beta_5 \ln Volume_{1,t}^i + \beta_6 \ln Size_{1,t}^i + \beta_7 r_{2to8,t-1}^i + \varepsilon_{2to8,t}^i$, where MA_t is set at 1 if day t is a macroeconomic news-release day; otherwise 0. $r_{1,t}^i$ is firm i 's first half-hour returns on day t . $r_{2to8,t}^i$ is firm i 's cumulative returns from the second to the eighth half-hour on day t . $Volatility_{1,t}^i$ is measured in terms of the absolute value of the first half-hour returns for firm i . $\ln Volume_{1,t}^i$ is the logarithm of firm i 's trading volume at the first half-hour on day t . $\ln Size_{1,t}^i$ is the logarithm of firm i 's size measured by the outstanding stock market value at the first half-hour on day t . $r_{2to8,t-1}^i$ is the lagged dependent variable. Each model is estimated based on Fama-MacBeth two-step regression with Newey-West robust standard errors, and the corresponding t -statistics are reported in parentheses. ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

where MA_t is set at 1 if day t is a news-release day, and otherwise 0.

Column (1) in Table 11 reports the results of a univariate regression of news-release days, and Column (2) reports the results of a univariate regression of non-news-release days; and Column (3) reports the results of multiple regressions of Equation (5). Columns (1) and (2) both show that the coefficients of $r_{1,t}^i$ are significantly negative at the 1 percent level. However, the coefficient of $r_{1,t}^i$ in Column (1) is -0.081, and the coefficient of $r_{1,t}^i$ in Column (2) is -0.117, 1.4 times the result in Column (1). Moreover, R^2 in Column (2) is 4.7 percent, which is larger in Column (1) (3.6 percent). In Column (3) in Table 11, the coefficient of $r_{1,t}^i \times MA_t$ is negative and significant at the 10 percent level. This result indicates that the effect of intraday reversals is stronger on news-release days, in line with our expectations. Early-informed traders have information advantages over late-informed traders and trade earlier. When the information is made public, early-informed traders reverse their transactions in order to earn profits.

6. Summary of findings and discussion

In this section, we summarize our findings and compare them with those in the literature.

First, we seek to determine whether the first half-hour returns have cross-sectional predictability for returns from the rest of the day, which has been an unanswered question until now. We provide empirical evidence of intraday returns cross-sectional reversals in emerging markets and confirm that the first half-hour returns can negatively predict the rest of the day's returns in the cross section. This finding is inconsistent with the literature on intraday returns prediction, which argues that the first half-hour returns can positively predict the last-half-hour returns (Chu et al., 2019; Elaut, Frömmel, & Lampaert, 2018; Gao et al., 2018; Zhang et al., 2019). However, these studies draw conclusions based on intraday time-series analysis. The predictability of cross-sectional returns is different from the predictability of time-series returns. Rather than focusing on a stock's prior returns in a time series, cross-sectional return predictability focuses on the relative returns of different stocks (Moskowitz et al., 2012). Our finding is also related to, but different from, Lou et al. (2019), which is based on overnight returns. Therefore, we present another method for predicting intraday returns, namely cross-sectional forecasting based on the first half-hour returns.

Second, we seek to determine which type of trader is the driving force behind intraday cross-sectional returns reversal. We find a relation between the predictability of intraday returns and heterogeneous investors, using trade volumes and order imbalances of different sizes to identify investors. Our findings demonstrate that the reversal of early-informed investors is responsible for intraday returns cross-sectional reversals. The results provide evidence that contradicts the conclusions by Lou et al. (2019), who attribute the reversal of intraday returns to a tug of war between individual and institutional investors. Our findings match those observed in earlier literature on private information (or early-informed investors). For example, Kadan et al. (2018) show that investors with private information buy assets when the information is private and then sell it when the information becomes public.

Third, we explore why no cross-sectional momentum effect is found in China's A-share market. The cross-sectional momentum effect, as documented by Jegadeesh and Titman (1993), is found all over the world, and it is economically large and statistically reliable. However, the extant literature finds no momentum effect or just a weak effect in China's stock market (Cheema & Nartea, 2014; Wu, 2011). Our results document that the returns from the second to the eighth half-hour is significantly and negatively related to the first half-hour returns in the cross section, indicating that stocks with a rise in price during the first half-hour tend to experience a drop in price during the rest of the day, and vice versa. The cross-sectional reversal of the A-share intraday returns might be the reason for the absence of a momentum effect, such as in monthly medium-term returns.

7. Conclusions and policy implications

In this paper, we confirm the intraday returns cross-sectional reversals in China's A-share market. Furthermore, the intraday reversals are robust to seasonality, alternative samples, and the daily price-limit rule. We also find that intraday returns cross-

sectional reversals are stronger on days with the release of important economic news.

To investigate the potential drivers of reversal effects, we use trade volumes and order imbalances of different sizes to identify investors. We find that small trades account for the smallest proportion in the first half-hour of the day, whereas large trades account for the largest proportion in the first half-hour. This result is consistent with theory on early-informed investors (e.g., institutional investors) because they prefer large orders, but late-informed investors (e.g., individual investors) prefer to initiate small trades. By comparing the relative changes in OIBs in the first half-hour to those during the rest of the day, we find that changes in small OIBs have no impact on the reversal effect, but changes in large OIBs are significantly correlated with the reversal effect. Interestingly, large order trades are the most active in the first half-hour of the trading day. However, in the following trading hours, large order trades drop sharply, and OIBs become negative. The result indicates that large traders reverse their position by trading against the first half-hour. Therefore, we conclude that the reversal of large trades (early-informed traders) is responsible for intraday returns cross-sectional reversals.

Our findings have important practical and policy implications. Given the existence of intraday returns cross-sectional reversal, investors should pay attention to the forecasting ability of the first half-hour returns information when making investment decisions. This is particularly important in emerging markets dominated by individual investors because they lack investment experience and often blindly follow trends. The management department of the market should strengthen investor education, by guiding investor expectations to enable them to make more rational investments. In addition, policy makers need to tighten oversight of information disclosure to increase transparency in market information. Investors are either early-informed or late-informed investors. Eliminating or minimizing information asymmetry between them is an important way to reduce the predictability of market returns and thus improve market efficiency.

Declaration of competing interest

We declare that we have no conflict of interest.

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