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Market intraday momentum☆

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ABSTRACT

Based on high frequency S & P 500 exchange-traded fund (ETF) data from 1993–2013, we show an intraday momentum pattern: the first half-hour return on the market as measured from the previous day's market close predicts the last half-hour return. This predictability, which is both statistically and economically significant, is stronger on more volatile days, on higher volume days, on recession days, and on major macroeconomic news release days. Intraday momentum also exists for ten other most actively traded domestic and international ETFs. Theoretically, the intraday momentum is consistent not only with Bogousslavsky's (2016) model of infrequent portfolio rebalancing but also with a model of late-informed trading near the market close.

1. Introduction

Since the seminal work of Jegadeesh and Titman (1993), it has been well known that winners (losers) over the past six months to a year tend to continue to be winners (losers) over the next six months to a year. Griffin et al. (2003) show that this type of momentum is common in global stock markets. In addition to this cross-sectional momentum, Moskowitz et al. (2012), Asness et al. (2013), and Huang et al. (2018) examine whether there is an annual time-series momentum: the previous 12-month returns of an asset positively predict its future returns. However, almost all momentum studies are confined to return patterns at the monthly or weekly frequency, to the best

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of our knowledge.[1] An open question is whether or not such return patterns can be observed at the intraday level. This question is critical to understanding intraday market efficiency and the role played by the growing number of high-frequency traders.

In this paper, we provide the first study of intraday time-series momentum, making a unique contribution to the large literature on momentum. Specifically, we find that the first half-hour return on the market since the previous day's market close significantly predicts the last half-hour return on the market.[2]

Why are the first and last half hours of a trading day so special? Almost all earnings and most major economic news are released before the market opens; hence, the market typically opens at a level that differs from the previous day's close because it reflects new information. The digestion of new information usually takes about 30 minutes, as evident from the high volume and high volatility in the first half hour of trading, after which the market cools off until the last half hour. Both intraday volume and volatility exhibit U-shaped patterns, with the high volume and high volatility in the last half hour, signaling the importance of market close. As emphasized by Cushing and Madhavan (2000) and Foucault et al. (2005), institutional traders place an enormous emphasis on closing stock prices, which are used to calculate portfolio returns, tally the net asset values of mutual funds, and mark-to-market various financial contracts; at the same time, market makers want to unload inventory to avoid exposures to overnight risk. Hence, on a typical trading day, the first and last half hours of trading are the most important. In this paper, we empirically show positive correlation between their returns.

In our empirical analysis, we measure the market return by using the tradable SPY, the most actively traded ETF that tracks the S&P 500.[3] The predictive R^2 of the first half hour return on the last half hour return is 1.6%, a level that matches or exceeds typical predictive R^2s at the monthly frequency (see, e.g., Rapach and Zhou, 2013). If the first half-hour return is combined with the twelfth half-hour return (the half hour before the last half hour of the trading day), the R^2 increases further to 2.6%. This predictability is significant not only in sample but also out of sample (OS). The R^2_{OS} is 1.4% using the first half-hour return as the only predictor and 2.0% using both the first half-hour and the twelfth half-hour returns. Similar to the in-sample results, the OS predictability is also greater than those typically found at the monthly frequency.

We show that the predictability of the last half-hour returns generally rises with volatility. For instance, when the first half-hour volatility is high, the R^2 increases to 3.3% when using both the first half-hour and the twelfth half-hour predictors. The predictability is also higher throughout the recent financial crisis. In addition, the predictive ability of the first half-hour return stays quite similar across stocks with high versus low liquidity and institutional holdings, while that of the twelfth half-hour return varies. Furthermore, the overall predictability is greater on low trade size days (measured using trades in the last half hour), recession days, or days when certain major economic news is released.

In terms of economic significance, for a mean-variance investor with a risk aversion of five, trading based on the first half-hour return can generate an extra risk-adjusted return or "certainty equivalent gains" of 6.02% per annum versus ignoring this predictor. These gains further improve to 6.18% per annum if the twelfth half-hour return predictor is also used. In terms of market timing, the economic value is also substantial — the average return of the timing strategy using the sign of the first half-hour return is 6.67% per annum with a standard deviation of 6.19%. The Sharpe ratio is thus 1.08, fairly remarkable compared to a ratio of 0.29 for a daily *Buy-and-hold* strategy, which delivers an average return of 6.04% per annum with a standard deviation of 20.57%. Moreover, the outperformance remains significant even after accounting for transaction costs, which have become increasingly lower due to quote decimalization in 2001 and advances in trading technology. Overall, the intraday momentum is both statistically and economically significant out of sample.

From the perspective of microfoundations, there are two economic explanations for the intraday momentum. First, Bogousslavsky (2016) shows theoretically that intraday momentum can be driven by investors' infrequent rebalancing of their portfolios. With data from actual brokerage accounts, Murphy and Thirumalai (2013) and Murphy and Thirumalai (2016) provide concrete evidence of such infrequent rebalancing by institutions via their repetitive order activity. Indeed, due to the slow movement of capital and various institutional factors, some institutional investors can rebalance their portfolios in the first half hour, while others or the same institutions can rebalance in the last half hour. Trading in the last half hour in the same direction as the first can generate the observed intraday momentum pattern. The second explanation is based on the presence of late-informed investors who trade the early morning information in the last half hour. For those who receive information late or are slow to process information, trading in the last half hour is desirable to avoid overnight risk and to take advantage of the high liquidity. Thus, trading by late-informed investors in the last half hour would have the same direction as the first half hour, creating intraday momentum.

Intraday momentum is quite robust. It persists after accounting for reasonable transaction costs; in addition to the S&P 500 ETF, it is also strong and significant for ten other most actively traded ETFs in the US.[4] These ETFs

[1] The important exceptions are Heston et al. (2010), Murphy and Thirumalai (2013), Murphy and Thirumalai (2016), and Lou et al. (2015), among others, who examine intraday cross-sectional momentum of individual stocks. In contrast, we study the time-series momentum of the market.

[2] We obtain similar results for the return measured from the previous day's close to any time leading up to the first half hour. In particular, the pattern holds when using the overnight return, which captures all the news prior to the market open, as the predictor.

[3] The results are similar when we use the S&P 500 futures, another tradable asset on the index, or the S&P 500 index itself (see the online Internet Appendix).

[4] We are grateful to Vincent Bogousslavsky who informed us that this pattern also holds for portfolios of micro, small, and large stocks.

represent alternative stock indices, such as the Dow, the Nasdaq, and the Russell 2000. They also cover financial, real estate, bond, and certain international equity indices. Interestingly, perhaps due to their lower liquidity, the out-of-sample predictability and the certainty equivalent gains on these ETFs are often greater than those on the S&P 500 ETF.[5]

Our paper is related to the literature on intraday asset prices. While many studies on this topic focus on trading activity and volatility (see, e.g., Chordia et al., 2011; Corwin and Schultz, 2012), Heston et al. (2010), Murphy and Thirumalai (2013), and Murphy and Thirumalai (2016) are more closely related to ours. They find strong evidence that returns on certain individual stocks tend to be persistent at the same half-hour intervals across trading days. Bogousslavsky (2016) explains this unique correlation in detail in his theoretical model on infrequent rebalancing. In contrast to these studies, we analyze market intraday momentum, namely the predictability of the market's last half-hour return based on the market's first half-hour return on the same day.

The remainder of the paper is organized as follows. Section 2 describes the data we use in the analysis. Section 3 presents the main results on intraday momentum and offers two explanations. Section 4 discusses the economic significance of our main finding. Section 5 presents the impact of macro events on intraday momentum. Section 6 details a series of robustness checks. Section 7 concludes.

2. Data

We compute half-hour returns using the intraday trading prices of SPY, the actively traded S&P 500 ETF, from the Trade and Quote database (TAQ). The sample period spans from February 1, 1993, through December 31, 2013. We exclude any trading days with fewer than 500 trades.[6] For major news releases, we obtain the historical release dates of the Michigan Consumer Sentiment Index (MCSI) from the University of Michigan, the historical release dates of the Gross Domestic Product (GDP) estimate from the Bureau of Economic Analysis, the historical release dates of the Consumer Price Index (CPI) from the Bureau of Labor Statistics, and the historical release dates of the Federal Open Market Committee (FOMC) minutes from the Federal Reserve Bank.[7]

Specifically, to examine the intraday return predictability on any trading day t, we calculate the first half-hour return using the previous day's close price and the price at 10:00am eastern time, and then every half-hour (30-min) return from 10:00am to 4:00pm eastern time. This gives us a total of 13 half-hour observations per day:

$$r_{j,t} = \frac{p_{j,t}}{p_{j-1,t}} - 1, \qquad j = 1, \ldots, 13, \tag{1}$$

where $p_{j,t}$ is the price at the jth half hour, and $p_{j-1,t}$ is the price at the previous half hour, for $j = 1, \ldots,$ 13. Note that $p_{0,t}$ is the previous trading day's price at the 13th half hour (4:00pm eastern time). That is, we use the previous trading day's closing price as the baseline for calculating the first half-hour return on day t (i.e., $p_{0,t} = p_{13,t-1}$), so that the first half hour return captures the impact of information released after the previous day's market close. To assess the impact of return volatility on return predictability, we also compute the volatility of the first half-hour return in two steps. First, we calculate the returns minute by minute within the first half hour. Then, we compute the realized volatility using the estimated one-minute returns to obtain an estimate of the volatility in the first half hour.

3. Intraday momentum

3.1. Predictive regression analysis

Consider first the simple predictive regression of the last half-hour return on the first half-hour return

$$r_{13,t} = \alpha + \beta r_{1,t} + \epsilon_t, \qquad t = 1, \ldots, T, \tag{2}$$

where $r_{13,t}$ and $r_{1,t}$ are the last half-hour return and the first half-hour return on day t, respectively, and T is the total number of trading days in the sample.[8]

Panel A of Table 1 reports the results. The first half-hour return, r_1, positively predicts the last half-hour return, r_{13}, with a slope of 6.94 (scaled by 100), statistically significant at the 1% level, and an R^2 of 1.6%. Such a high predictive R^2 is impressive, as almost all typical predictors have lower R^2s (see, e.g., Rapach and Zhou, 2013). Note that the same level of R^2 is better at a higher frequency than at a lower one, as more trades can be carried out based on the predictability.

The twelfth half hour (i.e., the second-to-last half hour), r_{12}, can also affect the last half-hour return if there is a strong price persistence during the day. The second column in Panel A of Table 1 reports the regression result using this predictor. It is clear that r_{12} predicts r_{13} at the 1% significance level with an R^2 of 1.1%. We later show that this predictability appears mainly during the recent financial crisis, while that of the first half-hour return is always significant whether there is a crisis or not.

Since r_1 and r_{12} can both predict r_{13} individually, we next ask how they predict r_{13} jointly, and extend the predictive regression in Eq. (2) to the following predictive regression,

$$r_{13,t} = \alpha + \beta_{r_1} r_{1,t} + \beta_{r_{12}} r_{12,t} + \epsilon_t, \qquad t = 1, \ldots, T, \tag{3}$$

[5] The online Internet Appendix further shows that intraday momentum is robust to market microstructure noises, and that its economic value is significant for various risk aversion parameters and leverage constraints.

[6] Alternative thresholds of 100 and 250 trades make little difference in the results. SPY surpassed 500 daily trades on July 16, 1996, and 10,000 daily trades on September 17, 2001. In 2013, daily average trades totaled 278,017.

[7] Historical MCSI releases can be found at http://www.sca.isr.umich.edu/data-archive/mine.php , GDP releases at http://bea.gov/newsreleases/relsarchivegdp.htm , Bureau of Labor Statistics announcements at http://www.bls.gov/bls/archived_sched.htm , and FOMC minutes releases at http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

[8] While we focus on how $r_{1,t}$ predicts $r_{13,t}$, Section 6 discusses how alternative predictors, overnight return, and return over any five-minute interval within the first half hour predict the last half-hour return.

Table 1
Predictability.
The table reports the results of regressing the last half-hour return, r_{13}, on the first half-hour return, r_1, and the twelfth half-hour return, r_{12}, of the day. The first half-hour return r_1 is calculated from the closing of the previous trading day at 4:00pm to 10:00am eastern time. Panel A shows the in-sample results, while Panel B shows the out-of-sample recursive regression results. The window of the estimation initially uses observations up to December 31, 1997, and progressively includes one more month of returns. The out-of-sample predictability is measured by the out-of-sample R^2:

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_{13,t} - \hat{r}_{13,t})^2}{\sum_{t=1}^{T}(r_{13,t} - \bar{r}_{13,t})^2}, \tag{10}$$

where $\hat{r}_{13,t}$ is the forecasted last half-hour return from the predictive regression estimated through period $t-1$, and $\bar{r}_{13,t}$ is the historical average return of the last half hour estimated through period $t-1$. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

Predictor	r_1	r_{12}	r_1 and r_{12}	r_1	r_{12}	r_1 and r_{12}
		Panel A In sample			Panel B Out of sample	
Intercept	−1.63	−1.33	−1.82	−0.40***	−0.28***	−0.41***
	(−1.16)	(−0.94)	(−1.28)	(−11.4)	(−10.4)	(−10.8)
β_{r_1}	6.94***		6.81***	3.43***		3.34***
	(4.08)		(4.14)	(8.47)		(8.35)
$\beta_{r_{12}}$		11.8***	11.4***		5.92***	5.74***
		(2.62)	(2.60)		(9.37)	(9.34)
R^2 (%)	1.6	1.1	2.6	1.4	0.9	2.0

The third column in Panel A of Table 1 reports the predictive regression results using both predictors. Surprisingly, the slopes barely change from their individual regression values. Moreover, the joint R^2, 2.6%, is roughly equal to the sum of the individual R^2s. The evidence suggests that r_1 and r_{12} are independent and complementary in forecasting the last half-hour return.

3.2. Out-of-sample predictability

Our previous intraday momentum analysis is based on the entire sample (in-sample) estimation. While in-sample estimation is econometrically more efficient if regressions are stable over time, the financial crisis clearly destabilizes the estimation as shown in the next section. At the monthly frequency, Welch and Goyal (2008) find that many macroeconomic predictors suffer from an instability problem, and their predictability largely vanishes once predictive regressions are estimated recursively out of sample. Thus, in-sample predictability does not necessarily imply out-of-sample (OS) predictability.

To assess whether intraday momentum persists out of sample, we run recursive regressions similar to other predictability studies at the monthly frequency. That is, to forecast return at any time t, we use data only up to time $t-1$. Starting the regression using returns before January 3, 1998, we progressively add one month of returns at a time to form the OS forecasts. Following Campbell and Thompson (2008), Rapach et al. (2010), Ferreira and Santa-Clara (2011), Henkel et al. (2011), and Neely et al. (2014), among others, we measure the OS predictability by using

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_{13,t} - \hat{r}_{13,t})^2}{\sum_{t=1}^{T}(r_{13,t} - \bar{r}_{13,t})^2}, \tag{4}$$

where $\hat{r}_{13,t}$ is the forecasted last half-hour return from the predictive regression estimated through period $t-1$, and $\bar{r}_{13,t}$ is the historical average forecast estimated from the sample mean through period $t-1$. A positive R^2_{OS} indicates that the predictive regression forecast beats the simple historical average. Welch and Goyal (2008) show that it is not an easy matter for a predictor to beat the historical average benchmark.

Panel B of Table 1 reports the results. When we use the first half-hour return alone, the R^2_{OS} is 1.4%. When we use the twelfth half-hour return alone, the R^2_{OS} is 0.9%. When we use both of them, the R^2_{OS} achieves its highest value of 2.0%. The R^2_{OS} match or exceed those at the monthly frequency. As shown by Campbell and Thompson (2008) for monthly returns, and confirmed here later, these levels of R^2_{OS} have substantial economic significance.

3.3. Financial crisis

The recent financial crisis is clearly a major outlier in the time series of market returns. The standard monthly momentum strategy is known to have performed poorly during the crisis. Thus, it is interesting to study how well the intraday momentum performs in this period.

Panel A of Table 2 reports the predictive regression results from December 2, 2007, through June 30, 2009. The predictive power of r_1 becomes stronger, with a larger slope of 13.6 and a higher R^2 of 4.1%. Moreover, the two predictors combined yield an incredibly high R^2 of 6.9%, rarely seen anywhere else. It is noteworthy that the predictive powers of r_1 and r_{12} are still complementary during the crisis period.

Panel B of the table, for comparison, provides the results excluding those crisis days, which show substantially weaker predictability. Although r_{12} is less significant, r_1 remains a powerful predictor of r_{13} with a sizable R^2 of 0.8%, comparable to many strong predictors at the monthly frequency. The combined predictors yield a higher R^2 of 1.1%. Therefore, despite the financial crisis, there is no doubt of

Table 2
Predictability and financial crisis.
Panels A and B of the table report the predictive regression results during the financial crisis period from December 3, 2007, through June 30, 2009 and the period excluding the crisis, respectively. Panels C and D report the results during the pre- and postcrisis periods. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

Predictor	r_1	r_{12}	r_1 and r_{12}	*r_1	r_{12}	r_1 and r_{12}
	Panel A Financial crisis			Panel B Excluding financial crisis		
Intercept	2.29	−1.66	1.36	−1.63	−1.25	−1.72
	(0.29)	(−0.20)	(0.17)	(−1.25)	(−0.97)	(−1.31)
β_{r_1}	13.6***		13.2***	4.45***		4.40***
	(2.76)		(2.88)	(3.38)		(3.36)
$\beta_{r_{12}}$		21.1*	20.2**		6.32*	6.13*
		(1.95)	(1.99)		(1.88)	(1.83)
R^2 (%)	4.1	3.1	6.9	0.8	0.3	1.1
	Panel C Before financial crisis			Panel D After financial crisis		
Intercept	−0.91	−0.80	−0.96	0.27	0.40	0.25
	(−1.37)	(−1.22)	(−1.43)	(0.31)	(0.47)	(0.28)
β_{r_1}	4.22**		4.16**	4.41**		4.39**
	(2.69)		(2.65)	(2.05)		(2.07)
$\beta_{r_{12}}$		5.00	4.80		12.49	12.41
		(1.45)	(1.38)		(1.16)	(1.18)
R^2(%)	0.6	0.2	0.8	1.2	1.0	2.1

the existence of intraday momentum over the entire sample period.

To further assess the relation between the intraday momentum and the crisis, Panel C and D of Table 2 report the predictive regression results for the pre- and postcrisis periods. It is interesting to note that the predictive ability of r_1 stays roughly the same in terms of its slope. However, the predictive ability of r_{12} is greater in the postcrisis period, albeit not statistically significant in either period. Note that the insignificant result here is due in part to the sample size of the postcrisis period. In contrast, the earlier results excluding the crisis have a much larger sample size, and so r_{12} there becomes significant.

To see whether the intraday momentum has any time trends, which is relevant given increasing market volume and liquidity over time, Fig. 1 plots the slopes of r_1 and r_{12}, estimated recursively over time. That is, on any day t, all data up to this day are used for the estimation, which is what investors can do in practice to form an out-of-sample forecast of the return on day $t+1$. After some initial volatility, the slope of r_1 remains fairly stable before the financial crisis but increases later due to the crisis's influence. In contrast, the slope of r_{12} is more volatile and rises much more substantially after the crisis. Overall, the predictive ability of r_1, which is the main predictor driving intraday momentum, is fairly stable over time.

3.4. Volatility and volume

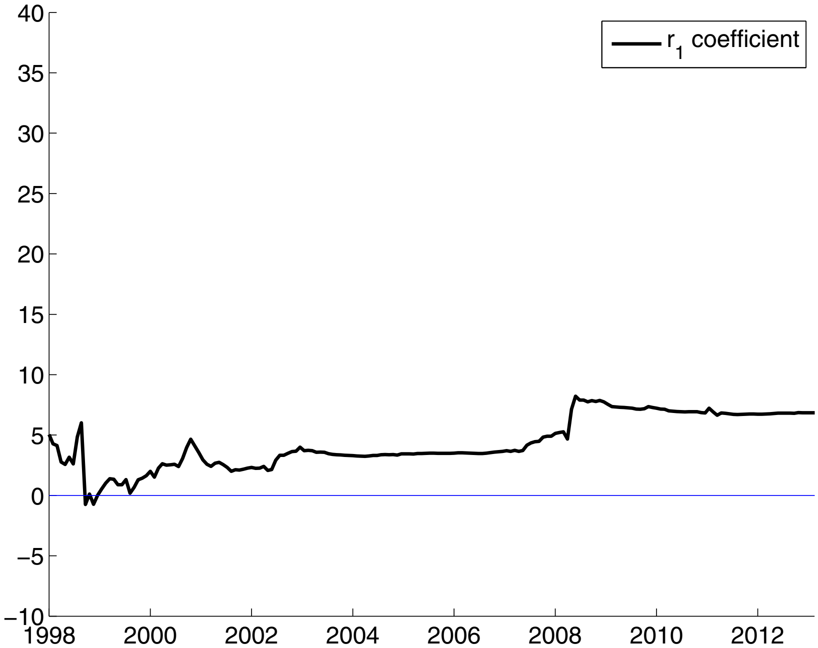
Given that the financial crisis was characterized by high volatility, a question arises with regard to how volatility impacts intraday momentum in general. To address this question, we sort all trading days in our sample by the first half-hour volatility, splitting them into three groups (terciles): low, medium, and high volatility days. For brevity, we only consider the case of two joint predictors, r_1 and r_{12}.

Panel A of Table 3 reports the results. The predictability of the last half-hour returns appears to be an increasing function of volatility. When the first half-hour volatility is low, predictability is minimal, with an R^2 of 0.6% and an insignificant coefficient for r_1. At the intermediate volatility level, the R^2 rises to 1.0%, which is economically significant, and the coefficient of r_1 becomes highly significant. Finally, when the first half-hour volatility is high, the R^2 increases to 3.3%, more than five times as high as the low-volatility case.

Overall, the intraday momentum seems to be highly related to volatility. The higher the volatility, the greater the predictability. This appears consistent with the empirical results of Zhang (2006), which suggest that the greater the uncertainty, the stronger the persistence of a trend. In our context, the greater the volatility, the greater the likelihood that the first half-hour trend carries over to the last half hour.

A related topic of interest is how volume impacts intraday momentum, since the first half hour of trading is characterized by both high volatility and high volume. Because trading volume increases over time, we sort the trading days for each year in our sample separately based on the first half-hour trading volume, splitting them into three equal groups: low, medium, and high volume days. Panel B

Panel A: Time series of r_1 coefficient



Panel B: Time series of r_{12} coefficient

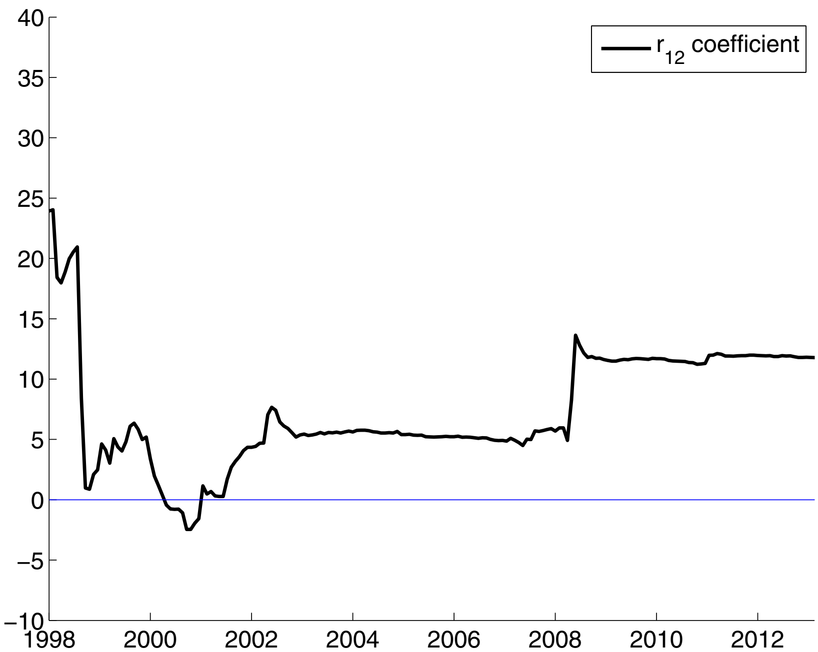


Fig. 1. Time series of r_1 and r_{12} coefficients. Panels A and B plot the coefficients of r_1 and r_{12} in the predictive regression (3), respectively, over the sample period. The coefficients are estimated recursively over time with the initial sample period of five years. r_1 is the first half-hour return, and r_{12} is the twelfth half-hour return.

Table 3
Impact of volatility and volume.
The table reports the predictive regressions under different levels of return volatility (Panel A) or trading volume (Panel B) of the first half hour. The first half–hour volatility is estimated using one-minute returns, and then all the trading days are split into terciles by their first half-hour volatility: low, medium, and high. We also split the trading days into low, medium, and high terciles by their first half-hour trading volume year by year to take into account the increases in trading volume over time, and then combine each volume tercile across all years to form three volume groups. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

	Panel A Volatility			Panel B Volume		
	Low	Medium	High	Low	Medium	High
Intercept	−2.18*	−3.07	0.26	−4.36***	1.22	−2.27
	(−1.76)	(−1.51)	(0.07)	(−2.62)	(0.58)	(−0.66)
β_{r_1}	2.34	5.40***	7.20***	4.32**	7.22***	7.08***
	(1.03)	(2.93)	(3.76)	(2.31)	(3.32)	(3.01)
$\beta_{r_{12}}$	8.81**	8.39**	12.7**	10.1**	6.16	13.7**
	(2.07)	(2.29)	(2.05)	(2.11)	(1.39)	(2.05)
R^2 (%)	0.6	1.0	3.3	1.1	2.3	3.1

of Table 3 reports the results. Similar to our findings for volatility, the predictability, as measured by the R^2s, is an increasing function of the first half-hour trading volume.

3.5. Trade size and liquidity

Another important question is whether it is individual or institutional investors who contribute most to the observed intraday momentum. Since information about institutions' and individuals' trades is not available, we investigate the impact of trade size and liquidity on intraday momentum to shed some light on this question.

We estimate the last half-hour trade size of SPY using the last half-hour volume divided by the number of trades. Because trade size exhibits a downward trend, we first sort all trading days within each year into small- and large-trade-size groups based on the last half-hour trade size, and then combine each group across all years to form the final two trade size groups: small- and large-trade-size days.

Panel A of Table 4 reports the predictive regression results for the two types of trading days. We can see that the predictive ability of r_1 is barely affected. However, the predictive ability of r_{12} is stronger on the large-trade-size days. Presumably, this occurs because institutions trade more actively throughout these days, including during both the last half hour and the half hour prior to it, which increases the predictive ability of r_{12}.

Further, to assess the impact of liquidity, we group all stocks in the S&P 500 into value-weighted low- and high-Amihud portfolios each day. Following Amihud (2002), we compute the daily illiquidity measure for each stock as the average daily ratio of the absolute stock return to the dollar trading volume over the previous five-day window. We then apply the predictive regression to the low- and high-Amihud portfolio returns separately.

Panel B of Table 4 reports the results. The predictive ability of r_1, as measured by its slope, t-statistic and R^2, is quite similar between low- and high-Amihud stocks. However, the predictive ability of r_{12} appears stronger for high-Amihud (less liquid) stocks, which seems intuitive as predictive ability is more difficult to exploit away with less liquidity.

3.6. Institutional trading

To further explore the question of who contributes most to the predictability of the last half-hour return, we examine how the trading patterns of institutions affect the intraday momentum.

First, we consider stocks held by institutional investors. Since holdings information is only available quarterly, we group the S&P 500 stocks into two value-weighted portfolios each quarter according to the percentage of their shares held by institutions in the previous quarter, and we run predictive regressions on the low- and high-institutional holdings portfolios separately.

Panel A of Table 5 reports the results. The predictive ability of r_1 is significant for both low- and high-institutional holdings stocks and is slightly greater for the former. In contrast, the slope of r_{12} is greater for high-institutional holdings stocks. This is consistent with earlier results that institutions contribute more to the predictive ability of r_{12}. However, the impact of r_{12} on the overall predictability of the last half-hour return is small, as the R^2 is only slightly greater for high-institutional holdings stocks.

Second, we consider days with institutional order imbalances. With data from Ancerno, we define a daily institutional order-imbalance measure on SPY as

(buy volume-sell volume)/(buy volume + sell volume),

where buy volume or sell volume is the total buy or sell volume across all Ancerno institutions on a given day.[9]

[9] Since the majority of the time stamps of the trades are unreliable according to Ancerno, we are unable to provide an intraday analysis of the institutional trades. Ancerno informed us that many of their clients randomly choose 9:30am as the order placement time and 4:20pm as the order execution time since they do not record the true order placement

Table 4
Trade size and liquidity.

Panel A of the table reports the predictive regression on days with small and large average trade sizes, respectively. Panel B shows the regression results for value-weighted portfolios formed from stocks in the S&P 500 sorted by their Amihud illiquidity measure, which is computed as the average daily ratio of the absolute stock return to the dollar trading volume over the previous five-day window. The returns are annualized and in percentage, and the regression coefficients are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

Panel A
Trade size

	Small trade size days			Large trade size days		
Intercept	−1.20	−1.16	−1.36	−0.96	−0.40	−0.98
	(−0.62)	(−0.61)	(−0.71)	(−0.57)	(−0.24)	(−0.58)
β_{r_1}	6.61***		6.42***	6.09***		6.05***
	(2.75)		(2.72)	(4.05)		(4.02)
$\beta_{r_{12}}$		11.13*	10.66*		10.48**	10.38**
		(1.69)	(1.66)		(2.53)	(2.52)
R^2 (%)	1.4	1.0	2.2	1.3	0.9	2.2

Panel B
Portfolios sorted on Amihud illiquidity measure

	Low Amihud stocks			High Amihud stocks		
Intercept	−0.70	−0.17	−0.92	3.31**	2.76*	2.52*
	(−0.46)	(−0.11)	(−0.62)	(2.23)	(1.92)	(1.76)
β_{r_1}	7.29***		7.15***	7.74***		7.56***
	(4.70)		(4.69)	(4.62)		(4.81)
$\beta_{r_{12}}$		12.32***	11.96***		27.00***	26.77***
		(2.59)	(2.58)		(5.40)	(5.58)
R^2 (%)	1.8	1.2	2.9	2.3	5.9	8.1

Table 5
Institutional trading.

The table reports the relation between institutional trading activity and the predictability of the last half-hour return based on the first and twelfth half-hour returns. Panel A reports the predictive regression results for low- and high-institutional holdings stocks in the S&P 500. The portfolios are sorted quarterly and value weighted. Panel B reports the predictive regression results for low- and high-order-imbalance days. The order imbalance, a daily measure for the SPY, is defined as (buy volume − sell volume)/(buy volume +sell volume), where "buy volume" or "sell volume" is the total buy or sell volume across all Ancerno institutions on a given day. We sort the trading days by this measure and run the predictive regressions separately on the low- and high-order-imbalance days. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013 for Panel A, and from October 1, 1998, through December 31, 2013 for Panel B.

Panel A
Portfolios sorted by institutional holdings

	Low-holdings stocks			High-holdings stocks		
Intercept	−1.27	−0.73	−1.32	2.56*	2.45*	2.13*
	(−1.28)	(−0.73)	(−1.35)	(1.84)	(1.82)	(1.57)
β_{r_1}	9.68***		9.59***	6.31***		6.17***
	(4.52)		(4.61)	(4.43)		(4.50)
$\beta_{r_{12}}$		11.62**	11.24**		19.06***	18.79***
		(2.23)	(2.16)		(3.74)	(3.78)
R^2 (%)	3.3	1.0	4.2	2.0	3.2	5.1

Panel B
Impact of Ancerno order imbalance

	Low-order-imbalance days			High-order-imbalance days		
Intercept	0.31	0.29	0.22	−1.11	−1.00	−1.12
	(0.34)	(0.32)	(0.24)	(−1.29)	(−1.17)	(−1.33)
β_{r_1}	6.91***		6.93***	7.91***		7.68***
	(2.77)		(2.78)	(3.41)		(3.42)
$\beta_{r_{12}}$		10.09	10.15		15.02***	14.46**
		(1.31)	(1.36)		(2.60)	(2.45)
R^2 (%)	1.5	0.8	2.3	2.4	1.9	4.1

Note that our measure is only a proxy for all institutional trading activities, since Ancerno tracks only about 10% of institutions. Then, we can sort the trading days into low- and high-order-imbalance groups and run predictive regressions on these groups separately.

Panel B of Table 5 reports the results. Again, the predictive ability of r_1 remains roughly the same, but that of r_{12} varies between the two groups. It seems likely that institutional investors make more trades near the market close, which make the return correlation stronger. Interestingly, the overall predictive ability for both r_1 and r_{12} is stronger, with both greater regression slopes and greater R^2s, on high-order-imbalance days. This is consistent with the results of the institutional holdings analyses above.

Finally, we investigate how the predictability of the last half hour is related to institutional trading patterns near month-end. Etula et al. (2016) show that, due to their month-end liquidity needs, institutional investors trade less near the end of the month. Strikingly, the market risk premium can be earned predictably in only seven days around the end of the month, from $T-3$ to $T+3$. To see if these month-end trades have any impact on intraday momentum, we run the predictive regressions on these seven month-end days and all other days. Though intraday momentum is present on both types of days, it is weaker near month-end. Consistent with our earlier findings, average trading volume over the seven month-end days is about 5.9% lower than that for the remaining days.

3.7. Explanations

Statistically, both the in- and out-of-sample analyses provide strong evidence of intraday momentum. From an economic perspective, it is also valuable to consider what economic forces can be behind this phenomenon. We provide two possible explanations below.

Before exploring these explanations, it is worthwhile to examine the volume and volatility patterns of the stock market. Fig. 2A plots the average trading volume of the S&P 500 ETF every half hour. For both the first and the last half hours, the trading volume reaches close to 15 million shares, as compared to approximately 5 million shares during the middle of the day. The plot has a perfect U-shape, consistent with earlier findings about intraday trading activity (see, e.g., Jain and Joh, 1988). Fig. 2B also displays a U-shaped volatility pattern. This pattern is stronger on high-volatility days, suggesting a stronger impact from informed trading as volatility rises. This is consistent with our earlier finding that intraday momentum is greater under higher volatility. Economically, as discussed earlier, the U-shaped patterns reflect the digestion of new information in the first half hour and the desire to trade in the last half hour for settlement and to avoid overnight risk. So what are the possible driving forces of intraday momentum? Bogousslavsky (2016) points to infrequent portfolio rebalancing as one of the economic driving forces. In his presidential address, Duffie (2010) emphasizes the important role of slow-moving capital and infrequent decisions in our understanding of a number of stylized facts in finance. Murphy and Thirumalai (2013) and Murphy and Thirumalai (2016) provide concrete evidence on infrequent rebalancing, showing that institutions do place repetitive orders in practice. Bogousslavsky (2016) focuses on using infrequent rebalancing to explain return autocorrelation and seasonality. In particular, he shows theoretically that intraday momentum can be driven by investors who simply delay their rebalancing trades to near the market close instead of the market open. Then, intuitively, trading in the last half hour moves in the same direction as in the first and leads to a positive correlation between the two returns.

The second explanation is based on the presence of late-informed investors. Consider a day on which good news is released. Some investors can react immediately and buy, pushing the market up in the first half hour. However, there are others who may learn the news later or simply process the news too slowly to react in the first half hour. For example, Baker and Wurgler (2006) show that investors still react to month-old sentiment measures, and Hong et al. (2007) and Cohen and Frazzini (2008) find that information transmission can last up to a month across certain industries. Therefore, information processing could easily take an entire day. As late-informed investors chase to buy, the last half hour of the trading day is clearly the optimal choice, since it is the most liquid period after the first half hour. Trading in the same direction as the first half hour can yield a positive return for the last half hour, thereby generating the positive correlation.[10]

In practice, some mutual funds prefer to trade at a price near the closing price. This is desirable not only for end-of-day settlements but also for applications of empirical factor models based on closing prices. Furthermore, mutual fund investors can trade only at the closing prices. Rationally, they will not instruct their fund managers to trade until near the market close to retain the option value of waiting. Technically, these investors can also be regarded as "late-informed," since they trade later in the day rather than earlier.

Both of the explanations above provide an economic basis for the strong statistical evidence for the existence of intraday momentum. Other explanations for this phenomenon are also likely. Future research is needed to develop a fully dynamic general equilibrium model for understanding intraday trading motives, risk factors, and the equilibrium risk premium associated with the intraday predictability.

4. Economic significance

4.1. Market timing

One way to assess the value of a predictor is to examine how well it performs in market timing. In our case, we use

and execution time. Our close examination confirms this: of all the intraday Ancerno trades of SPY, 61% are associated with an order placement time of exactly 9:30am, and 51% are associated with an order execution time of exactly 4:20pm, while only 5% (3%) of SPY trades are placed and executed within the first (last) half hour of a trading day.

[10] Based on Hirshleifer et al. (1994) and Cespa and Vives (2015), the online Internet Appendix provides a simple model for this.

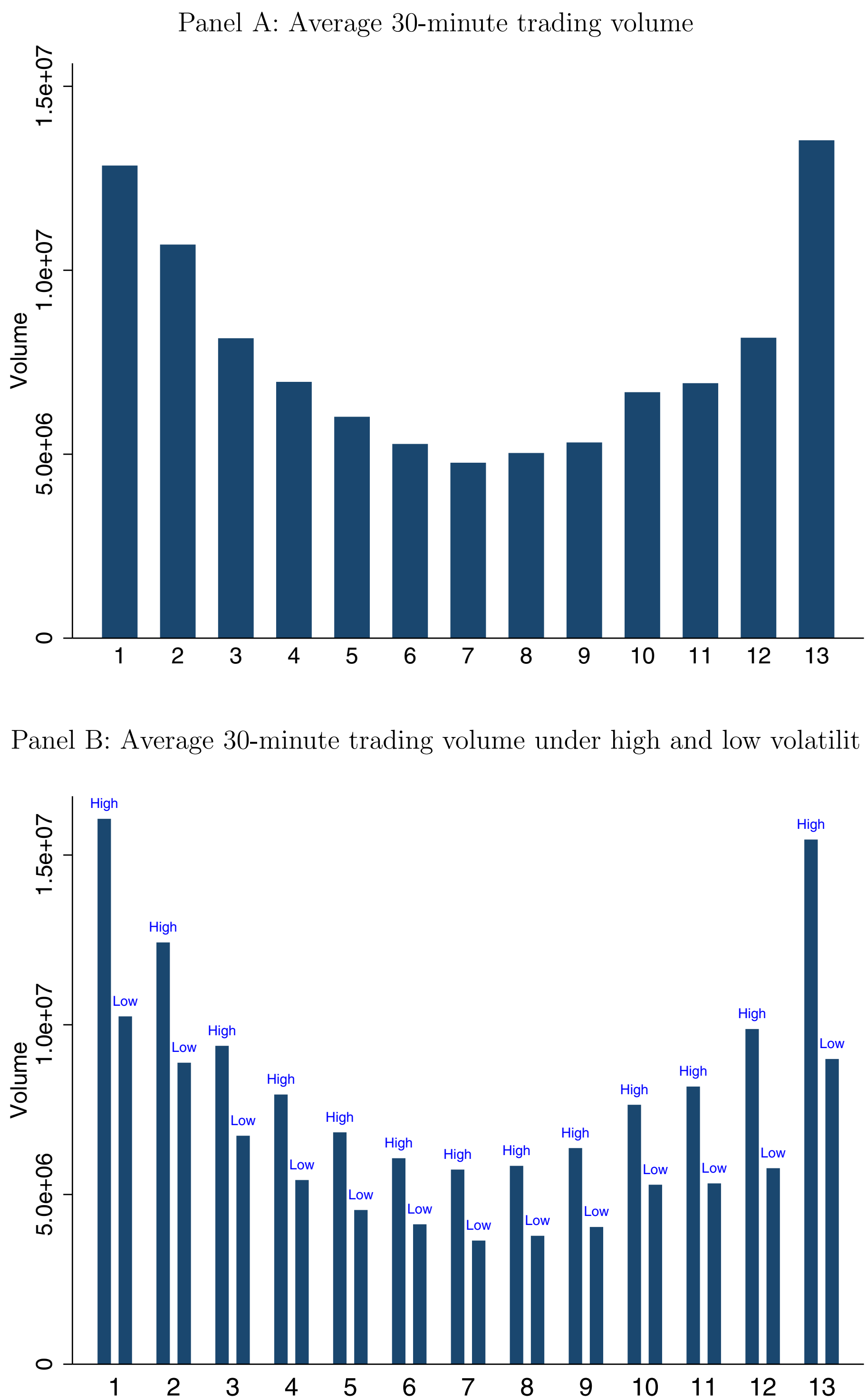


Fig. 2. Average 30-min. trading volume of SPY. For every 30-min. period from 9:30am to 4:00pm eastern time, Panel A shows the average trading volume for SPY from February 1, 1993, through December 31, 2013. Each 30-minute period is labeled from 1 to 13 sequentially. Panel B plots the same 30-min. average trading volume on high volatility (top tercile) and low volatility (bottom tercile) days.

Table 6
Market timing.
The table reports the economic value of timing the last half-hour market return using r_1, r_{12}, or both. The timing strategy $\eta(r_1)$ ($\eta(r_{12})$) takes a long position in the market when the first (twelfth) half-hour return is positive and a short position when the return is negative. The joint strategy $\eta(r_1, r_{12})$ trades only when both returns have the same sign — long when both are positive and short when both are negative. The benchmark *Always long* involves investing in the market during the last half hour of each trading day, and *Buy-and-hold* involves buying and holding the market on a daily basis. For each strategy, we report the average return (*Avg ret*), standard deviation (*Std dev*), Sharpe ratio (*SRatio*), skewness, kurtosis, and success rate (*Success*). The returns are annualized and in percentage. Newey and West (1987) robust *t*-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

Timing	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis	Success(%)
Panel A: Market timing						
$\eta(r_1)$	6.67***	6.19	1.08	0.90	15.65	54.37
	(4.36)					
$\eta(r_{12})$	1.77	6.20	0.29	0.38	15.73	50.93
	(1.16)					
$\eta(r_1, r_{12})$	4.39***	4.49	0.98	1.87	34.10	77.05
	(3.96)					
Panel B: Benchmarks						
Always long	−1.11	6.21	−0.18	−0.46	15.73	50.42
	(−0.73)					
Buy-and-hold	6.04	20.57	0.29	−0.16	6.61	
	(1.19)					

the first and twelfth half hour returns as timing signals to trade the market in the last half hour. Specifically, we take a long position in the market at the beginning of the last half hour if the timing signal is positive and a short position otherwise. We close the position (long or short) at the market close on each trading day.

Consider first the use of the first half-hour return r_1 as the trading signal. Mathematically, the market timing strategy based on signal r_1 on day t will have a return in the last half hour

$$\eta(r_1) = \begin{cases} r_{13}, & \text{if} \quad r_1 > 0; \\ -r_{13}, & \text{if} \quad r_1 \le 0. \end{cases} \tag{5}$$

When using both r_1 and r_{12} as the trading signal, we go long only if both returns are positive and go short when both are negative. Otherwise, we stay out of the market. Mathematically, the return is computed as

$$\eta(r_1, r_{12}) = \begin{cases} r_{13}, & \text{if} \quad r_1 > 0 \ \& \ r_{12} > 0; \\ -r_{13}, & \text{if} \quad r_1 \le 0 \ \& \ r_{12} \le 0; \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Panel A of Table 6 reports summary statistics on returns generated from the three timing strategies. When we use the first half-hour return as the timing signal to trade in the last half hour, the average return is 6.67% on an annual basis.[11] At first glance, this may not seem very high. To gauge the performance, we also report the performances of two benchmark strategies. The first is an *Always long* strategy, where we always take a long position in the market at the beginning of the last half hour and close it at the market close. The first row in Panel B of Table 6 shows that the annualized average return of this strategy is very poor, at −1.11% per year and statistically insignificant. Hence, the timing strategy $\eta(r_1)$ substantially outperforms this passive strategy.

The second benchmark is a *Buy-and-hold* strategy, where we simply take a long position in the market from the beginning of the sample and hold it until the end of the whole sample period. The results are reported in the second row of Panel B. The average return is 6.04% per year, which is much better than *Always long*, but is still below the average return delivered by the timing strategy $\eta(r_1)$ and statistically insignificant. Hence, 6.67% is remarkable, especially considering that we are in the market for only a half hour each trading day instead of six-and-a-half hours per day.

Of course, we must take risk into consideration. The standard deviation is 6.19% per annum for the timing strategy $\eta(r_1)$, resulting in a Sharpe ratio of 1.08. In contrast, the *Always long* strategy has a comparable standard deviation of 6.21% but a negative Sharpe ratio of −0.18. The long-term *Buy-and-hold* strategy has a much higher standard deviation of 20.57% and a much lower Sharpe ratio of 0.29. Note that the timing strategy $\eta(r_1)$ also exhibits a high positive skewness of 0.90 (versus −0.46 and −0.16 for the *Always long* and *Buy-and-hold* strategies, respectively) and a kurtosis of 15.65, suggesting that it often delivers high positive returns.

Finally, we report the success rate, which is defined as the percentage of trading days with zero or positive returns. The success rate of the *Always long* strategy is 50.42%, suggesting that the unconditional probability of the last half-hour return being positive is roughly 50%. In comparison, the success rate of the timing strategy $\eta(r_1)$ is higher, at 54.37%.

[11] We annualize the returns by multiplying by 252 because we trade once each trading day, even though we only trade for a half hour.

Using the twelfth half-hour return as the timing signal yields similar but weaker results. The average return is about 1.77% per annum, greater than *Always long*, but lower than *Buy-and-hold*. Its Sharpe ratio is 0.29, skewness is 0.38, kurtosis is 15.73, and success rate is 50.93%. Notably, this strategy has a greater Sharpe ratio than the benchmark strategies.

A trading strategy that uses both r_1 and r_{12} as timing signals performs better than the strategy based on the twelfth half-hour return alone. However, its performance is slightly worse than that achieved by using only the first half-hour return. For example, the average daily return is 4.39% versus 6.67% per annum, but the success rate is now much higher at an impressive value of 77.05%. This means that combining both r_1 and r_{12} substantially improves the probability of being correct. Then, why does a higher success rate yield lower average returns? The reason is that, when we combine the two signals, we take the long or short position only when both of them are positive or negative, which substantially reduces the number of days when we are in the market.[12]

4.2. Utility gains

In our next analysis, instead of using only the signs to form timing strategies, here we use both the signs and magnitudes of the predictors to forecast expected returns. We then apply these expected returns to construct the optimal portfolio for a mean-variance investor who allocates funds between the market (SPY) and the risk-free asset (the Treasury T-bill).

The optimal mean-variance portfolio weight on the market is

$$w_t = \frac{1}{\gamma}\frac{\hat{r}_{13,t+1}}{\hat{\sigma}^2_{13,t+1}}, \tag{7}$$

where $\hat{r}_{13,t+1}$ is the forecasted last half-hour return on day $t+1$ conditional on information available on or before day t and the predictor(s) on $t+1$, and $\hat{\sigma}_{13,t+1}$ is the standard deviation of the last half-hour return, both of which are estimated from the recursive regressions. γ is the relative risk aversion coefficient, which is set at five. To be more realistic, we impose the portfolio constraint that the weight on the market must be between −0.5 and 1.5, meaning that the investor is allowed to borrow or short no more than 50% on margin. This limits the potential economic gains as compared to the usual unconstrained weights.[13]

Over the out-of-sample period, the realized utility is

$$U = \hat{\mu}_p - \frac{\gamma}{2}\hat{\sigma}^2_p, \tag{8}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p$ are computed based on the realized portfolio returns. In the out-of-sample forecasting literature, the historical average is usually the benchmark, and the certainty equivalent return (CER) of predictability is computed as

$$CER = U_2 - U_1, \tag{9}$$

where U_2 is the realized utility of using the forecasted return $\hat{r}_{13,t+1}$, and U_1 is the realized utility of using the historical mean forecast, $\bar{r}_{13,t+1}$. From an economic perspective, CER can be interpreted as the gains captured by an investor who switches from believing in a random walk model of intraday prices to believing in intraday momentum.

The results are reported in Table 7. Using the first half-hour returns to forecast the last half-hour returns yields an average return of 6.51% per annum, with a standard deviation of 5.62% (indicating a Sharpe ratio of 1.16) and a large positive skewness. In sharp contrast, using the historical average $\bar{r}_{13}$ to predict the last half-hour return only generates an average return of 0.46% per annum, with a standard deviation of 3.06% per annum and hence a Sharpe ratio of merely 0.15. The CER using the first half-hour return is 6.02% per annum (the realized utility of using the historical average is only 0.46%), indicating sizable economic gains when investors switch from trading based on a random walk model to trading based on intraday momentum.

When both the first and the twelfth half-hour returns are used to forecast the last half-hour returns, the portfolio delivers the best results, with an average return of 6.68% per annum, a Sharpe ratio of 1.07, and a CER of 6.18% per annum. Note that, unlike the case with market timing, using both predictors is now slightly better than using the first half-hour return alone. This is because we are now always in the market, though with different allocations each day.

5. Macroeconomic events

5.1. Business cycles

We next consider how various macroeconomic events affect intraday momentum. First, we use the National Bureau of Economic Research (NBER) dates for expansions and recessions to divide all trading days into "expansion days" and "recession days," and we examine how intraday momentum varies over business cycles.

Table 8 reports the predictive regression results. It can be seen that intraday momentum is stronger during recessions than during expansions. During expansions, only the first half-hour return can predict the last half-hour return. Though statistically significant, its predictive ability is relatively weak, with an R^2 of 0.9% when using r_1 alone and 1.0% when using both r_1 and r_{12}. During recessions, however, both the first and the twelfth half-hour returns are highly significant, and the R^2 increases more than six times to 6.6% when using both of the predictors. These results are consistent with our earlier volatility regime results, which is to be expected because volatility is much higher in recessions than in expansions. This is also consistent with the results on liquidity. The market is less liquid during recessions, and hence intraday momentum is stronger due to the higher difficulty of arbitrage.

[12] If we exclude the nontrading days, on which the returns are zero, this strategy delivers the best performance as expected, with an annualized average return of 8.85%, a standard deviation of 6.36%, a Sharpe ratio of 1.39, a comparable skewness of 1.19, and a kurtosis of 18.30.

[13] The online Internet Appendix reports the much stronger performance of the unrestricted portfolio.

Table 7
Utility gains.
The table reports the economic value of recursively predicting the last half-hour market return using the first half-hour return alone or combining it with the twelfth half-hour return. We use the predicted returns to form a constrained mean-variance optimal portfolio for a mean-variance investor with a relative risk aversion of five. Portfolio weights are restricted to a range between −0.5 and 1.5. For each strategy, we report the average return (*Avg ret*), standard deviation (*Std dev*), Sharpe ratio (*SRatio*), skewness, kurtosis, and the certainty equivalent gain, *CER*, calculated as the difference in the certainty equivalent rate of return between the optimal mean-variance strategy and benchmark using the historical average returns instead of the forecasted last half-hour returns. The returns are annualized and in percentage. Newey and West (1987) robust *t*-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

Predictor	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis	CER(%)
$\bar{r}_{13}$	0.46 (0.57)	3.06	0.15	0.48	18.05	
$\beta_1 r_1$	6.51*** (4.33)	5.62	1.16	1.78	49.54	6.02
$\beta_1 r_1 + \beta_2 r_{12}$	6.68*** (4.00)	6.24	1.07	0.27	58.87	6.18

Table 8
Impact of business cycles.
The table reports the impact of business cycles on the predictability of the last half-hour return using the first half-hour return, the twelfth half-hour return, or both of them. The predictive regression results are provided for NBER expansions and recessions, respectively. The returns are annualized and in percentage, and the regression coefficients are scaled by 100. Newey and West (1987) robust *t*-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

Predictor	r_1	r_{12}	r_1 and r_{12}	r_1	r_{12}	r_1 and r_{12}
	Expansion			Recession		
Intercept	−2.34* (−1.76)	−1.81 (−1.39)	−2.41* (−1.80)	5.42 (0.89)	2.11 (0.34)	4.79 (0.78)
β_{r_1}	4.83*** (3.39)		4.80*** (3.39)	11.4*** (2.76)		11.0*** (2.87)
$\beta_{r_{12}}$		4.50 (1.31)	4.32 (1.26)		22.4** (2.25)	21.6** (2.30)
R^2 (%)	0.9	0.1	1.0	3.2	3.6	6.6

5.2. News releases

Previously, we found that intraday momentum is stronger on days with higher volatility and/or higher trading volume. One possible source of high volatility or trading volume may be the release of major economic news. It is thus interesting to investigate how news releases affect intraday momentum.

While many regular news releases exist, we focus on four major examples, which are released at different times throughout the trading day. The first is the MCSI, released monthly at 10:00am. The next two are the major macroeconomic variables: the GDP and the CPI. Both of these are released monthly on prespecified dates at 8:30am before the market opens, like most other macroeconomic news. Our last selected release is the minutes of the FOMC, released regularly at 2:15pm approximately every six weeks. We analyze the impact of the news releases by dividing all trading days into two groups: days with news releases and days without.

Panel A of Table 9 reports the performance of intraday momentum for the two groups of trading days. On days without MCSI news, the R^2 is 2.6%. On days with MCSI releases, the R^2 more than doubles to 5.5%, indicating that intraday momentum becomes stronger. The same holds true when we compare the R^2s on days with and without news announcements for GDP and CPI. These results seem to suggest that there is an information carryover effect of the news on market prices throughout the whole trading day.

The releases of the FOMC minutes yield the most astonishing result. While the no-release days have an R^2 of only 2.5%, the R^2 increases enormously to 11.0% on release days. There are two reasons why this result is astonishing. First, the latter R^2 is high by any standard, exceeding almost all predictors at the usual monthly frequency by far. Second, these results imply that market participants can correctly anticipate in the first half hour the message that the Federal Reserve (Fed) will send out to the market later that afternoon. Lucca and Moench (2015) find that preannouncement excess equity returns account for sizable fractions of total realized stock returns, a phenomenon that can be observed worldwide. Bernile et al. (2016) investigate market activity minutes prior to the release of the FOMC minutes.

Table 9
Impact of macro news releases.
The table reports the impact of macro news releases on the predictability of the last half-hour market return. Panel A compares the predictive regression results on days with macro news releases to those without. Panel B reports the profitability of the market timing strategies described in Table 6 on the news days and other days. MCSI is the survey of consumer confidence by the University of Michigan, released at 10:00am eastern time; GDP is the monthly GDP estimate, released at 8:30am eastern time; CPI is the monthly consumer price index, released at 8:30am eastern time; and FOMC is the Federal Open Market Committee minutes released at 2:15pm eastern time. The returns are annualized and in percentage, and the slope coefficients in Panel A are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

Panel A: Predictive regression

	Nonrelease	Release	Nonrelease	Release	Nonrelease	Release	Nonrelease	Release
	MCSI		GDP		CPI		FOMC	
Intercept	−1.70	−7.16	−1.72	−6.75	−1.93	0.42	−1.49	−12.6
	(−1.15)	(−1.21)	(−1.17)	(−0.94)	(−1.31)	(0.06)	(−1.03)	(−1.61)
β_{r_1}	6.61***	14.4***	6.60***	11.7**	6.63***	10.4*	6.68***	14.4**
	(3.90)	(3.40)	(3.90)	(2.37)	(3.90)	(1.95)	(3.98)	(2.35)
$\beta_{r_{12}}$	11.9***	−5.51	12.0***	−3.03	11.4**	11.7	10.9**	34.1*
	(2.64)	(−0.48)	(2.64)	(−0.24)	(2.56)	(0.78)	(2.51)	(1.69)
R^2 (%)	2.6	5.5	2.7	3.0	2.5	5.0	2.5	11.0

Panel B: Timing performance

	Macro news	Avg ret(%)	Std dev(%)	SRatio	Skewness	Kurtosis
Nonrelease	MCSI	6.05*** (3.83)	6.24	0.97	0.91	15.83
Release	MCSI	19.09*** (3.41)	4.94	3.86	0.91	2.28
Nonrelease	GDP	6.28*** (4.01)	6.19	1.01	0.91	16.26
Release	GDP	14.40** (2.08)	6.14	2.35	0.83	3.41
Nonrelease	CPI	6.10*** (3.88)	6.21	0.98	0.91	16.11
Release	CPI	18.03*** (2.75)	5.80	3.11	0.90	3.84
Nonrelease	FOMC	6.24*** (4.01)	6.20	1.01	0.90	15.88
Release	FOMC	20.04** (2.46)	5.84	3.43	1.07	7.22

Unlike these studies, we focus on intraday momentum. The high R^2 indicates that, even after a FOMC news release, the market has a strong tendency to continue to move in the same direction anticipated in the first half hour.

Do the higher R^2s on the news release days imply greater economic gains? To answer this question, we examine the performance of the earlier market timing strategies on days with and without news release. Panel B of Table 9 reports the results of using the first half-hour return, $\eta(r_1)$, for brevity. On days when MCSI and CPI news are released, the gains are around three times the gains on the days without news releases. For the GDP news, the profits on release days are about twice as much. The greatest economic gains are delivered on the release days of the FOMC minutes. The annualized average return reaches a high level of 20.04%. This is close to four times the level on days without FOMC news. Overall, the economic performance of intraday momentum is much stronger on the days with the four news releases.

6. Robustness

6.1. Conditional predictability

Murphy and Thirumalai (2013) show that the intraday cross-sectional momentum is much stronger conditional on negative past returns than on positive past returns. Inspired by their analysis, we consider how the predictability of r_{13} varies conditional on the sign of the first half-hour return.

The results are reported in Table 10. During the whole sample period, the R^2s for the three predictive regressions are 2.3%, 2.6%, and 4.5%, respectively, when the first half-hour return is positive. In contrast, the R^2s are only 0.5%, 0.3%, and 0.9% when the first half-hour return is negative. In the latter case, while r_1 is still marginally significant, r_{12} is insignificant. The results suggest that intraday momentum is stronger on days when the first half-hour returns are positive, presumably because of good economic news.

Table 10
Conditional predictability.
The table reports the predictive regression results conditioned on the sign of the first half-hour return. Panels A reports the regression results when r_1 is positive, while Panel B reports the regression results when r_1 is negative. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust *t*-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from February 1, 1993, through December 31, 2013.

	Panel A When $r_1 > 0$			Panel B When $r_1 < 0$		
Predictor	r_1	r_{12}	r_1 and r_{12}	r_1	r_{12}	r_1 and r_{12}
Intercept	−8.85**	4.56**	−8.47**	−1.07	−8.27***	−0.83
	(−2.52)	(2.41)	(−2.50)	(−0.28)	(−3.44)	(−0.21)
β_{r_1}	11.3***		10.5***	5.72*		5.90*
	(3.63)		(3.58)	(1.73)		(1.78)
$\beta_{r_{12}}$		18.4***	17.2***		6.60	6.93
		(2.97)	(2.85)		(1.06)	(1.11)
R^2 (%)	2.3	2.6	4.5	0.5	0.3	0.9

There are two explanations for the weaker predictability on days when the first half-hour return is negative. First, investors are net holders of stocks, and many of them, due to the disposition effect (Shefrin and Statman, 1985; Odean, 1998; Locke and Mann, 2000; Coval and Shumway, 2005; Haigh and List, 2005), can be reluctant to sell in the last half hour on a bad news day even when they should. Second, with asymmetric costs, arbitrageurs are less inclined to arbitrage in a down market. For example, Abreu and Brunnermeier (2002) argue that arbitrageurs who receive bad news have to short an asset to exploit its overpricing, which is more costly than arbitrage on good news. On the other hand, Cushing and Madhavan (2000) show evidence that those who sold short earlier in the day on bad news tend to cover their positions at the market close regardless of the cost. The behaviors of both investors and market arbitrageurs generate less selling pressure near the market close on a typical $r_1 < 0$ day than would otherwise be expected.

Note that the result conditional on the sign of r_1 is different from the cross-sectional results of Murphy and Thirumalai (2013). There are two reasons for this. First, cross-sectional predictability and time-series predictability can have different signs due to their differences (to be discussed in Section 6.5). Second, Murphy and Thirumalai (2013) focus on how specific half-hour returns predict the same half-hour returns on subsequent days, whereas we examine how r_1 predicts r_{13} on the same day, which is a different research question. This further weakens any link between the predictive signs.

6.2. Transaction costs

What are the impacts of transaction costs on our results? With technological advancements and ever increasing competition in the financial industry, we have witnessed a significant decline in transaction costs over the past two decades. This trend becomes even more evident after the decimalization of quotations.

We examine the impact of transaction costs on the profitability of intraday momentum using the market timing strategy as an example. To this end, we collect the bid and ask prices at 3:30 pm on each trading day from the TAQ database and use the ask (bid) price to calculate the last half-hour return if the market timing strategy takes a long (short) position.[14] Since SPY is traded at the market-clearing price for all the buys and sells at closing, there is no bid/ask spread effect for the price at 4:00pm. Due to autoquotes of non-NYSE securities in the TAQ data before decimalization, we examine the effect of transaction costs only after decimalization (after July 1, 2001).[15] Furthermore, we also examine the break-even implementation shortfall (IS) introduced by Perold (1988), which is defined as the difference between the theoretical return of a portfolio with no transaction costs and that of the real portfolio obtained by actual trading. In computing the IS, we account not only the bid/ask spread but also the real-life commissions and fees. Consider trading 1000 share of SPY that should have no impact on the market because the bid and ask sizes are typically over 10,000. Based on the commission schedules of TradStation Brokerages, we use both a high of $10 and a low of $2 for both sides of the trading, which applies to casual and active traders, to indicate some variations of the cost.

The results are reported in Table 11. Panel A of the table shows that, accounting for only the bid/ask spreads, the average return decreases to 4.46% per annum, 2.47% lower than the average return before transaction costs, while the standard deviation remains the same at 6.10%, if using the first half-hour return as the timing signal. Now, if accounting for the commissions and fees in addition, the high cost (HC) IS is 2.72% per annum and the low cost (LC) IS is 2.57% per annum. Clearly, the potential profits after actual

[14] We measure the bid and ask prices using the median bid and ask prices exactly at 3:30 pm. If there is no quote at 3:30 pm, we use the median bid and ask prices from the nearest previous second.

[15] Autoquotes in the TAQ data are passive quotes by official dealers who are not making the market. Such quotes usually add a mechanical fraction on either side of the posted primary market quote and hence will artificially inflate the quoted spread. The autoquotes issue is more severe in the predecimalization period; see Appendix B and Fig. B-1 in Chordia et al. (2001).

Table 11
Transaction costs.
The table reports the economic value of timing the last half−hour market return using the first half-hour return or combining with the twelfth half-hour return, incorporating all the transaction costs. The timing strategy is described in Table 6. For each strategy, we report the average return (*Avg ret*), standard deviation (*Std Dev*), and Sharpe ratio (*SRatio*) after accounting for the bid/ask spread. The last two columns estimate the break-even implementation shortfall to account for additional fees paid while trading 1000 shares: $ 10 (*HC IS*) and $2 (*LC IS*). Panel A shows the period after decimalization (after July 1, 2001), and Panel B shows the period when the spread is stabilized (after January 1, 2005). The returns are annualized and in percentage. Newey and West (1987) robust *t*-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is given by ***, **, or *, respectively.

Timing	Avg ret(%)	Std dev(%)	SRatio	HC IS(%)	LC IS(%)
Panel A: After July 1, 2001					
$\eta(r_1)$	4.46***	6.10	0.73	2.72	2.57
	(2.58)				
$\eta(r_1, r_{12})$	4.30***	4.40	0.98	1.40	1.28
	(3.44)				
Always long	−0.74	6.12	−0.12		
	(−0.42)				
Buy-and-hold	4.90	20.34	0.24		
	(0.85)				
Panel B: After January 1, 2005					
$\eta(r_1)$	6.52***	6.51	1.00	1.64	1.49
	(3.00)				
$\eta(r_1, r_{12})$	4.74***	4.72	1.00	0.93	0.80
	(3.01)				
Always long	−1.03	6.54	−0.16		
	(−0.47)				
Buy-and-hold	6.75	20.72	0.33		
	(0.98)				

trading are still economically significant. Better results are obtained when both the first and the twelfth half-hour returns are used to time the market. In contrast, the *Always long* strategy, which always invests in the market during the last half hour, yields an average return of −0.74% per annum. However, the daily average market return (*Buy-and-hold*) strategy is 4.90% per annum for the same time period. Note that *Always long* is a better benchmark for comparison with our timing strategies as all of them invest only in the last half hour, while the *Buy-and-hold* invests all the time (six-and-a-half hours).

Fig. 3 plots the time series of the proportional spread after decimalization (after July 1, 2001). It shows clearly that the proportional spread narrowed after decimalization, stabilizing at around 1.2 basis points after 2005. To better capture the impact of transaction costs on the future performance of intraday momentum, we consider the performance after January 1, 2005, reported in Panel B of Table 11. The average return of the market-timing strategy using the first half-hour return as a timing signal is 6.52% per annum after the bid/ask spreads, compared with 7.96% per annum before the bid/ask spreads. The HC IS and LC IS are 1.64% and 1.49% per annum, respectively, lower than those in Panel A. Similarly, the average return using both the first and twelfth half-hour returns for the timing is 4.74% per annum after the bid/ask spread (versus 5.50% per annum before). The HC IS and LC IS are even smaller, at 0.93% and 0.80% per annum, respectively. Overall, we find that the intraday momentum profit remains after accounting for all transaction costs.

Table 12
Summary of other ETFs.
The table describes the ten index ETFs used for the robustness analysis in Table 13. These are the most heavily traded ETFs as measured by average daily trading volume from their inception dates to December 31, 2013.

Symbol	Name	Inception
QQQ	Powershare NASDAQ 100	03/10/1999
XLF	Financial Select Sector SPDR	12/22/1998
IWM	iShares Russell 2000 ETF	05/26/2000
DIA	Dow Jones Industrial Average ETF	01/20/1998
EEM	iShares MSCI Emerging Markets ETF	04/11/2003
FXI	iShares China Large-Cap ETF	10/8/2004
EFA	iShares MSCI EAFE ETF	08/17/2001
VWO	Emerging Markets ETF	03/10/2005
IYR	iShares US Real Estate ETF	06/19/2000
TLT	20+ Year Treasury Bond ETF	07/26/2002

6.3. Other ETFs

Is the existence of intraday momentum unique to the S&P 500 ETF, or is it a general phenomenon in the stock market? To address this question, we analyze the intraday returns of ten additional ETFs. We choose the ten ETFs with the highest average daily trading volume from their inception dates to December 31, 2013.[16] Table 12 describes

[16] We exclude a couple of heavily traded ETFs, which yield similar results, with inception dates after 2005 and a few others, to create a diverse and manageable set of ETFs. For the early years of the data, we delete trading days with fewer than 100 trades.

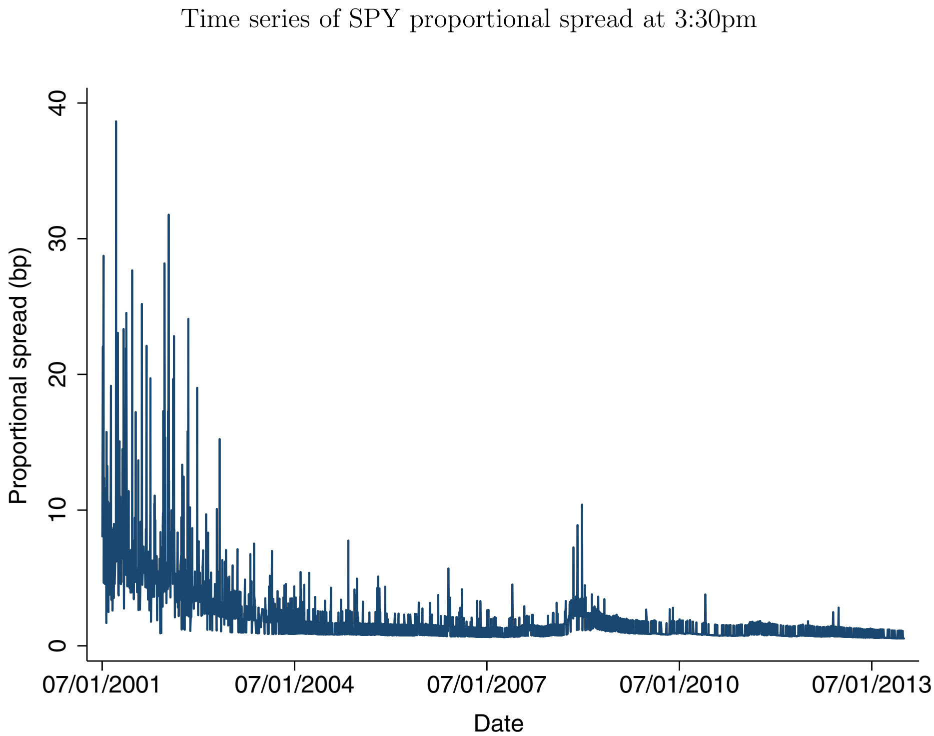


Fig. 3. Time series of proportional spread for SPY. The figure plots the proportional spread for SPY at 3:30 pm on each trading day after decimalization (after July 1, 2001). The proportional spread is defined as (ask-bid)/midquote, where the midquote price is the average of the bid and ask prices, $(\text{ask}+\text{bid})/2$.

these ETFs. The asset classes represented by our chosen ETFs are diverse. They include domestic alternative stock indices such as the Dow, the Nasdaq, and the Russell 2000 (DIA, QQQ, and IWM); international equity indices (EEM, FXI, EFA, VWO); two sector indices (XLF, IYR); and one bond index (TLT). If intraday momentum found in SPY is also present in this diverse set of ETFs, it should lend more support to our trading behavior explanations.

Table 13 reports the in-sample and out-of-sample R^2s and CER performance measures for each ETF. We see a consistent pattern: the first half-hour return significantly predicts the last half-hour return. Moreover, utilizing this predictability generates substantial economic value. When only the first half-hour return r_1 is used as a predictor (Panel A), the in-sample R^2 ranges from 1.16% for DIA to 8.54% for EEM, and the out-of-sample R^2 ranges from 0.70% for QQQ to 6.53% for EEM. All the R^2s strongly suggest that the first half-hour returns predict the last half-hour returns.

A further examination of the volatility and trading volume of these ETFs reveals that they all have similar U-shaped patterns (unreported here for brevity) as the SPY. Hence, the first half hour and the last half hour are also the most important trading periods for these ETFs. As a result, the two theoretical explanations presented above, infrequent portfolio rebalancing and late-informed trading, appear to apply to them as well. The desire to trade these ETFs in the last half hour can generate their intraday momentum.

In terms of economic value, the CER reaches as high as 17.71% per annum (for FXI) and is greater than 10.0% for many other ETFs. In comparison with the S&P 500 ETF, these ETFs are less liquid, so the price impact of the last half-hour trading is likely greater. This might help explain their generally higher CERs. Adding r_{12} to r_1 as an additional predictor (Panel B), we find a slight improvement over the single predictor r_1, but this improvement is not uniform. In summary, the results for various ETFs indicate a pervasive intraday momentum pattern in the US stock market.

6.4. Data snooping

Could our findings be caused by data snooping? Lo and Mac Kinlay (1990) point out that, due to the search of surprising results by various researchers from the same or similar data, there is a bias for a seemingly significant but false pattern. We argue that the intraday momentum pattern is strong and persistent, and so it is unlikely to be explained by chance alone.

First, our analysis shows that r_1 is a powerful predictor. In Panel A of Table 1, the robust t-statistic of r_1 is 4.08, substantially exceeding the usual range of t-statistics in the return predictive regressions (between 1 and 3). Moreover, the in-sample R^2 of 1.6% is exceedingly high for a short-horizon return prediction problem. Such significant levels not only guard against false discovery (see, e.g., Harvey et al., 2016) but also should bear a smaller discount or

Table 13
Other ETFs.
The table reports the average return (*Avg ret*), standard deviation (*Std dev*), in-sample R^2, out-of-sample R^2 (R^2_{OS}), and *CER* for the same utility gains analysis as in Table 7, replacing the market return with return for each of the ten other ETFs. All quantities are in percentage, and returns and standard deviations are annualized. Panel A reports the results using the first half-hour return (r_1) as the predictor, and Panel B reports the results using both r_1 and r_{12} as predictors. Newey and West (1987) robust *t*-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period for each ETF is from its inception date to December 31, 2013, excluding days with fewer than 100 trades.

Fund	Avg ret(%)	Std dev(%)	R^2(%)	R^2_{OS}(%)	CER(%)	Avg ret(%)	Std dev(%)	R^2(%)	R^2_{OS}(%)	CER(%)
	Panel A: $\beta_1 r_1$					Panel B: $\beta_1 r_1 + \beta_2 r_{12}$				
QQQ	7.75*** (3.65)	7.89	1.43	0.70	7.38	8.34*** (3.83)	8.08	2.26	0.50	7.96
XLF	12.04*** (4.36)	9.95	3.64	3.55	12.44	8.73*** (3.24)	9.70	4.37	2.19	9.13
IWM	11.72*** (5.18)	7.70	2.51	2.43	11.72	12.12*** (4.45)	9.26	4.53	3.81	12.09
DIA	3.46** (2.35)	5.69	1.16	1.03	4.16	4.63*** (2.79)	6.40	2.25	1.81	5.31
EEM	14.76*** (4.91)	9.01	8.54	6.53	14.69	18.46*** (6.01)	9.20	13.27	10.43	18.38
FXI	18.42*** (5.20)	10.17	7.80	5.90	17.71	15.98*** (4.35)	10.54	10.42	7.52	15.26
EFA	7.45*** (4.16)	5.82	3.53	1.90	7.18	6.53*** (3.69)	5.76	4.79	1.43	6.27
VWO	12.18*** (3.76)	8.72	5.72	4.39	12.12	13.61*** (4.15)	8.83	8.45	6.29	13.55
IYR	24.22*** (5.86)	12.29	5.29	4.60	14.98	29.80*** (6.43)	13.78	11.77	9.82	20.52
TLT	4.03*** (4.32)	2.89	1.77	1.65	2.26	4.50*** (5.14)	2.71	1.81	1.51	2.73

"haircut" due to backtesting biases (see, e.g., Harvey and Liu, 2015). Second, the performance of trading strategies based on intraday momentum is persistent throughout our sample; as summarized in Tables 1–9, intraday momentum consistently emerges under vastly different market conditions characterized by financial crisis, volatility levels, trading volume, institutional trading, business cycles, or macro news releases. Third, intraday momentum is pervasive. Consistent with Schwert (2003) who emphasizes the use of alternative data sets to mitigate the concern of data-snooping, the predicative power of the first half-hour return on the last half-hour return exists not only in SPY but also in other most actively traded ETFs (Section 6.3).[17] In short, due to the plausible economic explanations and strong statistical evidence, intraday momentum is likely to be a genuine phenomenon.

6.5. Previous day's last half-hour return

The intraday cross-sectional momentum literature (e.g., Heston et al., 2010; Murphy and Thirumalai, 2013; 2016) provides ample evidence on the strong relationship between a given half-hour return and returns in the same half hour on prior days. The immediate implication is that the previous day's last half-hour return r_{13_lag} might contribute to the intraday momentum as an additional predictor of r_{13}.

Table 14 reports the results. Consistent with Heston et al. (2010), Murphy and Thirumalai (2013), and Murphy and Thirumalai (2016), r_{13_lag} clearly has predictive power on r_{13}. Interestingly, the relationship between r_{13_lag} and r_{13} is negative, and this is the case across all the ETFs. On the other hand, the predictive ability of r_1 remains highly significant after controlling for r_{13_lag} and r_{12}, and r_1 has stronger predictive power than r_{13_lag}. Note that Heston et al. (2010), Murphy and Thirumalai (2013), and Murphy and Thirumalai (2016) find a positive cross-sectional relationship between r_{13_lag} and r_{13}, whereas we show a negative time-series predictability on the market. The reason is that market time-series predictability only partially depends on the cross-sectional predictability. To see this, consider a portfolio of N stocks. Following Lo and Mac Kinlay (1990) and Lewellen (2002), we can decompose the market autocovariance as

$$E[(r_{mt}-\mu_m)(r_{mt-1}-\mu_m)] = \sum_{i=1}^{N}(r_{it}-\mu_i)(r_{it-1}-\mu_i)w_i^2 + \sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}(r_{it}-\mu_i)(r_{jt-1}-\mu_j)w_i w_j,$$

where r_m is the market return, μ_m is the market expected return, r_i is the return of stock i, μ_i is the expected return of stock i, and w_i is the portfolio weight of the ith stock in the market portfolio. Then, consider for simplic-

[17] These results were found much later in response to helpful comments on an earlier version of the paper.

Table 14
Previous day's last half-hour return.

The table reports the results of regressing the last half-hour return, r_{13}, on the previous day's last half-hour return, r_{13_lag}, the first half-hour return, r_1, and the twelfth half-hour return, r_{12}. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period for each ETF is from its inception date to December 31, 2013, excluding days with fewer than 100 trades (500 for SPY).

	SPY	QQQ	XLF	IWM	DIA	EEM	FXI	EFA	VWO	IYR	TLT
Intercept	−0.72	−1.27	1.19	0.42	−0.3	−0.7	−0.77	0.54	0.64	5.45***	0.60**
	(−1.20)	(−1.45)	(1.24)	(0.49)	(−0.50)	(−0.74)	(−0.66)	(0.90)	(0.62)	(4.25)	(2.23)
$\beta_{r_{13\_lag}}$	−9.12**	−9.60***	−14.62***	−11.30**	−10.04**	−9.32	−15.13**	−12.27**	−7.78	−16.39***	−11.11***
	(−2.11)	(−2.69)	(−3.32)	(−2.57)	(−2.13)	(−1.46)	(−2.18)	(−2.19)	(−1.42)	(−3.22)	(−3.31)
β_{r_1}	6.68***	6.41***	8.66***	8.50***	5.75***	8.91***	7.83***	5.20***	7.12***	10.99***	2.98***
	(4.40)	(4.40)	(4.32)	(5.79)	(3.65)	(5.23)	(5.06)	(4.05)	(4.06)	(3.13)	(4.74)
$\beta_{r_{12}}$	10.88**	9.43**	9.98*	17.78***	11.38**	27.34***	20.40***	12.26*	19.63***	35.52***	−3.61
	(2.47)	(2.47)	(1.78)	(3.87)	(2.15)	(4.08)	(2.78)	(1.82)	(2.87)	(3.95)	(−1.07)
R^2 (%)	3.5	3.3	6.6	6.0	3.3	12.9	11.5	6.4	8.9	13.4	3.0

Table 15
Alternative definitions of the first half-hour return.

The table reports the predictive regression results for alternative definitions of the first half-hour return. In Panel A, r_1 is decomposed into returns from two subperiods: $r_{4:00pm-9:30am}$, the return from the previous day's market close to the current day's market open, and $r_{9:30am-10:00am}$, the return from the market open to 10:00am. In Panel B, r_1 is measured from the previous day's market close to the market open and to five-minute increment until 10:00am. The returns are annualized and in percentage, and the slope coefficients are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period for each ETF is from its inception date to December 31, 2013, excluding days with fewer than 100 trades (500 for SPY).

	SPY	QQQ	XLF	IWM	DIA	EEM	FXI	EFA	VWO	IYR	TLT
Panel A: Decomposing r_1 into two components											
$r_{4:00pm-9:30am}$	7.78***	6.86***	10.03***	11.04***	6.99***	12.23***	11.09***	6.33***	8.49***	17.60***	3.34***
	(4.66)	(4.23)	(4.52)	(6.22)	(3.91)	(5.91)	(6.24)	(4.46)	(4.14)	(4.03)	(5.01)
$r_{9:30am-10:00am}$	2.36	5.11*	8.81***	4.17	1.64	−0.82	−7.19**	0.97	4.24	9.41*	0.79
	(0.63)	(1.68)	(2.65)	(1.36)	(0.45)	(−0.21)	(−2.03)	(0.26)	(1.17)	(1.95)	(0.49)
R^2(%)	1.9	1.6	3.7	3.0	1.4	8.9	9.9	3.9	5.5	4.8	1.8
Panel B: Different measures of r_1											
$r_{4:00pm-9:30am}$	7.53***	6.21***	8.16***	10.41***	6.83***	12.23***	11.19***	6.29***	8.39***	15.99***	3.30***
	(4.52)	(3.78)	(3.88)	(5.66)	(3.79)	(5.92)	(6.16)	(4.51)	(4.11)	(3.86)	(4.94)
R^2(%)	1.8	1.3	2.6	2.8	1.4	8.9	9.3	3.9	5.2	3.8	1.7
$r_{4:00pm-9:35am}$	7.51***	6.59***	8.86***	10.70***	7.10***	11.52***	10.58***	6.24***	8.37***	18.11***	3.15***
	(4.68)	(4.15)	(4.00)	(6.20)	(4.16)	(5.70)	(5.95)	(4.52)	(4.34)	(4.48)	(4.79)
R^2(%)	1.8	1.5	3.0	3.0	1.5	8.7	8.9	4.0	5.7	5.9	1.6
$r_{4:00pm-9:40am}$	7.16***	6.46***	9.34***	9.94***	6.37***	11.45***	9.91***	6.26***	8.88***	17.80***	3.21***
	(4.51)	(4.19)	(4.40)	(6.33)	(3.78)	(5.93)	(5.70)	(4.56)	(4.66)	(4.17)	(4.94)
R^2(%)	1.7	1.4	3.1	2.7	1.2	8.7	7.8	3.9	6.6	5.9	1.6
$r_{4:00pm-9:45am}$	6.51***	6.52***	9.88***	9.36***	5.63***	10.85***	9.37***	6.02***	8.24***	16.99***	3.18***
	(4.02)	(4.35)	(4.67)	(6.13)	(3.24)	(5.62)	(5.58)	(4.37)	(4.27)	(4.18)	(4.94)
R^2(%)	1.4	1.5	3.5	2.4	1.0	7.9	7.2	3.6	5.6	5.6	1.6
$r_{4:00pm-9:50am}$	7.00***	6.95***	10.15***	9.77***	6.22***	11.29***	9.53***	6.13***	8.28***	17.40***	3.14***
	(4.24)	(4.55)	(4.78)	(6.23)	(3.55)	(5.78)	(5.70)	(4.26)	(4.24)	(4.25)	(4.97)
R^2(%)	1.6	1.7	3.7	2.7	1.2	8.9	7.6	3.7	5.8	6.0	1.6
$r_{4:00pm-9:55am}$	7.18***	6.65***	10.27***	9.51***	6.20***	11.04***	9.31***	6.07***	7.99***	17.60***	3.18***
	(4.35)	(4.50)	(4.94)	(6.32)	(3.57)	(5.69)	(5.72)	(4.20)	(4.07)	(4.59)	(4.91)
R^2(%)	1.7	1.6	3.9	2.6	1.2	8.6	7.3	3.7	5.5	6.2	1.7
$r_{4:00pm-10:00am}$	6.51***	6.08***	9.43***	8.74***	5.91***	10.86***	9.45***	5.94***	8.07***	15.74***	3.00***
	(4.16)	(4.06)	(4.82)	(5.99)	(3.66)	(5.77)	(5.86)	(4.27)	(4.32)	(4.03)	(4.86)
R^2(%)	1.6	1.5	3.8	2.6	1.2	8.6	7.1	3.6	5.3	5.2	1.6

ity the equal-weighted portfolio with standardization such that $Var(r_i) = 1$. Its predictive slope from the above decomposition is given by

$$\theta^{TS} = \frac{1}{\sigma_m^2 N}\theta^{XS} + \frac{1}{\sigma_m^2 N^2}[1_N'\Omega 1_N - tr(\Omega)],$$

where $\theta^{XS} = \sum_{i=1}^{N}(r_{it} - \mu_i)(r_{it-1} - \mu_i)/N$ is the cross-sectional regression slope, $\Omega = E[(r_{it} - \mu_i)(r_{jt-1} - \mu_j)]$ is the covariance matrix between the stock returns and their lags, 1_N is an N-vector of ones, and σ_m^2 is the market variance. Interestingly, the cross-sectional regression slope for all of the S&P 500 stocks is also positive with a value of 2.76, significant at the 1% level. This echoes the findings

Table 16
Predictability of the last half-hour returns: multiple regressions.

The table reports the multiple regression results of regressing the last half-hour return, r_{13}, on the remaining 12 half-hour returns for SPY and 10 other most heavily traded ETFs. r_k denotes the kth half-hour return of the day, where $k = 1, 2, \ldots, 12$. The returns are annualized and in percentage, and the coefficients are scaled by 100. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period for each ETF is from its inception date to December 31, 2013, excluding days with fewer than 100 trades (500 for SPY).

ETFs	Intercept	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{12}	$R^2(\%)$
SPY	−1.30	6.51***	6.58*	6.72	1.22	8.67*	6.61	−10.00	−5.83	−2.93	2.56	1.23	11.06**	4.10
	(−0.87)	(4.35)	(1.92)	(1.51)	(0.30)	(1.88)	(1.03)	(−1.58)	(−1.12)	(−0.49)	(0.50)	(0.27)	(2.53)	
QQQ	−2.51	5.67***	1.69	8.46**	3.60	8.12**	3.79	−1.74	2.40	−2.14	3.96	8.52**	9.76***	3.90
	(−1.15)	(3.79)	(0.61)	(2.30)	(0.89)	(2.10)	(0.76)	(−0.35)	(0.63)	(−0.47)	(0.98)	(2.25)	(2.59)	
XLF	2.61	8.48***	4.74	5.36	4.05	10.63**	14.62**	−3.23	−0.30	−4.82	2.19	10.53*	10.61*	6.70
	(1.07)	(4.47)	(1.13)	(1.02)	(0.87)	(2.05)	(2.02)	(−0.49)	(−0.06)	(−0.69)	(0.36)	(1.83)	(1.85)	
IWM	1.41	8.38***	6.41**	10.19**	2.05	12.56***	10.43	−8.17	−0.26	−2.71	6.27	2.87	18.83***	6.80
	(0.65)	(6.06)	(2.02)	(2.41)	(0.51)	(3.02)	(1.64)	(−1.13)	(−0.04)	(−0.45)	(1.06)	(0.55)	(4.03)	
DIA	−0.47	6.01***	6.37*	5.08	0.61	9.89**	5.83	−13.14*	−8.88	−0.74	3.43	1.74	11.47**	3.90
	(−0.32)	(3.81)	(1.73)	(1.07)	(0.14)	(2.03)	(0.93)	(−1.89)	(−1.58)	(−0.11)	(0.60)	(0.36)	(2.18)	
EEM	−1.71	9.59***	5.23	9.31	−2.56	4.42	7.09	−19.21*	0.96	4.35	3.23	9.43	26.73***	15.60
	(−0.74)	(5.71)	(1.02)	(1.31)	(−0.40)	(0.67)	(0.86)	(−1.89)	(0.09)	(0.42)	(0.43)	(1.40)	(4.08)	
FXI	−1.70	8.55***	6.63	6.52	1.74	5.03	7.21	−17.28	5.86	10.04	−4.23	5.54	21.98***	12.20
	(−0.61)	(5.70)	(1.15)	(0.86)	(0.24)	(0.62)	(0.71)	(−1.56)	(0.61)	(0.93)	(−0.43)	(0.70)	(2.95)	
EFA	1.42	5.46***	2.82	5.97	−1.64	3.82	5.83	−16.08*	−2.37	−5.36	7.72	5.41	12.21*	6.90
	(0.92)	(4.32)	(0.73)	(1.04)	(−0.39)	(0.85)	(0.77)	(−1.79)	(−0.34)	(−0.55)	(1.13)	(0.82)	(1.78)	
VWO	0.96	7.29***	4.24	8.49	0.67	7.68	4.89	−16.32*	3.10	−1.21	0.07	3.83	18.60***	10.20
	(0.37)	(4.31)	(0.78)	(1.23)	(0.11)	(1.23)	(0.58)	(−1.72)	(0.34)	(−0.11)	(0.01)	(0.57)	(2.79)	
IYR	12.93***	13.94***	1.99	6.54	−1.02	5.92	19.84**	−15.86	−10.19	−2.18	16.54*	1.53	35.01***	14.30
	(3.91)	(4.17)	(0.34)	(0.80)	(−0.13)	(0.66)	(2.08)	(−1.49)	(−1.10)	(−0.24)	(1.92)	(0.18)	(3.93)	
TLT	1.40**	2.96***	1.94	5.00**	1.56	−1.43	0.37	−0.32	0.59	0.20	1.75	−0.62	−3.72	2.20
	(2.06)	(4.60)	(1.28)	(2.16)	(0.68)	(−0.56)	(0.15)	(−0.14)	(0.31)	(0.07)	(0.84)	(−0.14)	(−1.10)	

of Heston et al. (2010), Murphy and Thirumalai (2013), and Murphy and Thirumalai (2016), who analyze all the stocks (we also confirm that their results are robust to subsets of small, medium, and large stocks). The point is that the second term of the decomposition is negative and larger in our application, which explains why r_{13_lag} negatively predicts r_{13}.

6.6. Other time frames

Because of the importance of the first half hour of trading and overnight news, our predictor r_1 is measured from the previous day's close to the end of the first 30 min of trading. Since r_1 consists of the overnight return and the return from the market open to the end of the first 30 min, it is useful to know which of the two components contributes more to the observed intraday momentum.

Panel A of Table 15 reports, for brevity, the slopes of individual predictive regressions. It is clear that the predictability comes largely from the return measured from the prior day's close to the market open (9:30am), rather than from the open to 10:00am. This is not unexpected, since most news and all earnings are announced by 8:30am. Therefore, by the start of the trading day, the market has already incorporated the major news, and the first 30 min of trading is simply a period of digesting this information.

A related question is how the predictive ability can change if we measure r_1 from the previous day's close to sometime before 10:00am. Panel B of Table 15 reports the results for every five-minute increment. The results barely change. Again, this occurs likely because, from the open to 10:00am, the market simply digests information released earlier, and these fluctuations have no impact on the intraday momentum.

So far, we have demonstrated that the first half hour and last half hour of a trading day are special and there is an interesting positive correlation between their returns. However, we have not provided any evidence on the relation between other half hours and the last half-hour return. Table 16 fills this gap by providing the multiple regression slopes of the last half-hour return on all the other half hours. It is clear that, at the 5% significance level, only r_1 and r_{12} matter. This is generally true across other ETFs as well. Again, this is likely due to investors' preference for trading in the first and last half hours, as evidenced by the U-shaped patterns of volatility and volume.

7. Conclusion

Our paper shows that the market return in the first half hour of the trading day predicts the market return in the last half hour. This intraday predictability is statistically significant both in and out of sample, and intraday momentum-based trading yields substantial economic gains in terms of market timing and asset allocation. We also find that market intraday momentum is stronger on high volatility days, high trading volume days, recession days, and important economic news (MCSI, GDP, CPI, FOMC) release days. Moreover, intraday momentum exists not only for the S&P 500 ETF but also for ten other most actively traded ETFs. Theoretically, intraday momentum is consistent with the trading behavior of investors who either infrequently rebalance their portfolios or have a delayed response to information released earlier.

There are a few open issues related to intraday momentum. First, the empirical facts shown in this paper call for new theoretical models of intraday trading to identify factors that determine its risk premium. Second, as trading costs become increasingly lower and trading execution becomes more automated, it is important to assess the asset pricing implications of intraday trading strategies and the associated implications for portfolio management. Third, there is a substantial literature on the predictability at the monthly frequency, but it is unknown how intraday predictability is related to monthly predictability. These would be fruitful topics for future research.

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