Intraday Momentum: The First Half-Hour Return Predicts the Last Half-Hour Return*

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Abstract

In this paper, using the intraday data of the S&P 500 ETF from February 1, 1993 to December 31, 2013, we document an intraday momentum pattern that the first half-hour return on the market predicts the last half-hour return on the market. The predictability is both statistically and economically significant, and is stronger on more volatile days, higher volume days, recession days and some macroeconomic news release days. Moreover, the intraday momentum is also strong for ten other most actively traded ETFs. Economically, the trading behavior of daytraders and informed traders seems to be the driving forces behind the intraday momentum.

JEL Classification: G11, G14

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1. Introduction

Since the seminal work of Jegadeesh and Titman (1993), it is well-known that winners of the past six months or a year tend to continue to be winners, and losers tend to continue to be losers for the next six months or a year. Griffin, Ji, and Martin (2003) show that such momentum is common in global stock markets. Recently, Moskowitz, Ooi, and Pedersen (2012) and Asness, Moskowitz, and Pedersen (2013) find evidence that time series momentum, where the past returns predicts positively the future returns, is pervasive across asset classes such as equities, bonds and currencies. However, to the best of our knowledge, almost all momentum studies are confined at the monthly frequency except for a couple of studies which use weekly returns. The open question is whether there is intraday momentum. This question is of interest not only for examining robustness of momentum strategies, but also for understanding intraday market efficiency and the role played by daytraders including in particular the high-frequency traders.

In this paper, we find strong evidence of market intraday momentum. The first half-hour return on the market, as represented by the actively traded S&P 500 ETF, predicts significantly the last half-hour return with a R^2 of 1.6%, matching or exceeding the level of a typical predictive R^2 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 prior to the last half-hour), the R^2 increases further to 2.6%. In addition, we find that the predictability rises generally with volatility and volume. When the first half-hour return volatility is high, the R^2 increases to 3.3% for the combined predictors. Moreover, we find that the predictability is stronger during recessions and on days when there are certain major economic news.

On the out-of-sample (OOS) predictability, the R^2 is 1.7% for using the first half-hour return as the single predictor, and 2.53% when this predictor is combined with the twelfth half-hour return predictor. Like the in-sample results, the degrees of OOS predictability are greater than that typically found at the monthly frequency. In terms of economic significance, the predictability from the two types of predictors (the first half-hour return alone or combined with the twelfth half-hour return) generates certainty equivalent annual returns of 6.35% and 6.44%, respectively, for a mean-variance investor with a risk aversion of 5. Moreover, the certainty equivalent gains remain significant even after accounting for transaction costs which are low due to advances in trading technology and to the decimalization since

2001. In terms of market timing, the economic value is also substantial. Overall, the intraday momentum is both statistically and economically significant.[1] Moreover, the intraday momentum is also strong and significant with other ten most actively traded ETFs.

What drives the intraday momentum? While there is a lack of theory at this time, we provide two explanations. The first is based on the trading behavior of daytraders. Most major macroeconomic news, such as GDP and CPI, are released prior to 8:30 am Eastern time, one hour before the stock market starts trading. There are in addition various overnight news. Hence, when the first half-hour return is up substantially, it is likely due to some good economic news. In response to the price rise in the first half-hour, many of the daytraders may go short to provide liquidity to the market. But they will almost surely unwind to go flat before the market closes. The findings of Shefrin and Statman (1985), Odean (1998), Locke and Mann (2000), Coval and Shumway (2005), and Haigh and List (2005) all suggest that daytraders can subject to the disposition effect — they may be more reluctant to unwind losing positions than winning ones. Thus, as many of them may wait to unwind in the last half-hour, their trading is likely to cause higher prices. Our empirical evidence seems consistent with this explanation. On a day when the first half-hour return is up substantially, the twelfth half-hour return is on average slightly positive, making those who procrastinate to unwind during this period to wait to do so in the last half-hour. This results more unwinding at the end. Moreover, the opening price on the following day is on average lower, suggesting that there is an adjustment of the price from the previous last half-hour buying pressure.

Our second explanation is based on the strategic trading of informed traders. It is a well-known empirical fact that the trading volume has a U-shaped pattern. Heavy trading occurs in the beginning and at the end of the trading day, while light trading happens in the middle of the day (see, e.g., Jain and Joh, 1988). This is particularly true for the trading activity on the S&P 500 ETF. Admati and Pfleiderer (1988) show theoretically that informed traders will time their trades to high trading volume periods, or during the first and last half-hours in our context. With a different preference specification, Hora (2006) also shows that an optimal trading strategy is to trade rapidly at the beginning and at the end of the trading horizon, and trade more slowly in the middle of the day. Therefore, given good

[1] Our paper here focuses on the market intraday momentum, while leaving the study of cross-section intraday momentum of stocks for future research.

economic news in the first half-hour, the informed trader are likely to bid up the asset price substantially. Then, in the last half-hour, their heavy buying is likely to continue to push the price up further. Both of the above explanations explain the intraday momentum that the market first half-hour return predicts the last half-hour return.

Our paper is related to the literature on intraday asset prices. Many of the existing studies have been focused on trading activity and volatility (see, e.g., Chordia, Roll, and Subrahmanyam, 2011; Corwin and Schultz, 2012). Heston, Korajczyk, and Sadka (2010) seem the only study that is closely related to ours. They find a striking intraday pattern that returns on individual stocks tend to continue at half-hour intervals across trading days, and that this pattern can last up to 40 trading days. In contrast to their study, we analyze intraday market momentum, the predictability of the first half-hour return on the last half-hour return on the same day.

Our paper is also related to the literature on price discovery. Barclay and Warner (1993), Chakravarty (2001) and Boehmer and Wu (2013) study how trading and traders of different types contribute to price discovery during a trading day and in longer horizons. In comparison, our paper seems to suggest that the price discovery process can take at least a full trading day for the market to digest the information, resulting in the intraday momentum.

The rest of the paper is organized as follows. Section 2 provides a description of the data. Section 3 documents the intraday momentum both in-sample and out-of-sample, in addition to their properties over volatility regimes. Section 4 provides an economic evaluation. Section 5 investigates its behavior over macroeconomic regimes and news announcements. Section 6 examines the robustness and Section 7 concludes.

2. Data

The intraday trading prices of actively traded S&P 500 ETF (ticker SPY) are taken from Trade and Quote database (TAQ) to compute the half-hour returns used in this paper. In addition, minute by minute prices are used to estimate half-hour volatilities. The sample period is from February 1, 1993 to December 31, 2013. We exclude any trading days when the total number of trades are less than 500. For the data on the major news releases, we obtain the historical release dates of the Michigan Consumer Sentiment Index (MCSI) from

University of Michigan, the historical release dates of the GDP estimate from Bureau of Economic Analysis, the historical release dates of the CPI from Bureau of Labor Statistics, and the historical release dates of the Federal Open Market Committee (FOMC) minutes from the Federal Reserve.[2]

Specifically, to examine the intraday return predictability, we calculate half-hour (30 minutes) returns on any trading day t from 9:30 am to 4:00 pm Eastern time, a total of 13 observations per day, from

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

where $p_{j,t}$ is the price at the j-th half-hour and $p_{j-1,t}$ is the price at the previous half-hour, for $j = 1, \ldots, 13$.[3] Note that $p_{0,t}$ is the previous trading day's price at the 13^{th} half-hour (4:00 pm). That is, we use the previous trading day's closing price as the starting price when 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 since the previous trading day's closing time. 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, and compute the realized volatility using the 30 one-minute returns. Then, we annualize the 30-minute realized volatility to obtain the estimate of the volatility of the first half-hour return.

3. Intraday momentum

In this section, we first run predictive regressions to uncover the intraday momentum, and next examine the impact of volatility on this momentum. Then we investigate its out-of-sample performance. Finally, we provide two intuitive explanations.

[2]The website for historical MCSI releases is http://www.sca.isr.umich.edu/data-archive/mine.php, for GDP releases is bea.gov/newsreleases/relsarchivegdp.htm, for Bureau of Labor Statistics announcements is www.bls.gov/bls/archived_sched.htm, and for FOMC minutes releases is www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

[3]Similar results are obtained using the log returns.

3.1. Predictive regressions

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

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

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 sample size or the total number of trading days.

The first column of Table 1 reports the results. The first half-hour return positively predicts the last half-hour return with a slope of 0.069 that is statistically significant at the 1% level. The R^2 is 1.6%. This magnitude of R^2 is impressive since almost all existing predictors have lower R^2's (see, e.g., Rapach and Zhou, 2013).

The twelfth half-hour, the half-hour prior to the last half-hour, may affect the last half-hour return too if there is a strong price persistence during the day. The second column of Table 1 reports the regression result with the use of this predictor. It is clear that the twelfth half-hour return predicts the last half-hour return at the 1% level, and it has an R^2 of 1.1%. However, as shown later, its predictability comes largely from the recent financial crisis period. On the other hand, the predictability of the first half-hour return is always significant whether there is a crisis or not.

Since r_1 or r_{12} predicts r_{13} individually, it is of interest to examine wether they can predict r_{13} jointly. The third column of Table 1 reports the predictive regression results with the use of both predictors. Surprisingly, the slopes are little changed from their individual regression values. Moreover, the R^2, 2.6%, is equal to the sum of the individual R^2's. The evidence suggests that r_1 and r_{12} are independent and complimentary in forecasting the last half-hour return.

The standard monthly momentum strategy is known to have performed poorly during the recent financial crisis, although it beats the market. How well the intraday momentum performs in this period is an interesting question. Panel B of Table 1 reports the predictive regression results from January 2, 2007 to December 31, 2009. The predictive power of r_1 in fact becomes stronger, with a larger slope of 0.124 and a greater R^2 of 3.7%. Moreover, the combined two predictors yield an amazingly large R^2 of 6.1%, rarely seen anywhere else. It may be noted that the predictive power of r_1 and r_{12} is complimentary during the crisis period too.

Since the performance during the crisis period is so remarkable, it is then a logical question as to how the crisis affects the results of the whole sample period. Panel C of Table 1 addresses this question. Excluding those crisis days, the performance clearly becomes much weaker. Although r_{12} is no longer significant, r_1 remains as a powerful predictor of r_{13} with a sizable R^2 of 0.7%, comparable to many good predictors at the monthly frequency. The combined predictors yield a higher R^2 of 1.0%. Therefore, although the predictability is not stable, like many other trading strategies, due to the financial crisis, there is no doubt for the validity of the intraday momentum over the entire sample period.

3.2. Volatility

Since financial crisis is characterized by high volatility, earlier results during the crisis period are a special case of how the intraday momentum performs under high volatility. In general, we can examine the impact of volatility by sorting all the trading days into three equal groups according to the first half-hour volatility, low, medium and high. For brevity, we consider the case of joint predictors of r_1 and r_{12} only.

Table 2 reports the results. The predictability appears an increasing function of volatility. When the volatility is low, the predictability is minimal with an R^2 of 0.6%. When the volatility is at intermediate level, the R^2 rises only slightly to 1.0%. This magnitude of R^2 is still economically significant. However, when the volatility is high, the R^2 increases more than five times to as high as 3.3%.

Overall, the intraday momentum seems highly related to volatility. The higher the volatility, the greater the predictability. This appears consistent with the theoretical model of Zhang (2006) that the greater the uncertainty, the greater the persistent of a trend. In our context, the greater the volatility, the greater the likelihood that the first half-hour trend (up or down) carries over to the last half-hour.

3.3. Out-of-sample predictability

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

To assess whether the intraday momentum still exists out of sample, we run recursive regressions similar to predictability studies at the monthly frequency. That is, to forecast return at any time t, we can only use data up to time $t-1$. Starting the regression using returns before January 3, 2000, we progressively add one more month of returns each time to form the OOS forecasts. Following Campbell and Thompson (2008), Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Ferreira and Santa-Clara (2011), and Neely, Rapach, Tu, and Zhou (2013), among others, we use the OOS R^2 to measure the OOS predictability, which is defined as,

$$OOS\ R^2 = 1 - \frac{\sum_{t=1}^{T}(r_{13,t} - \hat{r}_{13,t})^2}{\sum_{t=1}^{T}(r_{13,t} - \bar{r}_{13,t})^2}, \tag{3}$$

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 $OOS\ R^2$ indicates that the predictive regression forecast beats the simple historical average.

Table 3 reports the results. When we use the first half-hour return alone, the $OOS\ R^2$ is 1.69%. When we use the twelfth half-hour return alone, the $OOS\ R^2$ is 0.92%. When we use both of them, the $OOS\ R^2$ achieves the highest value of 2.53%. The $OOS\ R^2$'s are matching or exceeding those at the monthly frequency. As shown by Campbell and Thompson (2008) for monthly returns and confirmed later here, these levels of $OOS\ R^2$ are of substantial economic significance.

3.4. Explanations

Statistically, both the in- and out-of-sample analyses provide strong evidence on the intraday momentum. From an economic point of view, an interesting question is what economic forces drive it. We provide two intuitive explanations.

Our first explanation is based on the trading behavior of daytraders. On a day when the first half-hour return is up substantially, which might be due to overnight or morning news, some traders may expect price reversion and go short. Since they will almost surely unwind to go flat before the market closes, and some of them may wait to unwind in the last half-hour. Due to the disposition effect (see, e.g., Shefrin and Statman, 1985; Odean, 1998; Locke and Mann, 2000; Coval and Shumway, 2005; Haigh and List, 2005), they may be more reluctant to unwind losing positions than winning ones. On the other hand, on the days with substantial rise in price, the twelfth half-hour return is on average slightly positive, making those who plan to unwind during this period to wait to do so in the last half-hour. Therefore, there is likely even more unwinding of the losing positions than usual in the last half-hour. Collectively, their buying is likely to push the last half-hour return higher than otherwise. Indeed, the opening price on the following day is on average lower, suggesting an adjustment of the price from the last half-hour buying pressure.

Our second explanation is based on the strategic trading of informed traders. Admati and Pfleiderer (1988) show theoretically that informed traders will time their trades to high trading volume periods, and, with a different preference specification, Hora (2006) also shows that an optimal trading strategy is to trade rapidly at the beginning and at the end of the trading horizon, and to trade more slowly in the middle of the day. Figure 1A plots the average trading volume of the S&P 500 ETF every half-hour. Both the first and the last half-hours have trading volume close to 15 million shares, but the middle of the day has only about 5 million shares. The plot has a perfect U-shape, consistent with earlier findings about intraday trading activity (see, e.g., Jain and Joh, 1988). Now, based on the theories, given good economic news the informed traders are likely to trade more actively in the first half-hour and thus bid up the price substantially. In the last-half hour, their heavy buying is likely to continue to push the price up further. Figure 1B further shows that the U-shape trading volume pattern is stronger on high volatility days, suggesting stronger impact of the informed trading as volatility goes up. This is consistent with our earlier finding that the intraday momentum is greater with greater volatility.

A direct assessment of the impact of volume on intraday momentum is given in Table 4. Because trading volume recently exhibits an upward trend largely due to substantially lower trading cost (Chordia, Roll, and Subrahmanyam, 2011), we need to control for the time trend effect in studying the volume and intra-day momentum interaction. To do so, we first sort all trading days within each year into terciles based on the first half-hour trading volume, and then combine each volume tertile across all years to form the three volume groups. The predictive regression results in Table 4 confirm that the intraday momentum is stronger when the first half-hour trading volume is higher. The R^2 increases from 1.1% when the trading volume is low to 2.3% when the trading volume is increased, and finally to 3.1% when the trading volume is the highest.

Both of the above explanations corroborate the intraday momentum that the market first half-hour return predicts the last half-hour return. Clearly, our explanations are limited in their scope. Future research on developing rigorous theories for understanding fully the economic forces is called for.

4. Economic significance

In this section, we explore the economic significance of intraday momentum. We first use the first half-hour and twelfth half-hour returns as timing signals either individually or collectively to examine the performance relative to a passive strategy that always holds the market (SPY) during the last half hour, and then use the predicted returns to assess the certainty equivalent utility gains for a mean-variance investor.

4.1. Market timing

How well a predictor performs in market timing is a way to assess the value of the predictor. In our case, we use the first and twelfth half-hour returns as a timing signal to trade the market in the last half-hour. Specifically, we will take a long position of the market at the beginning of the last half-hour if the timing signal is positive, and take a short position otherwise. It is worth noting that the position (long or short) is closed at the market close each trading day.

Consider first the use of r_1, the first half-hour return, 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,

$$\eta(r_1) = \begin{cases} r_{13}, & \text{if} \quad r_1 > 0; \\ -r_{13}, & \text{if} \quad r_1 \leq 0. \end{cases} \tag{4}$$

The formula is clearly similar for using r_{12} as the timing signal.

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

$$\eta(r_1, r_{12}) = \begin{cases} r_{13}, & \text{if} \quad r_1 > 0 \ \& \ r_{12} > 0; \\ -r_{13}, & \text{if} \quad r_1 \leq 0 \ \& \ r_{12} \leq 0; \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

4.1.1. Out-of-sample performance

Panel A of Table 5 reports the summary statistics of returns generated from the three timing strategies. When using 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.[4] At a first glance, this does not seem too large. To gauge the performance, we report two benchmark returns. 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 closing of the market. The first row of Panel B of Table 5 shows that the annualized average return of this strategy is only −1.11%. Hence, the timing strategy $\eta(r_1)$ outperforms this passive strategy substantially.

The second benchmark is the buy-and-hold strategy of the market that we simply take a long position of the market from the beginning of the sample, and hold it till the end of the whole sample period. The results are reported on the second row of Panel B. The average return is 6.04% per year, which is still less than the average return delivered by the timing strategy, $\eta(r_1)$. Hence, it is remarkable considering that we are only in the market for a half hour each trading day instead of six and half hours each day or all the time.

Of course, we have to factor the risk into consideration. The standard deviation is 6.19% per annum for the timing strategy $\eta(r_1)$, and as a result the Sharpe ratio is 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 enjoys a large positive skewness of 0.90 and large kurtosis of 15.65, suggesting that it often delivers large positive returns.

We also compute the annual cumulative returns as another measure of performance. The

[4] Even though we are only in the market for the last half hour, we still annualize the returns by multiplying a factor of 252 because we only trade once per day.

average annual cumulative return is 6.08% for the timing strategy $\eta(r_1)$ and -1.02% for the 'Always Long' strategy, and 5.50% for the buy-and-hold strategy. It is even striking if we measure the cumulative return over the entire sample period. The timing strategy $\eta(r_1)$ delivers a cumulative return of 109.39%, whereas the other two benchmark strategies deliver -18.27% and 98.99%, respectively.

Finally, we report the success rate which is the percentage of trading days of positive returns. The success rate of the 'Always Long' strategy is 50.42%, suggesting that the unconditional probability for the last half-hour returns is roughly 50 to 50. However, the success rate of the timing strategy $\eta(r_1)$ is 54.37%, greater than 50.42%.

Using the twelfth half-hour return as the timing signal yields similar but weaker results. The average daily return is about 1.77% per annum, the Sharpe ratio is 0.29, skewness is 0.38, kurtosis is 15.73, and success rate is 50.93%. Overall, it still has a higher Sharpe ratio and greater annual cumulative return than the 'Always Long' benchmark.

Combining the two returns, r_1 and r_{12}, delivers an improved performance over using only the twelfth half-hour return. But the performance is slightly weaker than using just the first half-hour return signal. For example, the average daily return is now 4.39% vs. 6.67% per annum. However, the success rate[5] is now much higher, with an impressive value of 77.05%. This means that combining both r_1 and r_{12} does improve the percentage of being right substantially. Then, why does higher success rate yield lower average returns? The reason is that, when combining the two signals, we take the long or short position only when both of them are positive or negative, which reduces substantially the number of days we are in the market.[6]

4.1.2. The impact of volatility

In Section 3.2, the in-sample predictive regression analysis suggests that the intraday momentum is more profound in high volatility days. Here we move to examine the impact of volatility on the out-of-sample performance. Like before, we sort all trading days into terciles based on the first half-hour volatility, but now report their corresponding out-of-sample

[5]Recall that this timing strategy only trades when both r_1 and r_{12} have the same sign. The calculation of the success rate does not include days when the strategy is out of the market.

[6]If we exclude the no trading days with zero returns in the calculation, the strategy performs the best as expected, with an annualized average return of 8.85%, a standard deviation of 6.36%, thus a Sharpe ratio of 1.39, a comparable skewness of 1.19 and kurtosis of 18.30.

timing results in Panels A – C in Table 6.

Overall, Table 6 shows that timing strategies based on return predictability outperform the "Always Long" strategy under all scenarios as is evident by the higher average daily returns and Sharpe ratios. By looking at the impact of volatility, we find that the timing performance based on the first half-hour return is greater when the first half-hour volatility is higher. The average daily return per annum (and its t-statistic) of the $\eta(r_1)$ strategy substantially increases from 0.54% (0.43) in the low volatility group, to 4.75% (2.27) in the medium volatility group, and then to 14.73% (3.8) in the high volatility group. The Sharpe ratio also rises from 0.183 to 0.971 and then to 1.626. This enhanced out-of-sample performance of $\eta(r_1)$ in high volatility days is consistent with the better in-sample explanatory power of r_1 in high volatility days reported in Table 2. On the other hand, the first half-hour volatility seems to have little impact on the predicability of the twelfth half-hour return. The average daily return of the $\eta(r_{12})$ strategy stays relatively flat across terciles. Finally, combining the first and twelfth half-hour returns as the timing signal confirms the positive interaction between the volatility and the predicability of the first half-hour return. Under the $\eta(r_1, r_{12})$ strategy, both the average return and the Sharpe ratio monotonically increase from the low to the high volatility groups.

4.1.3. The impact of volume

We have shown that the first half-hour return predicts the last half-hour return even in the out-of-sample. If this is due to the strategic trading of informed traders as suggested by our second explanation, then we would expect the intraday momentum effect to be stronger when the first half-hour trading volume is higher. To test that, we sort all trading days into three terciles based on the first half-hour volume similar to Table 4, and run an out-of-sample timing performance analysis for days within each volume group.

Panels A–C in Table 7 report the out-of-sample performance in each volume tercile. Comparing the three r_1 rows, we see that the profitability based on signals from r_1 improves both statistically and economically as the first half-hour volume increases. The average daily return per annum and its t-statistic of the $\eta(r_1)$ strategy increase from 1.67% and 0.98 in the low volume days to 6.46% and 3.03 in the medium volume days, and then further to a much higher level of 11.87% and 3.23 in the high volume days. The increase of the Sharpe ratio from 0.420 to 1.292 and to 1.380 of the $\eta(r_1)$ strategy also supports the implication that the first half-hour returns predict better in high trading volume days. When the twelfth return r_{12} is used alone, we do not observe a monotonic pattern of its predictive power. The difference of the average daily return between the high and low volume tercile is only about $2.96\% - 2.16\% = 0.8\%$. However, under the combined signal strategy of $\eta(r_1, r_{12})$, there is an interaction effect that the volume has a significant impact on the predictive performance. The average returns move from 2.10% per annum to 3.35% and then to 7.73% along the low, medium and high volume terciles. Thus, the interaction of the trading volume and the intraday momentum is primarily driven by the impact of volume on the first half-hour returns. All in all, these findings are consistent with the interpretation that informed traders might time their traders in high volume periods and thus induce a positive correlation between returns in the first and last half-hour where trading volumes are usually the highest of the day.

4.2. Mean-variance portfolios

In contrast with using only the signs to form timing strategies, in this subsection we use both the signs and magnitudes of the predictors to forecast the expected returns. Then we 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 mean-variance efficient portfolio weights are given as

$$w_t = \frac{1}{\gamma}\frac{\hat{r}_{13,t+1}}{\hat{\sigma}^2_{13,t+1}}, \tag{6}$$

where $\hat{r}_{13,t+1}$ is the forecasted last half-hour return on day $t+1$ conditional on information available at or before t, $\hat{\sigma}_{13,t+1}$ is the standard deviation of the last half-hour return, both of which are estimated from the recursive regression, and the relative risk aversion coefficient, γ, is set to be 5. To be more realistic, we impose the portfolio constraint that weights on the risky asset must be between -0.5 and 1.5, meaning that the investor is allowed to borrow or short 50% on margin. This will limit the potential economic gains from the usual unconstrained weights.[7]

[7] The performance of the unrestricted portfolios is much stronger, which, though not reported for brevity, is indicated by Table 13.

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

$$U = \hat{\mu}_p - \frac{\gamma}{2}\hat{\sigma}_p^2, \tag{7}$$

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. The certainty equivalent gain of predictability is

$$CER = U_2 - U_1, \tag{8}$$

where U_1 is the realized utility of using the historical average mean forecast, and U_2 is the realized utility of using a predictive regression. CER can be interpreted as the economic gains of an investor who switches from believing a random walk model of the intraday prices to believing the intraday momentum.

The results are reported in Table 8. Using the first half-hour returns to forecast the last half-hour returns yields an average returns of 6.85% per annum and a standard deviation of 5.62% per annum. So the portfolio yields a Sharpe ratio of 1.22 with large positive skewness and kurtosis. The CER is 6.35% per annum (the realized utility of using the historical average is only 0.45%, which is not reported in the table), indicating a sizable economic gains when investors switching from believing a random walk model to believing the intraday momentum.

Weaker performance is observed when using the twelfth half-hour returns to forecast the last half-hour returns. However, when both the first and twelfth half-hour returns are used to forecast the last half-hour returns, the portfolio delivers the best result, with an average return of 6.94% per annum, a Sharpe ratio of 1.13, and a CER of 6.44% per annum. Note that unlike the case with the market timing, the performance of using both predictors is slightly better than using the first half-hour return alone. This is because we are now always in the market. It is just that the allocation varies daily.

What are the impacts of transaction costs on our results? Due to improvements in technology and competition in trading industry, we have witnessed a significant decrease in transaction costs over the last decade. Consider day trading 1000 shares of SPY. This trading size is not large for the SPY as there are tens of thousands of shares at both the ask and bid. At an online broker, such as Tradestation, an active individual investor can pay only $4.99

commission, and so the cost to active institutional investors can be even lower.[8] Then, the percentage cost of a daily round trip per year is bounded by $252 \times 10/(1000 \times 100) = 2.52\%$ as the price of the SPY is \$100 and above (up to about \$200) a majority of the time over the sample period. Because of the decimalization, the bid/ask spread is just 0.01/100 per trade. Since the closing of the SPY is uniquely traded at the market clearing price for all the buys and sells, there will be no bid/ask spread effect here. Therefore, the trading cost due to the bid/ask spread is only $0.5 \times 0.01/100 = 0.005/100$ per day, and $252 \times 0.005/100 = 1.26\%$ per year. Thus, the total trading cost is under 3.78% per year.[9] Since the average return is 6.85% per year when r_1 is used as the predictor, the economic gain is about 3.07% per year, a level usually regarded as of economic importance. Combining the two predictors, r_1 and r_{12} together generates slightly higher gains. In short, transaction costs alone cannot explain away all the potential gains from the intraday momentum.

5. Macroeconomic events

In this section, we explore the relation between the intraday momentum and macroeconomy. We examine its performance first over business cycles, and then on macroeconomic news releases.

5.1. Business cycles

With the NBER dates for expansions and recessions, we can divide all the trading days into these two types and ask the question of whether the intraday momentum interacts with the business cycle. We perform the in-sample predictive regression and the out-of-sample timing performances for these two periods and summarize the results in Table 9 and Table 10.

The comparison between these two periods suggests that the effect of intraday momentum is more significant during recessions than expansions. Table 9 shows that, during the expansions, only the first half-hour return can predict the last half-hour return in-sample. Albeit statistically significant, the predictability of r_1 is relatively weaker, with an R^2 of 1%.

[8]Some brokers even provide retail investors commission-free purchases and very low fees to sell. For example, Fidelity offers free commission to online purchases of Fidelity ETFs and selected iShares ETFs in a Fidelity brokerage account. The sale of ETFs is subject to an activity assessment fee (of between \$0.01 to \$0.03 per \$1,000 of principal.

[9]In practice, one may trade only on high volume or more profitable days to reduce total transaction costs.

However, during recessions, both the first and the twelfth half-hour returns are highly significant and the R^2 increases more than six times from 1% to 6.6%. Such stronger predictability during recessions also translates into higher profits in market timing. For example, Table 10 shows that, using the first and the twelfth half-hour return as the timing signal, the average return of the timing strategy is 16.79% per annum, seven times as high as 2.35% that is from the same timing strategy but for the expansion periods. As a result, the Sharpe ratio is 2.096 in the recession periods, more than three times higher than the Sharpe ratio in the expansion period, which is 0.658, despite the high volatility of the strategy (8.01% versus 3.57%). The timing results from the other two signals ($\eta(r_1)$ and $\eta(r_{12})$) also show that the intraday momentum strategies perform better during recessions than during expansions.

5.2. News releases

Previously, we have found that the intraday momentum is stronger with higher volatility and volume. One possible source of volatility and trading volume may come from the release of major economic news. It is hence of interest to examine news release empirically.

While there are many regular news releases, we here focus on four whose release dates are easily collected and represent different release times of the day. The first one is the Michigan Consumer Sentiment Index (MCSI) released monthly at 10:00 am. The next two are the major macro variables, the gross domestic product (GDP) and the consumer price index (CPI). Both of them are released monthly on pre-specified dates at 8:30 am before the market opens, like most other macroeconomic news. The last is the minutes of Federal Open Market Committee (FOMC), which is released regularly at 2:15 pm. We analyze the impact of news release by dividing all the trading days into two groups: days with news release, and days without.

Table 11 reports the performances of the intraday momentum on the two groups of days. On days without MCSI news, the R^2 is 2.6%. On days with MCSI releases, the R^2 is more than doubled to 5.5%. That is, the intraday momentum becomes stronger. The same holds true when we compare the R^2s on days without and on days with news announcements for GDP and CPI. These results seem to suggest there is an information carry over effect of the news on market prices during the whole trading day.

The most astonishing result is on the release of the FOMC minutes. While the no release days have only an R^2 of 2.5%, the R^2 increases enormously to 11% on release days. There are two reasons why this result is astonishing. First, the size of the R^2 is large by any standards, and exceeds by far almost all predictors at the usual monthly frequency. Second, the market participants seem to anticipate correctly in the first half-hour what message the Fed is going to send out to the market. Lucca and Moench (2013) find that the pre-announcement excess equity return is a global phenomenon. Bernile, Hu, and Tang (2014) investigate market activity minutes prior to the release of the FOMC. In contrast to these studies, we focus on the intraday momentum. The large R^2 indicates that, even after the FOMC news release, there is a strong reaction of the market to continue the trend of the same direction anticipated in the first half-hour.

Will the larger R^2s on the news release days imply greater economic gains? To answer this question, we examine the performances of the earlier market timing strategies on days with news release, and on days without. Table 12 reports the results using the first half hour return only for brevity. For the MCSI and CPI news, the gains are around three times of the gains of the usual time. For the GDP news, the profits on release days are about twice greater. The greatest economic gains occur 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 of that on the days without the FOMC news. Overall, the performance of the intraday momentum is much stronger economically on the days with the four news releases.

6. Robustness

In this section, we examine the robustness of the intraday momentum along two dimensions. First, we examine how the economic value measure may vary for various mean-variance portfolios. Then, we apply the same idea to a set of most actively traded ETFs to see whether there exists a similar intraday momentum.[10]

6.1. *Mean-variance portfolios*

In Table 13, we examine the robustness of the out-of-sample mean-variance portfolio performance by varying the relative risk aversion coefficient, γ, and/or imposing different re-

[10] On robustness of the usual momentum, see Schwert (2003), Griffin, Ji, and Martin (2003) and references therein.

strictions on portfolio weights. For brevity, we consider only portfolios based on forecasts from using both the first and the twelfth half-hour returns. In Panel A, we keep $\gamma = 5$ and change the portfolio weight restrictions. The first alternative restriction is no short sell and no borrowing ($\psi_2 : 0 \leq w \leq 1.0$), which is more restrictive than the one used in Table 8. Not surprisingly, the performance is weaker with an average return of 3.22% per annum but a Sharpe ratio of 0.82. The Sharpe ratio does not drop much because of the lower volatility of the portfolio. Relaxing the restriction by allowing shorting ($\psi_3 : -1.0 \leq w \leq 1.0$) increases the average return but also the volatility. In this case, the average return is around 7.35% per annum, CER is 6.61% per annum, and the Sharpe ratio is 1.26. Finally, we allow both shorting and borrowing ($\psi_4 : -1.0 \leq w \leq 2.0$), which delivers much higher return (10.33% per annum), Sharpe ratio (1.19), and CER (9.55% per annum).

In Panel B, we set $\gamma = 2$ and impose various portfolio weight restrictions, and in Panel C, we allow γ to have a high value of 10. The results overall are very similar to each other and to the previous case where $\gamma = 5$. Of course, when no restriction is imposed, the average return and standard deviation are indeed different for different γ, and the lower γ is, the higher the average return and standard deviation are. But the Sharpe ratio is the same because they are all on the same efficient frontier. Imposing portfolio restrictions, on the other hand, makes γ more or less irrelevant, and the portfolio performance is very close.

6.2. ETFs

To assess whether the intraday momentum exists for other assets in addition to the S&P 500 ETF, we analyze a set of ten most heavily traded index ETFs as measured by their average daily trading volume from their inception dates to December 31, 2013.[11] Table 14 provides a description of these ETFs. The asset classes of these ETFs are diverse. They contain both domestic (QQQ, XLF, IWM, DIA) and international (EEM, FXI, EFA, VWO) equity indices, two sector indices (XLF, IYR), one bond index (TLT), and one small cap index (IWM). If the intraday momentum found in SPY is also present in this diverse set of ETFs, it will lend more support to our trading behavior explanations as they do not have to be restricted to the SPY.

We evaluate both the statistical and economic significance of the intraday momentum in

[11] We exclude several heavily traded ETFs with inception dates later than 2005 and others to have a diverse and manageable set of ETFs.

the same way as before. Table 15 reports the in-sample R^2 and the out-of-sample performance measures for each ETF.[12] It shows a consistent pattern, where the first half-hour return significantly predicts the last half-return. Moreover, utilizing such predicability generates substantial economic values. When the first half-hour return r_1 is used alone as a predictor, the in-sample R^2 ranges from 1.81% for TLT to 11.77% for IYR, and the out-of-sample R^2 is from 0.70% for QQQ to 6.53% for EEM. All the R^2s suggest strongly that the first half-hour returns predicts the last half-hour returns. As for the economic value, the CER can be as high as 17.71% per annum for FXI, and many are greater than 10%. Adding r_{12} to r_1 as an additional predictor, we find slight improvements over the single predictor r_1, but the improvements are not uniform. In short, the results on various ETFs indicate that the intraday momentum pattern is pervasive in the stock market.

7. Conclusions

Extending to intraday the well-known momentum effect that winners of past six months or a year tend to be winners and the losers tend to be losers in the next six or 12 months (Jegadeesh and Titman, 1993), we, in this paper, document that the first half-hour return on the market predicts the market return in the last half-hour. The intraday predictability is statistically significant both in- and out-of-sample. In terms of market timing and asset allocation, the economic gains of using the predictability are substantial too. In addition, we find that the intraday momentum is stronger on high volatile days, high trading volume days, recession days, and some economic news (MCSI, GDP, CPI, FOMC) release days. Moreover, the intraday momentum is not only strong for the S&P 500 ETF, but also substantial for ten most actively traded ETFs. Economically, the trading behavior of daytraders and informed traders seems to be the driving forces behind the intraday momentum.

There are a number of open issues on the intraday momentum. For examples, while this paper studies the intraday momentum at the market level, it is unknown in the cross-section. In addition, while Griffin, Ji, and Martin (2003), Moskowitz, Ooi, and Pedersen (2012) and Asness, Moskowitz, and Pedersen (2013) show that momentum with monthly data holds internationally and across asset classes such as bonds and currencies, it is unknown whether there are similar empirical patterns for the intraday data. These are important topics for

[12] We delete any trading days with total number of trades less than 100.

future research.

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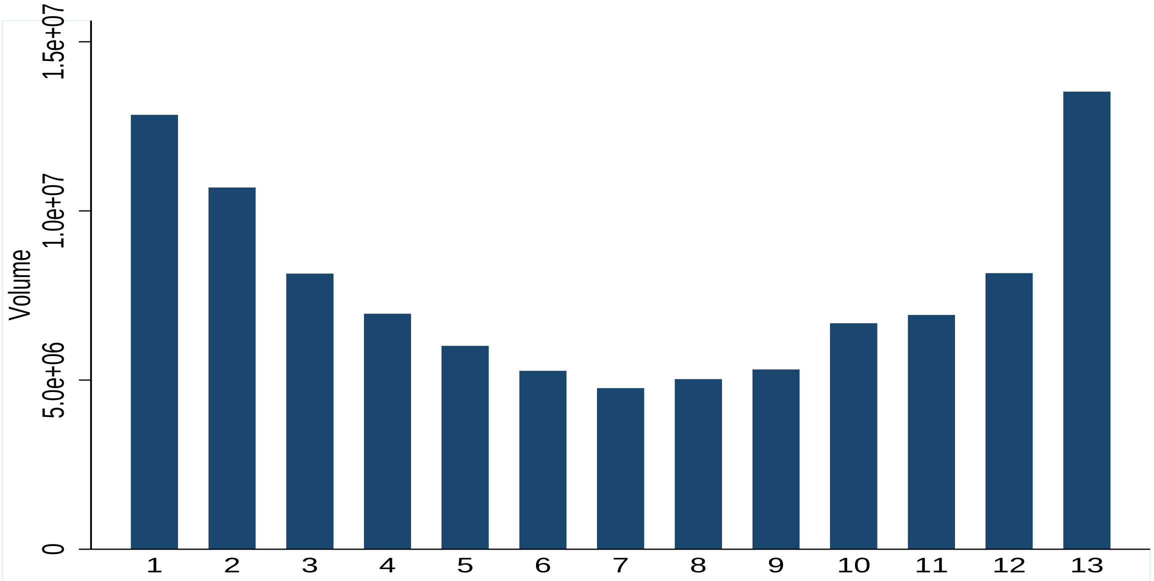
Panel A: Average 30 Minute Trading Volume



Panel B: Average 30 Minute Trading Volume Under High and Low Volatility

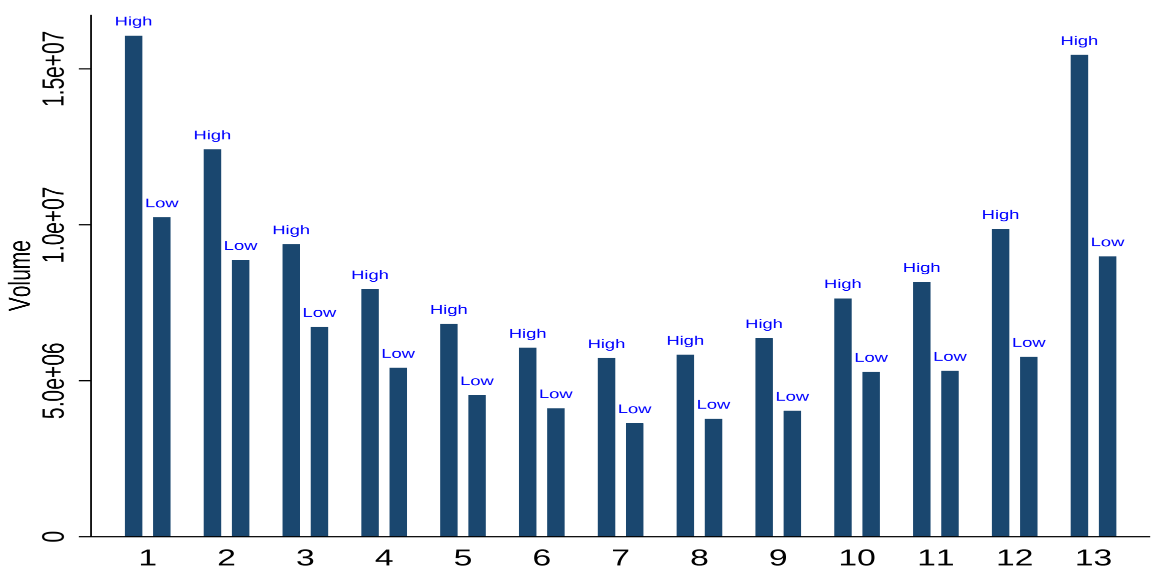


Figure 1: Average 30 minute trading volume of SPY.
For every 30 minute period from 9:30 am to 4:00 pm Eastern time, Panel A shows the average trading volume for SPY from February 1, 1993 to December 31, 2013. Each 30 minute period is labeled from one to thirteen sequentially. Panel B plots the same 30 minute average trading volume separating days with high volatility (top tercile) and low volatility (bottom tercile).

Table 1: Predictability of the Last Half-Hour Returns

This 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. Panel A, B, and C are the results for three periods: the whole sample period, the financial crisis period from January 2, 2007 to December 31, 2009, and the period excluding the financial crisis, respectively. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Predictor	r_1	r_{12}	r_1 and r_{12}	r_1	r_{12}	r_1 and r_{12}	r_1	r_{12}	r_1 and r_{12}
	Panel A: Whole Sample Period			**Panel B: Financial Crisis (2007 - 2009)**			**Panel C: Excluding Financial Crisis**		
Intercept	-0.645	-0.528	-0.724	-0.811	-1.460	-1.170	-0.470	-0.327	-0.498
	(-1.16)	(-0.94)	(-1.28)	(-0.44)	(-0.77)	(-0.61)	(-0.86)	(-0.60)	(-0.90)
β_{r_1}	0.069***		0.068***	0.124***		0.120***	0.043***		0.042***
	(4.08)		(4.14)	(2.96)		(3.05)	(3.06)		(3.05)
$\beta_{r_{12}}$		0.118***	0.114***		0.198**	0.189**		0.063*	0.062*
		(2.62)	(2.60)		(2.00)	(2.02)		(1.81)	(1.77)
R^2 (%)	1.6	1.1	2.6	3.7	2.7	6.1	0.7	0.3	1.0

Table 2: The Impact of Volatility

This table reports the regression 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}), under different levels of volatility. The first half-hour volatility is estimated using 1-minute returns within the first half hour period and volatilities over all trading days are ranked into three levels: low, medium and high. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Volatility	Low	Medium	High
Intercept	-0.000*	-0.000	0.000
	(-1.76)	(-1.51)	(0.07)
β_{r_1}	0.023	0.054***	0.072***
	(1.03)	(2.93)	(3.76)
$\beta_{r_{12}}$	0.088**	0.084**	0.127**
	(2.07)	(2.29)	(2.05)
R^2 (%)	0.6	1.0	3.3

Table 3: Out-of-Sample Predictability

This table examines the out-of-sample predictability of the last half-hour return (r_{13}) by the first half-hour return (r_1) and the twelfth half-hour return (r_{12}) based on recursive estimations. The window of the estimation initially uses the first year (1999) and progressively includes one more month of returns. The out-of-sample predictability is measured by the out-of-sample R-squared (OOS R^2),

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

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 $t-1$. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

	r_1	r_{12}	r_1 and r_{12}
β_{r_1}	0.05***		0.05***
	(31.8)		(31.9)
$\beta_{r_{12}}$		0.07***	0.07***
		(21.9)	(21.3)
OOS R^2(%)	1.69	0.92	2.53

Table 4: The Impact of Volume

This table reports the regression 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}), under different levels of trading volume in the first half-hour. Each year, first half-hour volume over all trading days are ranked into three levels: low, medium and high. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Volume	Low	Medium	High
Intercept	-0.000***	0.000	-0.000
	(-2.62)	(0.58)	(-0.66)
β_{r_1}	0.043**	0.072***	0.071***
	(2.31)	(3.32)	(3.01)
$\beta_{r_{12}}$	0.101**	0.062	0.137**
	(2.11)	(1.39)	(2.05)
R^2 (%)	1.1	2.3	3.1

Table 5: Market Timing

This table reports the economic value of timing the last half-hour market return using the first half-hour return, or the twelfth half-hour return or both. We use the sign of the first (twelfth) half-hour return as the timing signal - when the first (twelfth) half-hour return is positive (negative), we take a long (short) position in the market. When both returns are used, we only trade when both returns have the same sign - long when both are positive and short when both are negative. The benchmark (‘Always Long’) is to invest in the market for the last half hour each trading day; ‘Buy-and-Hold’ is to buy and hold the market on a daily basis. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Timing Signal	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis	Annual Cum Ret(%)	Cum Ret(%)	Success(%)
	Panel A: Market Timing							
r_1	6.67***	6.19	1.08	0.90	15.65	6.08	109.39	54.37
	(4.36)							
r_{12}	1.77	6.20	0.29	0.38	15.73	1.62	29.08	50.93
	(1.16)							
r_1 and r_{12}	4.39***	4.49	0.98	1.87	34.10	4.00	71.98	77.05
	(3.96)							
	Panel B: Benchmark							
Always Long	-1.11	6.21	-0.18	-0.46	15.73	-1.02	-18.27	50.42
	(-0.73)							
Buy-and-Hold	6.04	20.57	0.29	-0.16	6.61	5.50	98.99	
	(1.19)							

Table 6: The Impact of Volatility on Out-of-Sample Timing Performance

This table reports the impact of volatility on the economic value of timing the last half-hour market return using the first half-hour return, or the twelfth half-hour return or both. The timing strategy is described in the previous table with no restriction on the weights (Table 5). Panel A, B, or C reports the timing performance under different level of volatility. We report summary statistics such as average return (Avg Ret) in percentage, standard deviation (Std Dev) in percentage, Sharpe Ratio (SRatio), Skewness, and Kurtosis. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Timing Signal	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis
	Panel A: Low Volatility				
Always Long	-2.04	2.95	-0.692	-0.51	2.48
	(-1.62)				
r_1	0.54	2.95	0.183	-0.29	2.57
	(0.43)				
r_{12}	1.23	2.95	0.417	0.29	2.53
	(0.97)				
r_1 and r_{12}	0.97	1.93	0.503	0.12	5.87
	(1.17)				
	Panel B: Medium Volatility				
Always Long	-2.36	4.89	-0.483	-0.25	2.83
	(-1.13)				
r_1	4.75**	4.89	0.971	-0.14	2.91
	(2.27)				
r_{12}	2.96	4.89	0.605	0.46	2.79
	(1.41)				
r_1 and r_{12}	3.78***	3.28	1.152	0.79	9.07
	(2.69)				
	Panel C: High Volatility				
Always Long	1.05	9.10	0.115	-0.42	8.64
	(0.27)				
r_1	14.73***	9.06	1.626	0.76	8.50
	(3.80)				
r_{12}	1.14	9.10	0.125	0.29	8.62
	(0.29)				
r_1 and r_{12}	8.42***	6.77	1.244	1.44	17.62
	(2.91)				

Table 7: The Impact of Volume on Out-of-Sample Timing Performance

This table reports the trading impact of volume on the economic value of timing the last half-hour market return using the first half-hour return, or the twelfth half-hour return or both. The timing strategy is described in the previous table with no restriction on the weights (Table 5). Panel A, B, or C reports the timing performance under different level of volume. We report summary statistics such as average return (Avg Ret) in percentage, standard deviation (Std Dev) in percentage, Sharpe Ratio (SRatio), Skewness, and Kurtosis. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Timing Signal	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis
	Panel A: Low Volume				
Always Long	-4.03**	3.98	-1.013	-0.78	6.08
	(-2.37)				
r_1	1.67	3.98	0.420	-0.54	6.30
	(0.98)				
r_{12}	2.16	3.98	0.543	0.97	6.11
	(1.27)				
r_1 and r_{12}	2.10**	2.53	0.830	1.08	13.25
	(1.93)				
	Panel B: Medium Volume				
Always Long	1.96	5.01	0.391	-0.02	3.94
	(0.92)				
r_1	6.46***	5.00	1.292	0.09	3.95
	(3.03)				
r_{12}	0.21	5.01	0.042	0.28	3.93
	(0.10)				
r_1 and r_{12}	3.35**	3.50	0.957	0.74	14.09
	(2.24)				
	Panel C: High Volume				
Always Long	-1.29	8.63	-0.149	-0.44	10.84
	(-0.35)				
r_1	11.87***	8.60	1.380	0.96	10.68
	(3.23)				
r_{12}	2.96	8.63	0.343	0.26	10.84
	(0.80)				
r_1 and r_{12}	7.73***	6.45	1.198	1.63	21.00
	(2.80)				

Table 8: Mean-Variance Portfolio Performance

This table reports the economic value of recursively predicting the last half-hour market return using the first half-hour return, or the twelfth half-hour return or both. We use the predicted returns to form a constrained mean-variance optimal portfolio for a mean-variance investor with a relative risk aversion of 5. The portfolio weights are restricted between -0.5 and 1.5. We report summary statistics such as average return (Avg Ret) in percentage, standard deviation (Std Dev) in percentage, Sharpe Ratio (SRatio), Skewness, and Kurtosis. Also reported is the certainty equivalent rate of return in percentage, CER, which is calculated as the difference in the certainty equivalent rate of return between the optimal mean-variance strategy and the benchmark, which uses the recursively estimated average returns of the last half hour returns instead of the forecasted last half-hour returns. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Predictor	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis	CER(%)
βr_1	6.85***	5.62	1.22	1.74	48.81	6.35
	(4.55)					
βr_{12}	2.47	5.83	0.42	0.50	77.70	1.97
	(1.58)					
$\beta_1 r_1 + \beta_2 r_{12}$	6.94***	6.12	1.13	0.56	59.84	6.44
	(4.23)					

Table 9: The Impact of Business Cycle

This table examines the predictability of the last half-hour return (r_{13}) by the first half-hour return (r_1) and the twelfth half-hour return (r_{12}) in different stages of the business cycle. The expansion and recession periods are defined by the NBER. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Business Cycle	Expansion	Recession
Intercept	-0.00*	0.00
	(-1.80)	(0.78)
β_{r_1}	0.05***	0.11***
	(3.39)	(2.87)
$\beta_{r_{12}}$	0.04	0.22**
	(1.26)	(2.30)
R^2 (%)	1.0	6.6

Table 10: Out-of-Sample Timing Performance under Business Cycle

This table contrasts the results of regressing the last half-hour return (r_{13}) on the first and twelfth half-hour returns of the day (r_1 and r_{12}) when there are macro news releases with the regression results when there are no macro news releases. The first half-hour return (r_1) is calculated from the close price of the previous trading day to the first half hour (10:00 am Eastern Time). MCSI: monthly Michigan Consumer Sentiment Index release at 10:00am Eastern Time; GDP: monthly GDP estimate release at 8:30 am Eastern Time; CPI: monthly CPI release at 8:30 am Eastern Time; FOMC: Federal Open Market Committee minutes release at 2:15 pm Eastern Time. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Variable	Expansion					Recession				
	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis
Always Long	-1.73	5.05	-0.343	-0.03	8.53	2.64	10.83	0.244	-0.65	8.10
	(-1.29)					(0.37)				
r_1	4.63***	5.04	0.919	-0.13	8.61	19.05***	10.77	1.769	1.13	7.75
	(3.44)					(2.70)				
r_{12}	-0.35	5.05	-0.069	0.20	8.53	14.63**	10.79	1.356	0.21	8.10
	(-0.26)					(2.07)				
r_1 and r_{12}	2.35***	3.57	0.658	0.26	23.26	16.79***	8.01	2.096	1.96	15.88
	(2.46)					(3.19)				

Table 11: The Impact of Macro News Release on Predictive Regression

This table contrasts the results of regressing the last half-hour return (r_{13}) on the first and twelfth half-hour returns of the day (r_1 and r_{12}) when there are macro news releases with the regression results when there are no macro news releases. The first half-hour return (r_1) is calculated from the close price of the previous trading day to the first half hour (10:00 am Eastern Time). MCSI: Surveys of consumer confidence by University of Michigan release at 10:00 am Eastern Time; GDP: monthly GDP estimate release at 8:30 am Eastern Time; CPI: monthly release of CPI at 8:30 am Eastern Time; FOMC: Federal Open Market Committee minutes release at 2:15 pm Eastern Time. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

	No Release	Release	No Release	Release	No Release	Release	No Release	Release
	MCSI		**GDP**		**CPI**		**FOMC**	
Intercept	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00
	(-1.15)	(-1.21)	(-1.17)	(-0.94)	(-1.31)	(0.06)	(-1.03)	(-1.61)
β_{r_1}	0.07***	0.14***	0.07***	0.12**	0.07***	0.10*	0.07***	0.14**
	(3.90)	(3.40)	(3.90)	(2.37)	(3.90)	(1.95)	(3.98)	(2.35)
$\beta_{r_{12}}$	0.12***	-0.06	0.12***	-0.03	0.11**	0.12	0.11**	0.34*
	(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

Table 12: The Impact of Macro News Release on Timing Performance

This table reports the profitability of timing the last half-hour market return using the first half-hour return, contrasting the days with certain macro news release with the days with no macro news release. We use the sign of the first half-hour return as the timing signal - when the first half-hour return is positive (negative), we take a long (short) position in the market. We report summary statistics such as average return (Avg Ret) in percentage, standard deviation (Std Dev) in percentage, Sharpe Ratio (SRatio), Skewness, and Kurtosis. MCSI: monthly Michigan Consumer Sentiment Index release at 10:00am Eastern Time; GDP: monthly GDP estimate release at 8:30 am Eastern Time; CPI: monthly CPI release at 8:30 am Eastern Time; FOMC: Federal Open Market Committee minutes release at 2:15 pm Eastern Time. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

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

Table 13: Robustness of Out-of-Sample Mean-Variance Portfolio Performance

This table reports the out-of-sample performance of different combinations of the relative risk aversion coefficient, γ, and portfolio weight restrictions, $\psi_i, i = 1, \cdots, 4$. The recursive regression uses both the first half-hour return and the twelfth half-hour return as described in Table 8. We report summary statistics such as average return (Avg Ret) in percentage, standard deviation (Std Dev) in percentage, Sharpe Ratio (SRatio), Skewness, Kurtosis and the certainty equivalent rate of returns in percentage (CER). Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from Februry 1, 1993 to December 31, 2013.

Variable	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis	CER(%)
			Panel A: $\gamma = 5$			
$\psi_2 : 0 \leq w \leq 1.0$	3.22***	3.90	0.82	0.37	75.40	3.2
	(3.08)					
$\psi_3 : -1.0 \leq w \leq 1.0$	7.35***	5.84	1.26	0.60	21.15	6.61
	(4.70)					
$\psi_4 : -1.0 \leq w \leq 2.0$	10.33***	8.65	1.19	0.62	47.86	9.55
	(4.47)					
			Panel B: $\gamma = 2$			
$\psi_1 : -0.5 \leq w \leq 1.5$	7.16***	6.37	1.12	0.17	54.88	6.61
	(4.20)					
$\psi_2 : 0 \leq w \leq 1.0$	3.32***	4.00	0.83	0.22	70.30	3.28
	(3.10)					
$\psi_3 : -1.0 \leq w \leq 1.0$	7.70***	6.02	1.28	0.55	19.28	6.77
	(4.78)					
$\psi_4 : -1.0 \leq w \leq 2.0$	10.85***	9.08	1.20	0.22	42.58	9.81
	(4.47)					
			Panel C: $\gamma = 10$			
$\psi_1 : -0.5 \leq w \leq 1.5$	6.48***	5.84	1.11	0.72	71.26	6.09
	(4.15)					
$\psi_2 : 0 \leq w \leq 1.0$	3.10***	3.74	0.83	0.82	84.77	3.09
	(3.09)					
$\psi_3 : -1.0 \leq w \leq 1.0$	7.08***	5.61	1.26	0.83	24.28	6.73
	(4.72)					
$\psi_4 : -1.0 \leq w \leq 2.0$	9.69***	8.16	1.19	0.80	59.49	9.33
	(4.44)					

Table 14: Summary of ETFs

This table describes the additional ten index ETFs used for the robustness check analysis in Section 6.2. These ETFs are the most heavily traded ETFs as measured by their average daily trading volume from inception date to December 31, 2013.

Symbol	Name	Inception
QQQ	Powershare NASDAQ 100	3/10/1999
XLF	Financial Select Sector SPDR	12/22/1998
IWM	iShares Russell 2000 ETF	5/26/2000
DIA	Dow Jones Industrial Average ETF	1/20/1998
EEM	iShares MSCI Emerging Markets ETF	4/11/2003
FXI	iShares China Large-Cap ETF	10/8/2004
EFA	iShares MSCI EAFE ETF	8/17/2001
VWO	Emerging Markets ETF	3/10/2005
IYR	iShares U.S. Real Estate ETF	6/19/2000
TLT	20+ Year Treasury Bond ETF	7/26/2002

Table 15: Out-of-Sample Portfolio Performance using ETFs

This table reports the economic value of recursively predicting the last half-hour returns using ten most traded ETFs excluding SPY as the underlying asset, respectively. We form mean-variance efficient strategies using the predicted returns, respectively. The weights are given as $w_t = \frac{\hat{r}_{13,t+1}}{\gamma \hat{\sigma}^2_{13,t+1}}$. The variance $\hat{\sigma}^2_{13,t+1}$ is estimated in the recursive estimation, and γ is set to be 5. The portfolio weights are restricted between -0.5 and 1.5. We report summary statistics such as average return (Avg Ret) in percentage, standard deviation (Std Dev) in percentage, the certainty equivalent rate of return in percentage, $CER = \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}^2_p$, and the out-of-sample R^2. We use the average return of the last-half hour as the benchmark. All quantities are in percentage, and returns and standard deviations are annualized. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively.

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