Reversal, Momentum and Intraday Returns

Haoyu Xu*

April 30, 2017

Abstract

This paper studies the trades immediately after the market open and immediately before the market close. The trades in the morning positively predict future returns and cause price continuation. The trades in the afternoon negatively predict future returns and cause price reversals. The momentum trading strategies based on morning returns and the reversal trading strategies based on afternoon returns generate significant abnormal returns, which cannot be explained by standard risk factors including momentum and reversal factors. The results provide strong evidence that trades in the morning are mostly information driven and trades in the afternoon are mostly liquidity driven.

Keywords: Reversal, Momentum, Liquidity

JEL Codes: G11, G12, G14

*Shanghai University of Finance and Economics, haoyu.xu@mail.shufe.edu.cn

Electronic copy available at: https://ssrn.com/abstract=2991183

1 Introduction

The middle of the day has become awfully quiet on the U.S. stock market. During these hours, some Wall Street veterans walk out of their offices and take a long break. Trading has become increasingly concentrated in the first and last hours of the session. Those two hours now make up more than half of the entire day's trading volume.[1] In this study, I deliver remarkable new evidence that trading in the morning and afternoon is driven by different motivations and have different implications for future returns.

Microstructure models often group traders in two categories: liquidity traders and informed traders. The former trade to rebalance their portfolios and manage their inventories, and the latter trade to profit from their private information. Barclay and Hendershott (2003) find these two types of traders to have different participation rates in the pre-open and post-close period. They analyze the price discovery processes during the pre-open (from 8:00 to 9:30 A.M.) and post-close (from 4:00 to 6:30 P.M.). They find that there is a higher fraction of liquidity-motivated trades in the post-close and a higher fraction of informed trades in the pre-open. A natural question raised by these results is whether trades immediately after open and before close exhibit similar patterns. In this paper, I study whether the trades after the market open (from 9:30 to 11:30 A.M.) are mostly information-driven and whether the trades before the market close (from 14:00 to 16:00 P.M.) are mostly liquidity-driven. I expect these two types of trades to have different participation rates in the morning and afternoon.

Microstructure literature suggests that information asymmetry declines over the trading periods (Kyle, 1985; Glosten and Milgrom, 1985; Foster and Viswanathan, 1990; Easley and O'Hara, 1992). Both public and private information accumulate overnight. Meanwhile, there is little trading during this period. Therefore information asymmetry will be highest before the open. Barclay, Hendershott, and McCormick (2003) find that informed traders value the speed and anonymity. It should be no surprise that most informed investors will want to trade on their information as soon as possible. I expect the trades immediately after open are highly informative.

Brock and Kleidon (1992) find that there are large costs associated with holding a sub-optimal portfolio overnight. Many investors and professional money managers may want to rebalance their portfolios before the market close. For example, Edelen and Warner (2001) find that mutual fund managers' trading in response to a day's flow is concentrated later in the day. Such flow-driven trades are mostly uninforma-

[1]See "The Traders Who Skip Most of the Day," Wall Street Journal, Sept 10, 2010

Electronic copy available at: https://ssrn.com/abstract=2991183

tive. Barclay and Hendershott (2003) argue that such liquidity-motivated trades cause temporary stock price changes that are subsequently reversed. I expect the trades immediately before market close are mostly liquidity-driven and will cause subsequent price reversals.

To address these questions, I link the literature in microstructure, short-term reversal, and momentum. My basic approach is to look at the predictability in returns based on the trades executed in the first 2 hours and the last 2 hours of the day. Previous literature has documented many different forms of return predictability. Short-term reversals and momentum are two well-known return patterns. I will use these two patterns to identify the difference between the trades in the morning and afternoon.

Short-term return reversal in the stock market is a well-established phenomenon. Lehmann (1990) and Jegadeesh (1990) document stock prices exhibit short-term reversal over one-week and one-month intervals. Lehmann (1990) finds that the winners and losers in the previous week have sizable return reversals in this week. Jegadeesh (1990) finds similar predictability for individual stocks using monthly returns. Such phenomenon cannot be explained by traditional asset pricing theories or direct transaction costs. Both of them think that it reflects the inefficiency in the market. Later, many researchers try to explain this short-term predictability from different aspects. Kaul and Nimalendran (1990) and Jegadeesh and Titman (1995) argue that bid-ask spreads can explain short- term reversals. Lo and MacKinlay (1990) show that it is caused by the lead-lag effects between stocks. DeBondt and Thaler (1985, 1987), and Chopra, Lakonishok, and Ritter (1992) use investor overreaction to explain this phenomenon.

Campbell, Grossman and Wang (1993) first theoretically investigate the relationship between reversals and non-informational trading. They show that market makers accommodate buying or selling pressure from liquidity or non-informational traders and later changing expected stock returns reward market makers for playing this role. Demand shocks from non-informational traders are absorbed by market makers who require compensation for holding non-optimal inventories. This compensation is provided in the form of short-run reversal. Campbell, Grossman and Wang (1993) provide empirical evidence at the daily frequency. Avramov, Chordia and Royal (2006) further explore this idea at weekly and monthly frequencies. Nagel (2012) shows that the returns of short-term reversal strategies can be interpreted as a proxy for the returns from liquidity provision. The expected return from liquidity provision rises in times of financial crisis.

In this study, I use reversal strategies to identify the liquidity-motivated trades. My first hypothesis is that if liquidity driven trades are more likely to arise in the afternoon, then one expects these trades to cause greater price reversal. The trades in the morning should not have any reversal effects if they are primarily driven by information.

Since Jegadeesh and Titman (1993), momentum has been extensively studied (see Jegadeesh and Titman, 2011). Many recent studies suggest that momentum can be explained by investor underreaction and slow information diffusion. Chan, Jagadeesh and Lakonishok (1996) study the relationship between past earning news and momentum and find that there is a delayed reaction of stock prices to the information in past returns. Hong and Stein (1999) and Hong, Lim and Stein (2000) suggest that information diffuses gradually across investors, which can generate underreaction and positive return autocorrelation. Zhang (2006) investigates the relationship between information uncertainty and price momentum and presents clear evidence that the initial market reaction to new public information is incomplete. In a recent study, Jiang, Li and Wang (2015) find strong evidence of return continuation for news-driven return. They construct a news momentum strategy which buys stocks with high news return and sells stocks with low news returns in the previous day with a one-week holding period. And such strategy can generate significantly positive 4-factor alpha. All these results suggest that slow information diffusion is an essential part to drive the momentum phenomenon. My second hypothesis is that if the trades in the morning are highly informative, then one expects these trades to exhibit greater price continuation; the trades in the afternoon should not have any momentum effects.

Indeed, the results show that the short-term reversal phenomenon is primarily driven by the last 2-hour returns and momentum is primarily driven by the first 2-hour returns.

Specifically, I calculate the first 2-hour (last 2-hour) returns of each stock every day using TAQ data, then accumulate these intraday returns each month to get the monthly accumulated first 2-hour (accumulated last 2-hour) returns. I use Fama-MacBeth regressions to test the predictability of these two accumulated intraday returns for next month's stock returns. The results show that the monthly accumulated first 2-hour returns positively predict the next month returns with a significantly positive slope of 0.0134 (t-value = 2.37). The monthly accumulated last 2-hour returns negatively predict next month returns, with a significantly negative slope of -0.0293 (t-value = -4.88). The results suggest that morning returns and afternoon returns predict future returns in the opposite directions.

Next, I construct 2 reversal strategies using the monthly accumulated first 2-hour and last 2-hour returns respectively. I sort stocks into deciles on the basis of the monthly accumulated first 2-hour returns (accumulated last 2-hour returns); then buy losers and sell winners. I hold the long-short portfolios for one month. The two strategies generate drastically different results. The strategy based on the last 2-hour returns is able to generate significantly positive 4-factor alpha of 0.59% (t-value = 3.24). Meanwhile, the alpha of the strategy based on the first 2-hour returns is -0.74% (t-value = -3.02). It clearly shows that the last 2-hour returns cause price reversals and the first 2-hour returns cause price continuation. These two phenomena coexist within the same time horizon.

Further analysis shows that reversal strategies based on afternoon returns provide more robust results and higher profits than the conventional reversal strategy. For example, even after controlling for conventional short-term reversal (adding a short-term reversal factor), the intraday return strategy is able to generate a monthly 5-factor alpha of 0.50% (t-value = 3.46) in a time series regression. It suggests that the winners and losers selected by afternoon returns exhibit much stronger price reversal than those selected based on close-close returns. When I use the last 1-hour returns and the last 10-minute returns to replicate the reversal strategy, the results are even stronger. The last 1-hour strategy has 5-factor alpha of 0.62% (t-value = 4.37), and the last 10-minute strategy has 5-factor alpha of 0.85% (t-value = 6.72). The profit of the conventional reversal strategy has been declining over time, which has been widely documented. Over my sample period, the conventional reversal strategy is unable to generate significant excess return on average. The improvement of market liquidity and price efficiency are the major reasons. The profitability of afternoon intraday return based strategies provides strong evidence that the liquidity-motivated trades are mostly concentrated during the time before the market close.

One closely related study is Da, Liu and Schaumburg (2014). They argue that stock returns unexplained by fundamentals, such as cash flow news, are more likely to reverse in the short term. They use residual return, which is computed by subtracting the estimated expected return and cash flow news from the realized return, to sort stocks, and they find such strategy can generate higher profits than conventional reversal strategy. If the afternoon returns are less informative, then the effect of using afternoon returns is similar to subtracting the cash flow news from realized returns. Indeed, the results of reversal strategies in this study are very close to the findings in Da, Liu and Schaumburg (2014).

Momentum strategies based on first 2-hour returns also exhibit more robust results than conventional strategies. Following the convention of momentum literature, I accumulate the first 2-hour returns over six-month periods and use this accumulated intraday returns to predict the future returns. When I use Fama-Macbeth regressions to test the predictability, this accumulated first 2-hour returns exhibit strong result, with significantly positive slope of 0.0072 (t-value = 3.39). Meanwhile, the coefficients on close-close returns are insignificant.

The results suggest the morning returns positively predict future returns. When I use six-month sorting period and six-month holding period to construct momentum strategies, the first 2-hour based strategy generate 4-factor alpha of 0.53% (t-value = 2.59). The 4-factor alpha of conventional method is insignificant. Further analysis demonstrates that conventional momentum and first 2-hour strategy generate similar raw returns and 3-factor alphas. But the first 2-hour strategy has higher 4-factor alpha and higher Sharpe ratio.

The conventional momentum experienced a huge crash during 2009 financial crisis, as it declined by 73.42% in three months. The crash of the strategy based on the first 2-hour returns is much smaller, which is about 60% of the conventional strategy. Another feature of conventional momentum is that its profitability reverses after 12 months. I find this long-term reversal phenomenon is much weaker in the strategy based on the morning returns. When focusing on NYSE and AMEX stocks, this new strategy does not exhibit a reversal in 48 months. It suggests that the trades in the first 2-hours contain fundamental information, which the market has not completely reacted. It is consistent with the slow information diffusion theory.

Finally, I conduct spanning tests, in which I regress the returns of conventional momentum and first 2-hour returns based momentum on Fama-French 3 factors and each other. The results show that the abnormal returns of conventional momentum are completely subsumed by the new strategy. Meanwhile, the conventional strategy cannot absorb the abnormal returns of the first 2-hour based strategy. It suggests that the new morning returns based strategy provides additional investment opportunity beyond the span of 3 factors plus conventional momentum.

Most studies of return predictability focus on using close-close returns at daily or monthly frequencies. Existing work is typically silent about the relation between past intraday returns and long-term future returns. This study is partially motivated by recent papers on intraday return predictability. Heston, Korajczyk and Sadka (2010) find an interesting pattern of periodicity in intraday returns. A stock's return over a given half-hour interval is positively related to the same half-hour interval in the following days. Such effect lasts for at least 40 trading days. The authors conjecture that it is caused by institutional fund flows and systematic trading. However, they think these reasons cannot fully address the problem of stock return predictability. Gao, Han, Li and Zhou (2015) find that the first half-hour return on the S&P 500 ETF can predict the last half-hour return. Both of the researches clearly state that the intraday returns have predictive power within specific structures. This paper tries to extend this stream of research to longer horizons.

This study is also closely related to Lou, Polk and Skouras (2015). They decompose the momentum returns into overnight and intraday (9:30-16:00) components. Their sorting method is the same as conventional momentum, their holding method is new. They have two holding strategies. One is to hold the long-short portfolio during the trading hours (9:30-16:00) every day for one month. The other is to hold the long-short portfolio during the overnight (16:00-9:30) every day for one month. Both strategies require rebalancing every day. They find that all of the abnormal returns occur overnight. They employ the conventional sorting method and investigate the holding period with intraday returns. Meanwhile, I use accumulated intraday returns at sorting stages to construct portfolios and employ the conventional holding method. Therefore, although both studies use intraday returns, the methods and objectives are very different.

The first contribution of this study is that I use two well-established anomalies, short-term reversal and momentum, to provide evidence that trades in the morning are mostly information driven and trades in the afternoon are mostly liquidity driven. To understand such difference is important for both practitioners and researchers. Investors can more efficiently make decisions when and how to participate in trading activities. For researchers, using this natural separation can help test different finance theories more efficiently. The second contribution of this study is that it provides clear evidence that morning returns and afternoon returns have strong predictability for future returns, though in opposite directions. This paper is the first to document this phenomenon.

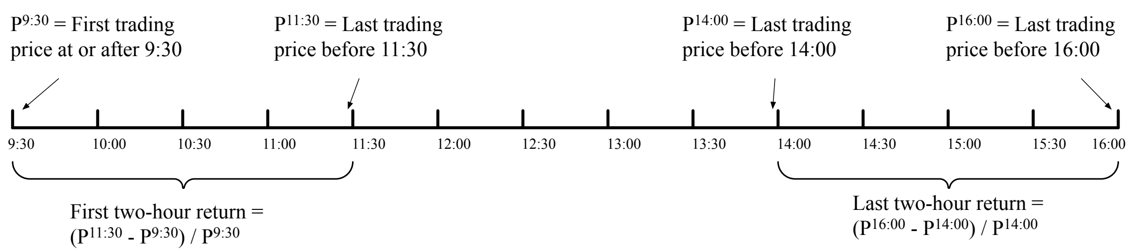
2 Data and Methodology

2.1 Data

The data covers the sample period from 1993 to 2014 and include all domestic, primary stocks listed on the New York (NYSE), American (AMEX), and Nasdaq stock markets. Closed-end funds, Real Estate Investment Trust (REITs), trusts, American Depository

Receipts (ADRs), and foreign stocks are excluded. Following previous literature, stocks with prices less than \$5 or in the smallest NYSE size decile are excluded.

To calculate intraday stock returns, I use intraday trading prices from the Trade and Quote (TAQ) database. Most of the tests in this paper focus on the returns of the first two-hour and last two-hour in each trading day. To compute the first two-hour returns, I use the first trading price at or after 9:30 and the last trading price before 11:30, denoted as $P^{9:30}$ and $P^{11:30}$. This two-hour return is $\frac{P^{11:30}}{P^{9:30}} - 1$ and denoted as r^{F2H}. For the last two-hour returns, I use the last trading price before 14:00 ($P^{14:00}$) and the last trading price before 16:00 ($P^{16:00}$). This intraday return is $\frac{P^{16:00}}{P^{14:00}} - 1$ and denoted as r^{L2H}. Similarly, I calculate the first one-hour return, r^{F1H}, the last one-hour return, r^{L1H} and last ten-minute return, r^{L10M}. The following figure illustrates how the intraday returns are calculated.

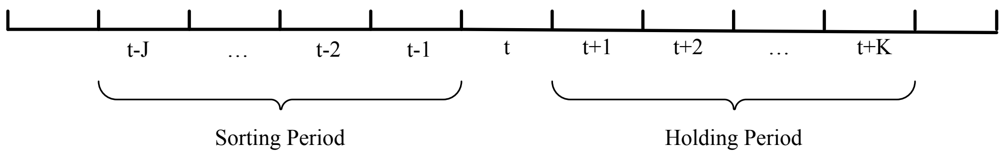


I accumulate these intraday returns respectively over one-month or six-month periods to acquire the accumulative intraday returns as the basis for performance ranking. For example, I accumulate the first 2-hour returns in month t to get the accumulated first 2-hour return of month t, and denote it as $R^{F2H}_{i,t}$. Similarly, $R^{L2H}_{i,t}$ denotes the accumulated last 2-hour return of month t. When I accumulate intraday returns over 6 months from month t to $t+5$, the accumulated intraday returns are denoted as $R^{F2H}_{i,t,t+5}$ and $R^{L2H}_{i,t,t+5}$. Similarly, $R^{F1H}_{i,t}$, $R^{F1H}_{i,t,t+5}$, $R^{L1H}_{i,t}$, $R^{L1H}_{i,t,t+5}$ denotes the accumulated intraday returns using first 1-hour and last 1-hour returns. $R^{L10M}_{i,t}$ denotes the monthly accumulated intraday return using the last 10-minute returns.

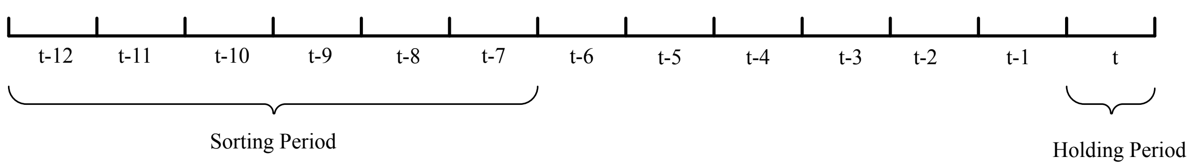
2.2 Reversal and Momentum Methodology

The conventional short-term reversal strategy sorts stocks into deciles on the basis of prior-month returns and buys the losers (bottom decile) and sells the winners (top decile). The zero-investment portfolio is held for one month and rebalanced every month. I denote this conventional strategy as REV. In this study, I construct the short-term reversal strategy by sorting stocks on the basis of prior-month accumulated intraday returns. For example, I sort stocks into deciles by $R^{L2H}_{i,t}$ at the end of month t. Then I buy losers and sell winners and hold this long-short portfolio in month $t+1$. This reversal strategy is denoted as REV^{L2H}. Similarly, I construct reversal strategies using the last 1-hour and the last 10-minute returns; they are denoted as REV^{L1H} and REV^{L10M}.

Since Jagadeesh and Titman (1993), researchers and practitioners have developed many different momentum strategies. I select 3 representative momentum strategies to replicate using accumulated intraday returns. Jegadeesh and Titman (1993) consider the J/K-strategies, which form portfolios based on stock performance over the previous J months, excluding the last month prior to portfolio formation, and hold the portfolios for K months, where J, K can be 3, 6, 9 or 12. The following figure illustrates the J/K-strategies.



The first strategy I use is $J = 6, K = 6$. To implement this strategy using first 2-hour returns, I sort stocks into deciles by $R^{F2H}_{i,t-6,t-1}$ at the end of month $t-1$. At the beginning of month $t+1$, I buy winners and sell losers and hold the equal-weighted long-short portfolio from $t+1$ to $t+6$. Fama and French construct a momentum factor by holding the portfolio for one month. My second strategy is $J = 6, K = 1$. In a recent study, Novy-Marx (2012) argues that momentum is primarily driven by firms' performance 12 to 7 months prior to portfolio formation. He sorts stocks on the basis of this 6-month return and holds for one month. He names this strategy echo. My third strategy is this echo strategy. The following figure illustrates the echo strategy.



The momentum strategies based on the first 2-hour and first 1-hour returns are denoted MOM^{F2H} and MOM^{F1H}.

3 Reversal

3.1 Main Results

First, I use Fama-MacBeth regressions to test whether or not monthly accumulated intraday returns have predictability for next month's returns. Table 2.1 reports the results of regressions of monthly returns on lagged close-close monthly returns (R_t), monthly accumulated first 2-hour returns (R_t^{F2H}) and monthly accumulated last 2-hour returns (R_t^{L2H}). In column (1), the coefficient on R_t is negative but not significant. It shows the short-term predictability of close-close returns is negligible.

In column (2), the coefficient on R_t^{F2H} is significantly positive, 0.0134 (t-value = 2.37). It shows that the first 2-hour returns can positively predict the returns in the next month. In column (3), the coefficient on R_t^{L2H} is significantly negative, -0.0293 (t-value = -4.88). Clearly, the last 2-hour returns can negatively predict the returns in the next month.

In column (4), I regress monthly returns on both lagged monthly close-close returns and lagged monthly accumulated first 2-hour returns. The coefficient on R_t becomes significantly negative after controlling for the first 2-hour returns. The coefficient on R_t^{F2H} is 0.0244 (t-value = 4.11), which is larger and more significant than in column (2).

The results suggest that it is the price movements in the morning that make the traditional reversal effect weak over the sample period. The returns in the morning cause price continuation; the returns in the afternoon cause price reversals. When using close-close returns, the two effects cancel each other. This is the reason that the coefficient on R_t is insignificant in column (1) and becomes significant in column (4). These results are consistent with my hypotheses.

In column (5), I regress monthly returns on both lagged monthly close-close returns and lagged monthly accumulated last 2-hour returns. As a result, the slope on the close-close returns is flat. The coefficient on R_t^{L2H} is almost the same as in column (3), -0.0283 (t-value = -5.07). The last 2-hour returns completely subsume the predictability of the close-close returns. By this result, we can conclude that the conventional short-term reversals are primarily caused by the trades before the market close.

In column (6), I regress monthly returns on both lagged monthly accumulated first

2-hour returns and lagged monthly accumulated last 2-hour returns. Both coefficients on R_t^{F2H} and R_t^{L2H} are significant but with opposite signs. It suggests that the price continuation caused by morning returns and the price reversals caused by afternoon returns are two independent phenomena, which coexist over the same time horizon.

Next, I implement 3 short-term reversal strategies using close-close, first 2-hour and last 2-hour returns respectively. Their raw and risk-adjusted returns are reported in Table 2.2.

The standard reversal strategy generates a raw return of 0.13% per month (t-value = 0.33), which is much lower than the 2.49% return documented in Jegadeesh (1990). The risk-adjusted returns are not significantly different from zero either. The sample period of Jegadeesh (1990) is from 1929 to 1982, and my sample period is from 1993 to 2014 due to the restriction of TAQ data. The results suggest that the profitability of reversal strategy declines significantly over time. This is consistent with the results in Da, Liu and Schaumburg (2014). They argue that the decline in profitability is due to the improvement of overall market liquidity and price efficiency. Another possibility is that I exclude stocks with prices less than $5 or in the smallest NYSE size decile. Da, Liu and Schaumburg (2014) also suggest that short-term reversal has become less likely recently among all but the smallest stocks.

Columns (3) and (4) report the results of the reversal strategy based on the first 2-hour returns. When I sort stocks into deciles on the basis of their prior-month accumulated 9:30-11:30 returns, and buy losers/sell winners, the strategy generates a return of -0.58% per month (t-value = -2.06). The 3-factor and 4-factor alphas are -0.78 (t-value = -3.24) and -0.74 (t-value = -3.02). This is a surprise because the results suggest a momentum effect instead of a reversal. To the best of my knowledge, such momentum phenomenon has not been documented in the literature.

Columns (5) and (6) report the results of the reversal strategy based on last two-hour returns. I sort stocks into deciles on the basis of their prior-month accumulated 14:00-16:00 returns, and buy losers/sell winners. The strategy generates a raw return of 0.61% per month (t-value = 3.28). Risk adjustment reduces but does not eliminate the profit. The 3-factor and 4-factor alphas are 0.53% (t-value = 2.98) and 0.59% (t-value = 3.24). These results show that the reversal effect still exists among large stocks for recent years, but only if stocks are sorted by afternoon returns.

These results provide strong evidence that momentum and reversal coexist for a holding period of one month. Most of the existing studies treat momentum and reversals as separate phenomena over different horizons. The only study I know that documents the coexistence of momentum and reversals is Wei and Yang (2012). They find large-cap/low-volatility stocks exhibit reversals while large-cap/high-volatility stocks experience momentum. Their results are divided along the volatility dimension and restricted to large-cap stocks. In this study, I study the returns in different trading hours. It is a new dimension which has not been explored.

3.2 Reversals and the Trades before the Market Close

In the previous section, I find that short-term reversal effect can be generated by using only the last 2-hour returns. Here, I am going to further explore the relationship between reversals and the trades before the market close. I replicate the reversal strategy by sorting stocks on the basis of prior-month accumulated 15:00-16:00 and 15:50-16:00 returns and denote these two strategies as REV^{L1H} and REV^{L10M}.

Table 2.3 reports the raw and risk-adjusted returns of three reversal strategies, REV^{L2H}, REV^{L1H} and REV^{L10M}. Columns (1) and (2) are same as columns (5) and (6) of Table 2.1. In column (3), I add a fifth factor which is the short-term reversal factor, DMU (down-minus-up).[2] The loading on the DMU factor is 0.48 (t-value = 11.90). The R^2 of 4-factor model is 11.55%, about 1/4 the R^2 for 5-factor model. The large t-statistics and R^2 suggest that the returns of REV^{L2H} are highly correlated with the returns of the standard reversal strategy. Meanwhile, DMU factor does not completely subsume the profits of REV^{L2H} strategy. The 5-factor alpha of REV^{L2H} is 0.50% per month with a healthy t-value of 3.46, only 10 bps lower than the raw return. The returns of REV^{L2H} is largely unexplained by standard risk factors including DMU.

As mentioned in previous sections, there are a large number of studies that show short-term reversals are caused by non-informative or liquidity driven trades. When I focus on the last two hours, the reversal effect becomes much stronger than using close-close returns. If liquidity driven trades are homogeneously distributed across the six and a half trading hours, no particular intraday returns should cause stronger reversals than close-close returns. The results provide strong evidence to support the hypothesis that trades before market close are mostly liquidity driven.

Columns (4)-(6) report that raw and risk-adjusted returns of REV^{L1H} strategy, which sorts stocks into deciles on the basis of prior-month accumulated 15:00-16:00

[2] DMU is the short-term reversal factor from French's data library, defined as the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios. It is designed to capture the standard short-term reversal effect.

returns. The raw return is 0.72% (t-value = 4.52). The alphas with respect to 3, 4, 5-factor are 0.65% (t-value = 4.38), 0.66% (t-value = 4.35) and 0.62% (t-value = 4.37). The risk-adjustment does not lower the profits much, only 5-10 bps. The raw and risk-adjusted profits of REV^{L1H} strategy are higher than those of REV^{L2H} strategy.

Columns (7)-(9) report that raw and risk-adjusted returns of REV^{L10M} strategy, which sorts stocks into deciles on the basis of prior-month accumulated 15:50-16:00 returns. The raw return is 0.85% (t-value = 5.86). The alphas with respect to 3, 4, 5-factor are 0.88% (t-value = 6.88), 0.87% (t-value = 6.75) and 0.85% (t-value = 6.72). The risk-adjusted returns are almost the same as the raw return.

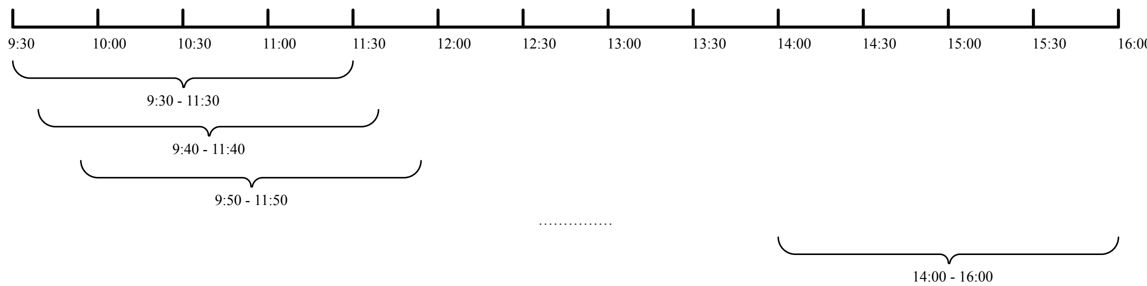
Examining the raw and risk-adjusted returns, the REV^{L10M} strategy performs better than the REV^{L1H} strategy, and REV^{L1H} strategy performs better than the REV^{L2H} strategy. The REV^{L10M} has the highest monthly Sharpe ratio of 0.36, and the REV^{L2H} has the lowest monthly Sharpe ratio of 0.20. It seems that the reversal is driven by the returns in the last 10 minutes. According to a Wall Street Journal report, more than one in six trades in S&P 500-listed stocks took place between 15:30 and the 16:00, and the final five minutes accounted for 6% of all volume in 2014.[3] Thus, it is not a surprise that the trades in the last 10 minutes cause the stronger reversal effect.

One concern here is that the results are probably caused by the nonsynchronous trading or bid-ask bounce within the 10 minutes before the market close. First, the sample excludes the stocks with prices less than $5 or in the smallest NYSE size deciles. Those stocks are most severely affected by nonsynchronous trading and bid-ask bounce. Excluding those stocks greatly reduces the bias from microstructure problems. Second, the nonsynchronous trading related autocorrelation is more prominent at the daily level. At the weekly level, it becomes much weaker. Butler, Atchison, and Simonds (1987) and Lo and MacKinlay (1990) find that nonsynchronous trading explains only a small part of the portfolio autocorrelation (16% for daily autocorrelation in Butler et al. (1987); 0.07, a small part of the total autocorrelation, for weekly autocorrelation in Lo and MacKinlay (1990)). I use the monthly accumulated intraday returns to sort stocks. There is no reason to believe the monthly accumulated intraday returns will be contaminated by the nonsynchronous trading and bid-ask bounce.

Finally, I use a moving window method to study the performance of the two-hour reversal strategies at different time points of the trading hours. Specifically, I compute 28 accumulated monthly intraday returns, $R^{9:30-11:30}$, $R^{9:40-11:40}$, $R^{9:50-11:50}$, ...

[3]See "Stock-Market Traders Pile In at the Close," Wall Street Journal, May 27, 2015

,$R^{13:50-15:50}$, $R^{14:00-16:00}$. The following figure illustrates this moving window method.



Based on these 28 monthly accumulated intraday returns, I construct 28 reversal strategies and compute their 5-factor alphas. Figure 2.1 plots these 28 alphas and t statistics along the trading hours. The x-axis is the time of the trading hours. It begins with 11:30 because the first two-hour reversal strategy uses 9:30-11:30 returns. I use 11:30 to indicate this strategy. Similarly, 11:40 indicates the strategy based on 9:40-11:40.

Panel A plots the monthly 5-factor alphas of these 28 strategies. We can see that 9:30-11:30 strategy has the lowest alpha of -0.76% (t-value = -3.89). All of the 7 strategies before 12:40 have significantly negative monthly 5-factor alphas, ranging from -0.32% to -0.76%. The 18 strategies from 12:40 (10:40-12:40 strategy) to 15:30 (13:30-15:30 strategy) are unable to generate significant 5-factor alphas. And the last 3 strategies from 15:40 (13:40-15:40 strategy) to 16:00 (14:00-16:00 strategy) all have significantly positive monthly 5-factor alphas. There is clearly an increasing pattern, which is consistent with the results in Table 2.1.

The returns after the market open cause price continuation and the returns before the market close cause price reversals. Here, we can see the returns in between have no short-term predictability. It suggests that only the trades in morning or afternoon matter, which has been noticed by practitioners.[4] This increasing pattern is exactly what I expect in my hypotheses. Informed trades rush in immediately after the market open, and the market is crowded with liquidity driven trades before the close. Afterwards, these two types of trades cause prices to move in opposite directions.

The results in Table 2.3 show that the reversal caused by the last 10-minute returns is greater than those caused by the last 2-hour and 1-hour returns. One concern is that the results are completely driven by the last 10 minutes. Here, we can see it

[4] See "The Traders Who Skip Most of the Day," Wall Street Journal, Sept 10, 2010

is not the case. The strategies based on 13:40-15:40 and 13:50-15:50 returns generate significant positive risk-adjusted returns. It confirms that the results are sensitive to the microstructure problems, such as bid-ask bounce. Meanwhile, if I exclude the last 30 minutes, the intraday returns based reversal strategies cannot make significant profits. It suggests that most liquidity driven trades are concentrated in the last 30 minutes. As previously mentioned, large amount of trades are pushed toward the last 30 minutes, even the last 10 minutes. It is expected that reversal effects are driven by the trades in the last 30 minutes.

3.3 Portfolio Characteristics

Although the strategy based on the last 10 minutes provides the best performance, I choose to be conservative and use two-hour based strategy in the following tests.

Table 2.4 reports average portfolio characteristics across the decile portfolios sorted on the basis of prior-month accumulated 14:00-16:00 returns. Portfolio 1 has the lowest performance in the prior-month, and portfolio 10 has the highest performance in the prior-month. The subsequent raw returns decline monotonically from losers portfolio to winners portfolio. The losers portfolio has the subsequent raw return of 1.19%, and the winners portfolio has the subsequent raw return of 0.47%. The difference of raw returns between portfolio 1 and 9 is 0.34% and is 0.38% between portfolio 9 and 10. It suggests that the short side of the reversal strategy contributes the most of the profitability. Although the losers portfolio has the highest raw return, its 4-factor alpha is not the highest. The portfolio 2 has the highest 4-factor alpha of 0.38%. Again, the winners portfolio has the lowest alpha of -0.35%.

The two extreme portfolios hold stocks that are relatively small and with low prices. The losers and winners portfolios have an average price of $38.61 and $44.28. Their average firm sizes are 2.1 and 1.4 billion dollars. Although portfolio 1 and 10 are relatively small, they are clearly not penny stocks. There should not be too much worry about microstructure problem within these two portfolios. Using the illiquidity measure in Amihud (2002), I compute the liquidity level of each portfolio. The two extreme portfolios are more illiquid, and they are more volatile as well. It is not a surprise that two extreme portfolios contain smaller and less liquid stocks. Small and illiquid stocks are more susceptible to the impact of liquidity trading. I also compute the average mutual fund ownership of each portfolio, which is defined as the shares owned by active mutual funds divided by a total number of outstanding shares.

The two extreme portfolios have relatively lower mutual fund ownership. This ownership can be viewed as the proxy for the degree of short-selling constraint. Lower ownership means tighter constraint. When there is buying pressure, the prices of the stocks with lower mutual fund ownership will increase more. We can see the portfolio 10 (winner) indeed has the lowest mutual fund ownership. These characteristics are consistent with the idea that liquidity trading is a key driver of the short-term reversal.

3.4 Robustness and Subsample Results

Jegadeesh (1990) documents that a reversal strategy is much more profitable in the month of January. As a robustness check, I report in panel A of Table 2.5 the results after removing January from the sample. When I exclude January, the reversal strategy based on the last 2-hour returns has monthly raw return of 0.74% (t-value = 4.44) and 5-factor alpha of 0.71% (t-value = 4.79). It is better than the strategy including January, which has raw return of 0.61% (t-value = 3.28) and 5-factor alpha of 0.50% (t-value = 3.46).

Many anomalies in the finance literature are driven by small stocks. To examine whether the result may vary depending on size, I sort stocks into three groups based on NYSE size deciles in each month. Since I already excluded the smallest NYSE size decile, the rest 9 size deciles are grouped into 3 subsamples, small, mid and large. Within each group, I replicate the REV^{L2H} strategy. The Panel B of Table 2.5 reports the performance of reversal strategy in each size group. The profit is higher among the small group. The middle and large groups have similar performance. Although the profit of the large group is about half of the small group, all results are statistically significant. For example, the 5-factor alpha for the large group is 0.31% per month with t-value = 2.04.

Panel C of Table 2.5 reports the reversal profits across two sub-periods: 1993-2003 and 2004-2014. In the first half of the sample, the reversal strategy based on the last two-hour is able to generate a raw return of 1.04% per month (t-value = 3.83) and 4-factor alpha of 1.03% per month (t-value = 3.92). In the second part of the sample, the raw return declines to 0.40% per month (t-value = 2.45), and 4-factor alpha declines to 0.34% (t-value = 2.10). Da, Liu and Schaumburg (2014) also find that the profitability of reversal strategies decline in recent years. They argue the reason is the improvement of overall market liquidity and price efficiency. My reversal strategy is based on the last 2-hour returns, which are concentrated with liquidity driven trades. The improvement of market liquidity is going to reduce the impact of liquidity-motivated trading, thus makes the profit of reversal strategies lower. So the declination in profitability in this study is consistent with the results in Da, Liu and Schaumburg (2014).

4 Momentum

The results in the previous sections show that the first 2-hour returns cause subsequent price continuation. It suggests that it is possible to construct momentum strategies using only the morning returns. In this section, I will explore the role of morning returns in momentum phenomenon.

4.1 Momentum and the Trades After the Market Open

First, I use Fama-MacBeth regressions to show that first 2-hour returns have predictability within the framework of conventional momentum strategies. Table 2.6 reports the results of regression of returns on lagged close-close monthly returns (R_t), six-month accumulated first 2-hour returns from month $t-6$ to $t-1$ ($R^{F2H}_{t-6,t-1}$) and six-month accumulated first 2-hour returns from month $t-12$ to $t-7$ ($R^{F2H}_{t-12,t-7}$). The results show that the coefficients on $R^{F2H}_{t-6,t-1}$ and $R^{F2H}_{t-12,t-7}$ are both significantly positive. It suggests that these accumulated first 2-hour returns have predictability for future returns.

Table 2.7 reports the raw and risk-adjusted returns of 3 momentum strategies based on 3 different past performance measures. Panel A reports the results with $J = 6, K = 6$. Columns (1) and (2) are the results of standard momentum (MOM) which sorts stocks based on close-close 6-month returns. The raw return and 3-factor alpha are 0.89% per month (t-value = 2.16) and 1.14% per month (t-value = 2.72). These results are consistent with the findings in previous literature that momentum is able to generate returns about 1% per month. When I include a fourth UMD factor, the abnormal return becomes insignificant. It is not a surprise because the UMD factor is designed to capture the momentum effect.

Columns (3) and (4) report the results of MOM^{F1H} strategy which sorts stocks on the basis of the accumulated 9:30-10:30 returns over past 6 months. The raw return and 3-factor alpha are 0.67% per month (t-value = 2.13) and 0.86% per month (t-value = 3.33). They are about 20 bps lower than MOM strategy. Meanwhile, when I include the UMD factor, the alpha is still significantly positive, which is 0.47% per month (t-value = 2.16). It suggests that UMD factor is unable to completely capture the returns of this intraday momentum strategy.

Columns (5) and (6) report the results of MOM^{F2H} strategy which sorts stocks on the basis of cumulative 9:30-11:30 returns over past 6 months. The raw return and 3-factor alpha are 0.83% per month (t-value = 2.59) and 1.04% per month (t-value = 3.78). They are 10 bps lower than the MOM, but with higher t statistics. Including the UMD factor lower the alpha by half, but it is still significantly positive, 0.53% per month (t-value = 2.59).

All 3 strategies have significant loadings on UMD factors, especially MOM strategy, whose coefficient on UMD is 1.27 (t-value = 30.89). Using morning returns obviously creates new investment opportunity which cannot be explained by current risk factors.

Panel B reports the results using setting $J = 6, K = 1$. MOM is able to generate slightly better raw return and 3-factor alpha, which are 1.14% per month (t-value = 2.43) and 1.39% (t-value = 3.08) respectively. Its abnormal return is still subsumed by UMD factor. The raw return and 3-factor alpha of MOM^{F1H} are 0.67% (t-value = 2.16) and 0.88% (t-value = 3.60). Including UMD lowers the abnormal return to 0.59% (t-value = 2.64). The raw return and 3-factor alpha of MOM^{F2H} are 1.00% (t-value = 3.18) and 1.24% (t-value = 4.78). Its 4-factor alpha is 0.83% (t-value = 3.90).

Novy-Marx (2012)'s echo strategy sorts stocks on the basis of 6-month returns from month $t-12$ to $t-7$, then holds the portfolio in month t for one month. Panel C of Table 2.7 reports the results. The original echo strategy ($ECHO$) generates raw return of 0.67% (t-value = 1.73) and 3-factor alpha of 0.84% (t-value = 2.19). Similar as above, its 4-factor abnormal return is insignificant. Here, $ECHO^{F1H}$ has better performance than $ECHO$. Its raw return and 3-factor alpha are 0.74% (t-value = 2.15) and 0.88% (t-value = 3.08). $ECHO^{F2H}$ performs even better, with raw return of 0.85% (t-value = 2.48) and 3-factor alpha of 1.00% (t-value = 3.36). Both of the intraday strategies have significantly positive 4-factor alphas.

4.2 Robustness and Subsample Results

It is generally accepted that momentum is concentrated in small stocks. Similar to the previous section, I divide the sample into 3 size groups and replicate all strategies within each size group. Table 2.8 reports the 3-factor and 4-factor alphas from all strategies.

The performance of MOM^{F2H} strategy shows some dependence on firm size. For example, in Panel A, its 3-factor alphas are 1.22% (t-value = 4.27) for small group and 0.84% (t-value = 3.29) for large group. Although such dependence exists, it is able to generate significantly positive alpha for the large group in all settings. The standard momentum performs slightly better than MOM^{F2H} in the large group, but its abnormal returns are unable to survive the 4-factor model.

Panel A of Table 2.9 reports the results after excluding January from the sample. It shows that removing January makes the performance of both strategies better. For example, the 3-factor alpha of MOM^{F2H} in column (2) is 1.28% (t-value = 5.34), almost a 27% increase from its full sample result.

Panel B of Table 2.9 reports the momentum profits across two subperiods: 1993-2003 and 2004-2014. We can see that the momentum is more profitable in the first half of the sample period. The standard momentum strategy can generate 3-factor alpha of 1.99% per month (t-value = 2.70) using $J = 6, K = 6$ setting. However, it declines to almost zero in the second half of the sample period. It is probably due to the momentum crash in 2009. Barroso and Santa-Clara (2014) document that winner-minus-loser strategy experienced a crash of -73.42% in three months in 2009. Profitability of MOM^{F2H} also decline in the subperiod 2004-2014, but it is still able to generate significantly positive risk-adjusted returns. For example, using $J = 6, K = 6$ setting, its 3-factor and 4-factor alphas are 0.63% (t-value = 2.36) and 0.42% (t-value = 2.61).

Next, I use the value-weighted method to replicate both momentum strategies, and Panel C of Table 2.9 reports the results. The performance of MOM^{F2H} declines when using the first two settings and increases when using echo method.

When I use 9:30-11:30 returns to construct momentum strategy, a natural concern is how much of the results are affect by the opening prices. To address this concern, I use the moving window method to show the performance of the 2-hour momentum strategies at different time points of the trading hours. Similar to Figure 2.1, I construct 28 momentum strategies and plot their monthly 4-factor alphas along the trading hours. The 4 strategies before 12:10 have significant positive risk-adjusted returns. The rest 24 strategies are unable to generate significant alphas. We can see that the profit of MOM^{F2H} is not sensitive to the open prices, because when I skip the first 10 or 20 minutes, the strategies are still able to generate significant alphas. The returns in the afternoon have no predictability in the 6-month horizon. If the momentum effect is caused by slow information diffusion, then this result suggests that the informed trades are concentrated in the morning.

In summary, the momentum strategy based on first two-hour returns is robust to different subsamples and subperiods. It consistently provides abnormal returns, which cannot be explained by current risk factors.

4.3 Comparing Two Momentum Strategies

The results in previous sections suggest that the first two-hour returns of each day are enough to construct a profitable momentum strategy. In this section, I am going to compare this new strategy with the standard momentum strategy to identify the difference between them.

Figure 2.3 plots the monthly returns of two strategies in each month of year 2009. The black bar is the conventional strategy, and the white bar is the strategy based on 9:30-11:30 returns. The biggest crash happened in April. The conventional momentum strategy lost nearly 35% in one month. In the next month, it lost 15% again. The MOM^{F2H} suffered a big loss too, but the magnitude was much smaller than MOM. In July and August, MOM^{F2H} also had much smaller decline than MOM.

Daniel and Moskowitz (2013) argue that the changing beta of the momentum portfolios partly drives the momentum crashes. Following market declines, the momentum portfolio is likely to be long low-beta stocks (the past winners), and short high-beta stocks (the past losers). When the market rebounds quickly, momentum strategies will crash because they have a large negative beta. Sorting stocks on the basis of first two-hour returns could partially avoid this problem. Thus, even following market declines, MOM^{F2H} strategy is less likely to short high-beta stocks than conventional strategy. The results in Figure 2.3 are consistent with this logic.

Another difference between MOM and MOM^{F2H} is their loadings on risk factors. MOM has significantly positive coefficient on SMB factor. As a striking contrast, MOM^{F2H} has significantly negative loading on SMB factor. Similarly for HML factor, MOM^{F2H} has opposite loading as MOM. These results suggest the momentum strategies based on morning returns have different behavior from standard momentum; they have opposite exposure to risk factors, although they all employ the same trading rule.

Next, I conduct spanning tests which regress a test strategy's returns on the returns to an explanatory strategy. An insignificant intercept suggests the test strategy is inside the span of the explanatory strategies. In this case, the test strategy does not add significantly to the investment opportunity set. A statistically significant intercept suggests that adding the test strategy to the investment opportunity set results in an attainable Sharpe ratio that significantly exceeds that which can be achieved with the explanatory strategies alone. Here, the test strategies are MOM and MOM^{F2H}. I run time-series regressions on these two strategies' return on the Fama-French three factors and each other.

Table 2.10 reports the results of the spanning tests. The column (1), (3) and (5) present results of regressing the returns of MOM on the returns of MOM^{F2H}. We can see that all the intercepts of these 3 regressions are insignificant, and the coefficients on MOM^{F2H} are significantly positive with large t statistics. For example, the coefficient on MOM^{F2H} in column (1) has t-value 20.29. It shows that the returns of MOM and MOM^{F2H} are highly correlated and the MOM strategy is inside the span of MOM^{F2H}. Comparing to MOM^{F2H}, conventional momentum does not add new investment opportunity. Columns (2), (4) and (6) present the results of regressing the returns of MOM^{F2H} on the returns of MOM. The coefficients on MOM are significantly positive as well. The intercepts are significantly positive in all 3 regressions. For example, in column (2), the intercept is 0.44% (t-value = 2.56).

The conclusion is clear. MOM^{F2H} is able to provide an investment opportunity that significantly exceeds that which can be achieved with MOM. One possible explanation is that the trades immediately after market open are mostly information driven. If the slow information diffusion theory is true, then reactions of the market in response to this information are incomplete. Then constructing momentum strategy based on first 2-hour returns exploits the slow information diffusion more efficiently.

Conventional momentum strategy is able to generate positive monthly returns when the holding period is less or equal to 12 months. After one year, the momentum profits are negative on average. This long-term reversal phenomenon has been documented in Jegadeesh and Titman (1993, 2001). Previously, when researchers build models to explain momentum, they also try to explain this long-term reversal at the same time. Momentum and reversal are usually treated as separate phenomena over different horizons. Daniel et al. (1998) use investor under- and overreaction to explain the price momentum and eventual reversal. Hong and Stein (1999) consider a model with two classes of investors, newswachthers and technical traders, to match the momentum and reversal. More recently, Vayanos and Woolley (2013) propose a theory of momentum and reversal based on flows between investment funds.

Next, I am going to examine the long-term performance of the intraday momentum strategies by extending the holding period to 60 months. Figure 2.4 presents the long-term performance of the two momentum strategies, MOM and MOM^{F2H}. Panel A presents the results using NYSE and AMEX stocks, and Panel B uses stocks on NASDAQ. The thin solid line (blue line) is the average 60-month cumulative returns of MOM strategy. The bold solid line is the returns of MOM^{F2H} strategy.

In Panel A, the profit of MOM increases until the month 10. Afterward, it keeps declining. This long-term reversal pattern is similar to the Figure 2.3 in Jegadeesh and Titman (2001). Their results also show a continuous decline of the cumulative returns after month 11. The profit of MOM^{F2H} exhibits a different pattern. It keeps increasing until month 12 and is almost flat until month 50. After this, there is a mild decline. The difference in the long-term performance between MOM and MOM^{F2H} is striking. The long-term reversal of conventional momentum is usually thought as the evidence that momentum is caused by bounded rationality of investors. With the NYSE and AMEX sample, the momentum strategy based on the first 2-hour returns shows little sign of long-term reversal, which suggests the profit is due to fundamental information about stocks. This result supports the hypothesis that the trades immediately after the market open are informative. In Panel B, the reversal of MOM strategy happens in month 8, and by the end of month 60 the cumulative return is -15%. MOM^{F2H} start to decline in month 22. By the end of month 60, its cumulative return is still above zero.

5 Conclusion

Monthly accumulated morning returns positively predict next month returns; monthly accumulated afternoon returns negatively predict next month returns. The information contained in morning and afternoon price movements is drastically different. Such difference has not been documented before, and there is no existing asset pricing theory to explain this phenomenon.

The trading strategies based on this finding provide new investment opportunities which cannot be explained by current popular risk factors. In contrast, the returns of conventional reversal and momentum trading strategies can be completely captured by the new intraday strategies. The profits of the new strategies are robust to different subsample and subperiods, while conventional strategies are losing predictive power in recent years.

One possible explanation is that the trading before market close is mostly liquidity driven. If an investor is not willing to hold a sub-optimal portfolio overnight, he needs to rebalance before market close. To provide liquidity to such investors, liquidity providers are willing to take the sub-optimal position in exchange for higher expected returns. Thus, prices are pushed away from fundamental values before the market close. If such liquidity demand persists, asset prices will not correct immediately. Coval and Stafford (2007) show that some liquidity-driven price pressure may last a few months. When I sort stocks on the basis of accumulated afternoon returns, I pick out those stocks. Then a reversal strategy will make profits when the price pressure alleviated.

News accumulates overnight, but overnight trading is extremely thin, and there is not enough liquidity to accommodate large trading. Investors have to wait for the market open to trade on their information. Thus the price movements in the morning could be more informative than other hours. If slow information diffusion indeed exists, then informative morning returns should positively predict future returns.

These are some preliminary conjectures on the subject. A satisfying explanation will require many further studies. Microstructure literature has provided some empirical and theoretical evidence which is consistent with this reasoning.

Overall, separating morning and afternoon returns provides new investment opportunities and adds a new dimension to the research of asset pricing.

References

[Amihud(2002)] Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

[Atchison et al.(1987)Atchison, Butler, and Simonds] Atchison, Michael D, Kirt C Butler, and Richard R Simonds, 1987, Nonsynchronous Security Trading and Market Index Autocorrelation, *Journal of Finance* 42, 111–118.

[Avramov et al.(2006)Avramov, Chordia, and Goyal] Avramov, Doron, Tarun Chordia, and Amit Goyal, 2006, Liquidity and Autocorrelations in Individual Stock Returns, *Journal of Finance* 61, 2365–2394.

[Barclay and Hendershott(2003)] Barclay, Michael J., and Terrence Hendershott, 2003, Price Discovery and Trading After Hours, *Review of Financial Studies* 16, 1041–1073.

[Barroso and Santa-Clara(2015)] Barroso, Pedro, and Pedro Santa-Clara, 2015, Momentum has its moments, *Journal of Financial Economics* 116, 111–120.

[Brock and Kleidon(1992)] Brock, William A., and Allan W. Kleidon, 1992, Periodic market closure and trading volume. A model of intraday bids and asks, *Journal of Economic Dynamics and Control* 16, 451–489.

[Campbell et al.(1993)Campbell, Grossman, and Wang] Campbell, John Y., Sanford J. Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *The Quarterly Journal of ...* 905 – 939.

[Chan et al.(1996)Chan, Jegadeesh, and Lakonishok] Chan, Louis K C, Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum Strategies, *Journal of Finance* 51, 1681–1713.

[Chopra et al.(1992)Chopra, Lakonishok, and Ritter] Chopra, Navin, Josef Lakonishok, and Jay R. Ritter, 1992, Measuring abnormal performance: Do stocks overreact?, *Journal of Financial Economics* 31, 235–268.

[Coval and Stafford(2007)] Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

[Da et al.(2014)Da, Liu, and Schaumburg] Da, Zhi, Qianqiu Liu, and Ernst Schaumburg, 2014, A Closer Look at the Short-Term Return Reversal, *Management Science* 60, 658–674.

[Daniel et al.(1998)Daniel, Hirshleifer, and Subrahmanyam] Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *The Journal of Finance* LIII.

[Daniel and Moskowitz(2013)] Daniel, Kent D, and Tobias J Moskowitz, 2013, Momentum crashes, *Swiss Finance Institute Research Paper* 14–16.

[DeBondt and Thaler(1985)] DeBondt, Werner F M, and Richard H. Thaler, 1985, Does the Stock Market Overreact?, *the .Journal of Finance* XL.

[DeBondt and Thaler(1987)] DeBondt, Werner F.M., and Richard H. Thaler, 1987, Further Evidence on Investor Overreaction and Stock-Market Seasonality, *Journal of Finance* 42, 557–581.

[Easley and O'Hara(1992)] Easley, David, and Maureen O'Hara, 1992, Time and the Process of Security Price Adjustment, *The Journal of Finance* 47, 577–605.

[Edelen and Warner(2001)] Edelen, Roger M, and Jerold B Warner, 2001, Aggregate price effects of institutional trading : a study of mutual fund flow and market returns, *Journal of Financial Economics* 59, 195–220.

[Fama and Macbeth(1973)] Fama, Eugene F, and James D Macbeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607–636.

[Foster and Viswanathan(1990)] Foster, F. Douglas, and S. Viswanathan, 1990, A Theory of the Interday Variations in Volume, Variance, and Trading Costs in Securities Markets, *Review of Financial Studies* 3, 593–624.

[Gao et al.(2015)Gao, Han, and Zhou] Gao, Lei, Yufeng Han, and Guofu Zhou, 2015, Intraday Momentum: The First Half-Hour Return Predicts the Last Half-Hour Return, Working Paper .

[Glosten and Milgrom(1985)] Glosten, Lawrence R, and Paul R Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

[Heston et al.(2010)Heston, Korajczyk, and Sadka] Heston, Steven L., Robert a. Korajczyk, and Ronnie Sadka, 2010, Intraday patterns in the cross-section of stock returns, *Journal of Finance* 65, 1369–1407.

[Hong et al.(2000)Hong, Lim, and Stein] Hong, Harrison, Terence Lim, and Jeremy C Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *The Journal of Finance* 55, 265–295.

[Hong and Stein(1999)] Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* LIV, 2143 – 2184.

[Jagadeesh and Titman(1995)] Jagadeesh, Narasimhan, and Sheridan Titman, 1995, Short-Horizon Return Reversals and the Bid-Ask Spread, *Journal of Financial Intermediation* 4, 116–132.

[Jegadeesh and Titman(1993)] Jegadeesh, N, and S Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *The Journal of Finance* 48, 65.

[Jegadeesh(1990)] Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *The Journal of Finance* 45, 881–898.

[Jegadeesh and Titman(2011)] Jegadeesh, Narasimhan, and Sheridan Titman, 2011, Momentum.

[Kaul and Nimalendran(1990)] Kaul, Gautam, and M Nimalendran, 1990, Price reversals: Bid-ask errors or market overreaction?, *Journal of Financial Economics* 28, 67–93.

[Kyle(1985)] Kyle, Albert, 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315–1335.

[Lehmann(1990)] Lehmann, Bruce N., 1990, Fads, martingales, and market efficiency, *The Quarterly Journal of Economics* CV, 1–28.

[Lo and MacKinlay(1990a)] Lo, Andrew W., and A. Craig MacKinlay, 1990a, An econometric analysis of nonsynchronous trading, *Journal of Econometrics* 45, 181–211.

[Lo and MacKinlay(1990b)] Lo, Andrew W., and A. Craig MacKinlay, 1990b, When Are Contrarian Profits Due to Stock Market Overreaction?, *Review of Financial Studies* 3, 175–205.

[Lou et al.(2015)Lou, Polk, and Skouras] Lou, Dong, Christopher Polk, and Spyros Skouras, 2015, A Tug of War : Overnight Versus Intraday Expected Returns, Working Paper .

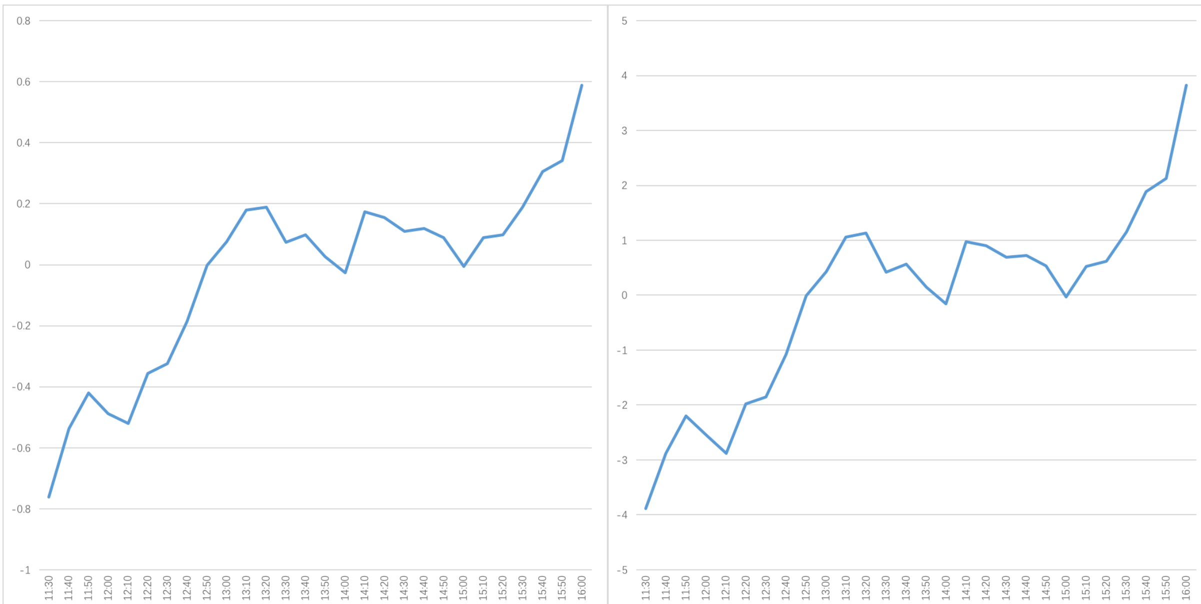
[Nagel(2012)] Nagel, Stefan, 2012, Evaporating Liquidity, *Review of Financial Studies* 25, 2005–2039.

[Novy-Marx(2012)] Novy-Marx, Robert, 2012, Is momentum really momentum?, *Journal of Financial Economics* 103, 429–453.

[Vayanos and Woolley(2013)] Vayanos, Dimitri, and Paul Woolley, 2013, An Institutional Theory of Momentum and Reversal, *Review of Financial Studies* 26, 1087–1145.

[Wei and Yang(2012)] Wei, Jason, and Liyan Yang, 2012, Short-term momentum and reversals in large stocks, Working Paper .

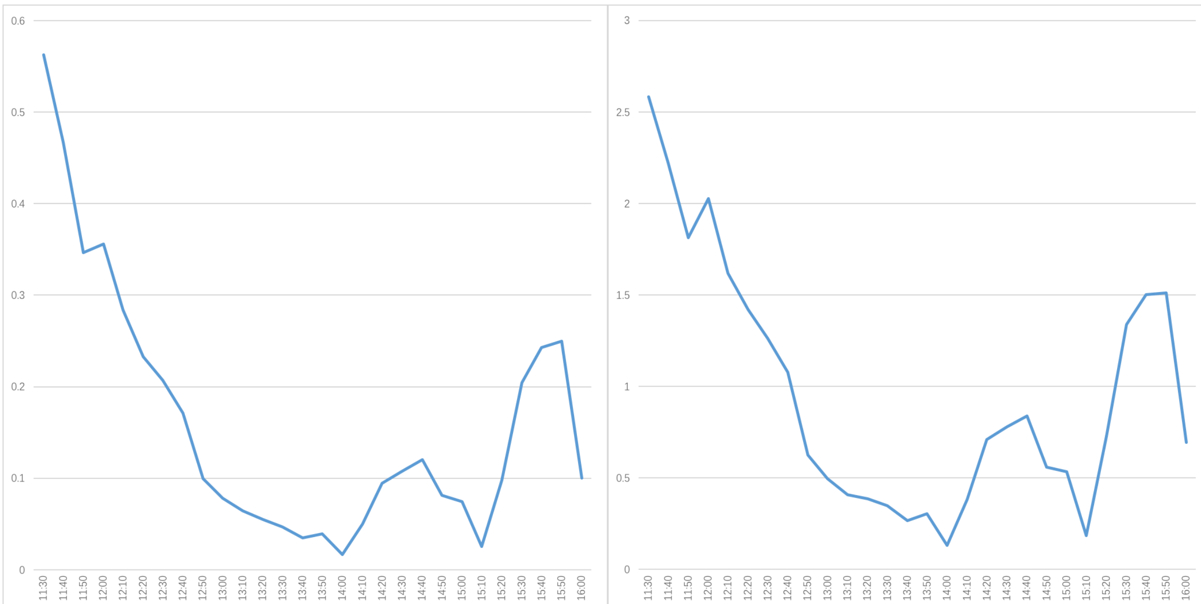
[Zhang(2006)] Zhang, X Frank, 2006, Information Uncertainty and Stock Returns, *The Journal of Finance* 61, 105–137.



(a) Five-Factor Alpha, Reversal (b) Test Statistic, Reversal

Figure 1: **The Performance of Reversal Strategies Based on 2-hour Intraday Returns Across The Trading Hours**

28 reversal strategies are constructed based on 28 2-hour intraday returns. At the end of each month, stocks are sorted into deciles on the basis of monthly accumulated 9:30-11:30 returns, $R^{9:30-11:30}$. Then a reversal strategy is constructed by buying losers and selling winners. This portfolio is held for one month. The same strategy is repeated for $R^{9:40-11:40}$, $R^{9:50-11:50}$, $\ldots$,$R^{13:50-15:50}$, $R^{14:00-16:00}$. Total 28 reversal strategies are constructed based on these 2-hour intraday returns. The 5-factor alphas and t statistics are calculated for each strategy and plotted as time series from 11:30 to 16:00. The time 11:30 on x-axis indicates the strategy based on $R^{9:30-11:30}$. Similarly, 11:40 indicates the strategy based on $R^{9:40-11:40}$. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than \$5 or in the bottom NYSE size decile are excluded.



(a) Four-Factor Alpha, Momentum (b) Test Statistic, Momentum

Figure 2: **The Performance of Momentum Strategies Based on 2-hour Intraday Returns Across The Trading Hours**

28 momentum strategies are constructed based on 28 2-hour intraday returns. At the end of each month, stocks are sorted into deciles on the basis of accumulated 9:30-11:30 returns, $R^{9:30-11:30}$, over past 6 months. Then a momentum strategy is constructed by buying winners and selling losers. This portfolio is held for 6 months. The same strategy is repeated for $R^{9:40-11:40}$, $R^{9:50-11:50}$, ... ,$R^{13:50-15:50}$, $R^{14:00-16:00}$. Total 28 momentum strategies are constructed based on these 2-hour intraday returns. The 4-factor alphas and t statistics are calculated for each strategy and plotted as time series from 11:30 to 16:00. The time 11:30 on x-axis indicates the strategy based on $R^{9:30-11:30}$. Similarly, 11:40 indicates the strategy based on $R^{9:40-11:40}$. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than \$5 or in the bottom NYSE size decile are excluded.

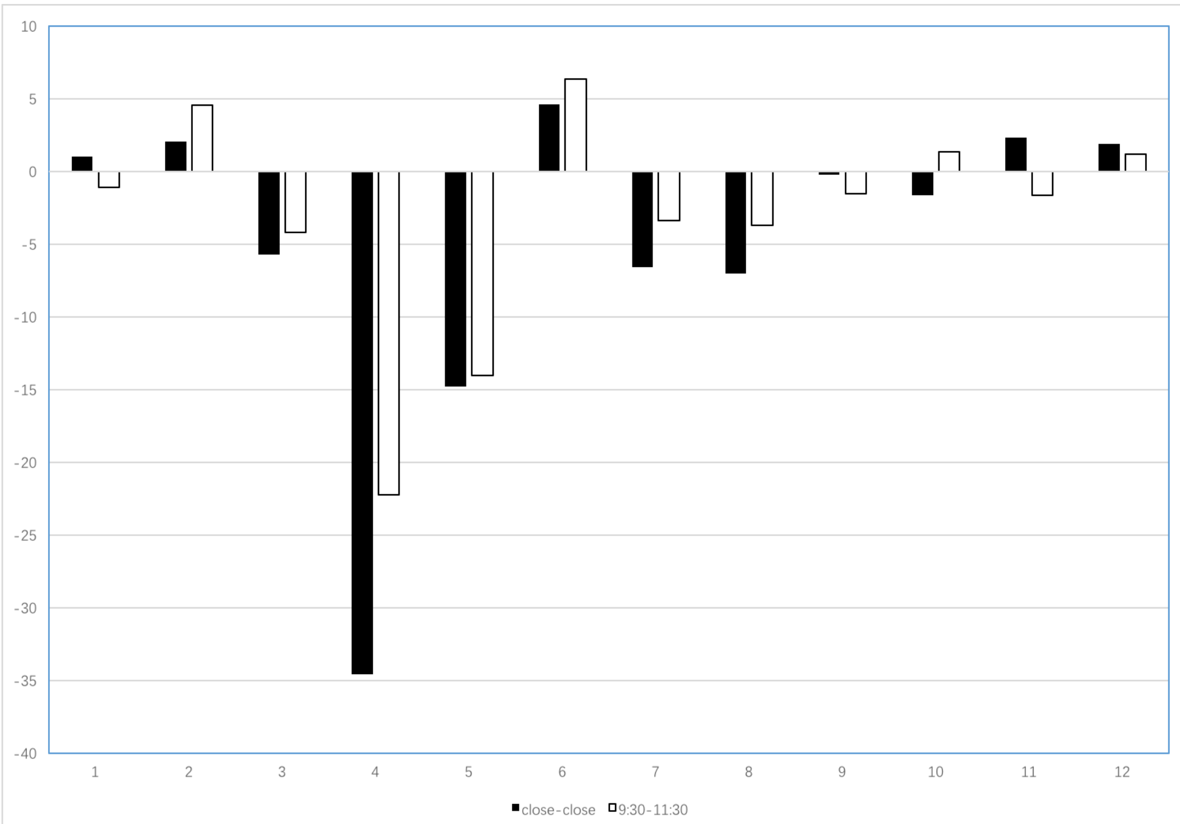
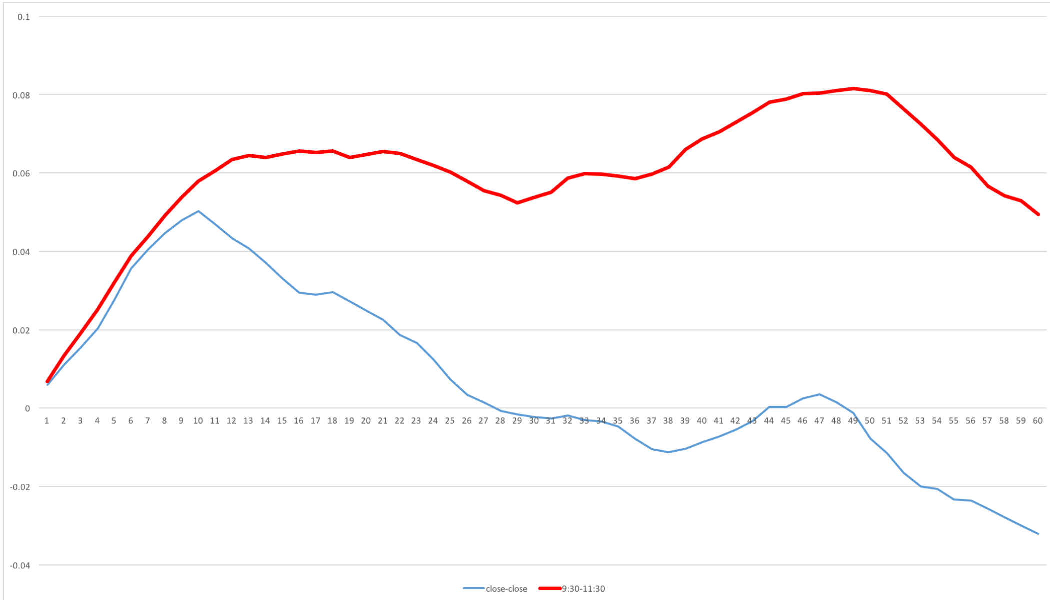
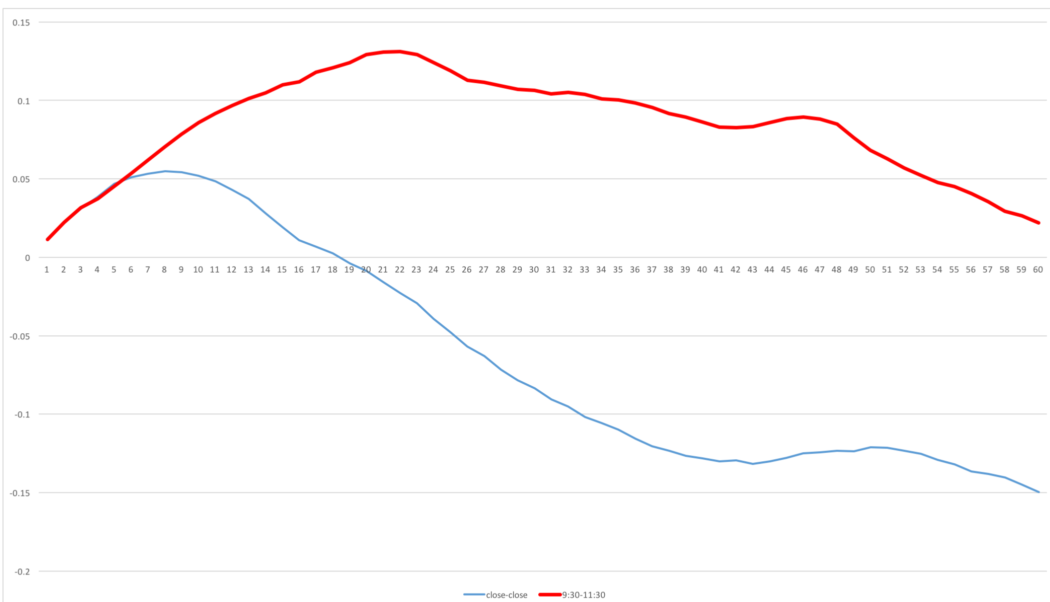


Figure 3: **The Performance of Momentum Strategies in 2009 Momentum Crash**

The figure shows the monthly returns of 2 momentum strategies in 2009 from January to December. The black bar is the conventional strategy, and the white bar is the strategy based on 9:30-11:30 returns.



(a) NYSE and AMEX



(b) NASDAQ

Figure 4: **The Long-term Performance of Momentum Strategies**

This figure presents long-term performance of two momentum strategies. The blue line is the conventional momentum strategy (MOM). It sorts stocks into deciles on the basis of past six month returns, then holds the long-short portfolio for 60 months. The red line is the momentum strategy based on first 2-hour returns (MOM^{F2H}). It sorts stocks into deciles on the basis of accumulated first 2-hour returns over past six months, then holds the long-short portfolio for 60 months. The figure shows the average monthly returns in the 60-month holding period. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than \$5 or in the bottom NYSE size decile are excluded.

Table 1: **Fama-MacBeth Regressions using Intraday Returns**

The table reports the estimated coefficients from Fama-Macbeth regressions of monthly stock returns on prior-month performance. The dependent variable is the monthly return from month $t+1$. The independent variables are stock performance from month t. R_t is the monthly return from month t. R_t^{F2H} is the accumulated 9:30-11:30 returns from month t. R_t^{L2H} is the accumulated 14:00-16:00 returns from month t. $LogSize_t$ is the log firm size at the end of month t. $LogBM_t$ is the log of firm book-to-market ratio at the end of month t. $Illiq_t$ is Amihud (2002) illiquidity measure in month t. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than $5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			R_{t+1}			
Intercept	2.7062*	2.8617**	2.7340*	2.7007*	2.7903**	2.8851**
	(1.93)	(2.08)	(1.94)	(1.92)	(1.97)	(2.06)
log $Size_t$	-0.0535	-0.0515	-0.0543	-0.0622	-0.0616	-0.0623
	(-1.04)	(-1.00)	(-1.04)	(-1.19)	(-1.17)	(-1.19)
log BM_t	0.1169	0.1407	0.1216	0.0963	0.1091	0.1208
	(0.73)	(0.86)	(0.72)	(0.62)	(0.69)	(0.74)
$Illiq_t$	-1.7903	-1.9583	-1.3356	-1.8292	-1.5128	-1.6576
	(-1.39)	(-1.54)	(-1.07)	(-1.43)	(-1.14)	(-1.30)
R_t	-0.0056			-0.0154***	-0.0000	
	(-1.13)			(-3.01)	(-0.01)	
R_t^{F2H}		0.0134**		0.0244***		0.0120**
		(2.37)		(4.11)		(2.14)
R_t^{L2H}			-0.0293***		-0.0283***	-0.0267***
			(-4.88)		(-5.07)	(-4.40)
Observations	636158	636158	636158	636158	636158	636158
R^2	0.0341***	0.0298***	0.0273***	0.0364***	0.0356***	0.0322***

Table 2: **Profits of Monthly Reversal Strategies (Losers minus Winners)**

This table reports the results from time series regressions of reversal strategies' returns on the Fama-French three factors and four factors. At the end of each month, stocks are ranked into deciles on the basis of lagged performance; then an equally weighted loser-minus-winner portfolio is immediately formed and held for one month. Columns (1) and (2) present the results of conventional reversal strategy (REV), which uses monthly return as performance measure. Columns (3) and (4) present the results of reversal strategy based on accumulated first 2-hour returns (REV^{F2H}), which uses monthly accumulated first 2-hour return as performance measure. Columns (5) and (6) present the results of reversal strategy based on accumulated last 2-hour returns (REV^{L2H}), which uses monthly accumulated last 2-hour return as performance measure. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than $5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	REV		REV^{F2H}		REV^{L2H}	
Raw Returns	0.1260		-0.5819**		0.6072***	
	(0.33)		(-2.06)		(3.28)	
Intercept	-0.1555	0.0268	-0.7786***	-0.7354***	0.5345***	0.5854***
	(-0.42)	(0.07)	(-3.24)	(-3.02)	(2.98)	(3.24)
MKT	0.4656***	0.3783***	0.3720***	0.3504***	0.1773***	0.1518***
	(5.34)	(4.16)	(6.57)	(5.86)	(4.20)	(3.42)
SMB	-0.1737	-0.1429	0.2334***	0.2421***	-0.2351***	-0.2249***
	(-1.48)	(-1.23)	(3.05)	(3.15)	(-4.13)	(-3.94)
HML	0.1346	0.0612	-0.3351***	-0.3514***	0.0227	0.0035
	(1.09)	(0.49)	(-4.18)	(-4.31)	(0.38)	(0.06)
UMD		-0.2224***		-0.0554		-0.0654*
		(-2.95)		(-1.11)		(-1.77)
Observations	263	263	263	263	263	263
R^2	0.0967	0.1248	0.3073	0.3106	0.1048	0.1155

Table 3: **Short-Term Reversal Based on Returns Before the Market Close**

This table reports the results from time series regressions of reversal strategies' returns on the Fama-French three factors, four factors, and five factors. At the end of each month, stocks are ranked into deciles on the basis of lagged performance; then an equally weighted loser-minus-winner portfolio is immediately formed and held for one month. Columns (1), (2) and (3) present the results of reversal strategy based on accumulated last 2-hour returns (REV^{L2H}), which uses monthly accumulated last 2-hour return as performance measure. Columns (4), (5) and (6) present the results of reversal strategy based on accumulated last 1-hour returns (REV^{L1H}), which uses monthly accumulated last 1-hour return as performance measure. Columns (7), (8) and (9) present the results of reversal strategy based on accumulated last 10-minute returns (REV^{L10M}), which uses monthly accumulated last 10-minute return as performance measure. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than $5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2) REV^{L2H}	(3)	(4)	(5) REV^{L1H}	(6)	(7)	(8) REV^{L10M}	(9)
Raw Returns		0.6072***			0.7182***			0.8547***	
		(3.28)			(4.52)			(5.86)	
Sharpe Ratio		0.20			0.28			0.36	
Intercept	0.5345***	0.5854***	0.5037***	0.6542***	0.6600***	0.6177***	0.8791***	0.8743***	0.8538***
	(2.98)	(3.24)	(3.46)	(4.38)	(4.35)	(4.37)	(6.88)	(6.75)	(6.72)
MKT	0.1773***	0.1518***	0.0390	0.1510***	0.1481***	0.0896**	-0.0164	-0.0140	-0.0423
	(4.20)	(3.42)	(1.05)	(4.29)	(3.97)	(2.50)	(-0.54)	(-0.44)	(-1.31)
SMB	-0.2351***	-0.2249***	-0.2352***	-0.2586***	-0.2574***	-0.2627***	-0.2750***	-0.2760***	-0.2785***
	(-4.13)	(-3.94)	(-5.12)	(-5.44)	(-5.38)	(-5.89)	(-6.77)	(-6.75)	(-6.95)
HML	0.0227	0.0035	-0.0181	0.0746	0.0724	0.0613	0.1553***	0.1571***	0.1517***
	(0.38)	(0.06)	(-0.37)	(1.50)	(1.43)	(1.29)	(3.64)	(3.62)	(3.57)
UMD		-0.0654*	-0.0125		-0.0075	0.0199		0.0062	0.0195
		(-1.77)	(-0.42)		(-0.24)	(0.68)		(0.23)	(0.74)
DMU			0.4770***			0.2472***			0.1198***
			(11.90)			(6.35)			(3.42)
Observations	263	263	263	263	263	263	263	263	263
R^2	0.1048	0.1155	0.4290	0.1572	0.1574	0.2714	0.2674	0.2675	0.2994

Table 4: **Characteristics of Afternoon-Return-Sorted Decile Portfolios**

This table reports the average characteristics of ten portfolios sorted on the basis of prior-month accumulated last 2-hour returns. At the end of month t, stocks are sorted into deciles on the basis of $R_{i,t}^{L2H}$. Ten equal-weighted portfolios are constructed by holding the stocks in each decile in month $t+1$. The average characteristics of each portfolio are calculated. The characteristics include raw returns, 4-factor alphas, stock prices, firm sizes, illiquidity measure, volatility and institutional ownership. The raw returns and alphas are expressed in percentage terms. The stock prices are expressed in dollar term. The firm sizes are expressed in millions of dollars. The illiquidity measure is based on Amihud (2002). The volatility is defined as the standard deviation of a stock's daily return in each month. The institutional ownership is defined as the shares owned by active mutual funds divided by the total number of outstanding shares.

Portfolio	Return	4-Factor Alpha	Price	Size	Amihud Illiquidity	Volatility	Institutional Ownership(%)
1	1.190	0.31	38.61	2,104	0.44	3.40	14.9
2	1.184	0.38	42.82	4,826	0.27	2.72	16.2
3	1.131	0.36	62.99	6,180	0.20	2.45	16.1
4	1.114	0.35	68.37	7,141	0.18	2.30	16.1
5	1.096	0.35	84.82	7,206	0.18	2.26	16.0
6	1.012	0.29	81.21	6,904	0.18	2.27	16.0
7	0.922	0.16	91.85	6,055	0.19	2.37	16.1
8	0.911	0.16	91.24	4,763	0.24	2.54	16.0
9	0.854	0.10	57.80	3,002	0.29	2.83	15.9
10	0.471	-0.35	44.28	1,367	0.51	3.42	13.9

Table 5: **Subsamples and Subperiods Results**

This table reports the performance of the reversal strategy based on accumulated last 2-hour returns (REV^{L2H}) within different subsamples and subperiods. REV^{L2H} strategy sorts stocks into decile on the basis of monthly accumulated last 2-hour returns, and buys losers and sells winners, then holds the long-short portfolio for one month. Panel A presents the results when excluding January. Panel B presents the results in size terciles. The Small Size sample includes the stocks within NYSE size deciles of 2, 3 and 4. The Mid Size sample includes the stocks within NYSE size deciles of 5, 6 and 7. The Large Size sample includes the stocks within NYSE size deciles of 8, 9 and 10. Panel C presents the performance of REV^{L2H} in subperiods of 1993-2003 and 2004-2014. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than $5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Return	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha
Panel A: Excluding January				
	0.7421***	0.6545***	0.6651***	0.7117***
	(4.44)	(4.12)	(4.08)	(4.79)
Panel B: Size Terciles				
Small	0.7049***	0.6465***	0.6619***	0.6217***
	(5.11)	(4.79)	(4.83)	(4.91)
Mid	0.4366**	0.3749**	0.3555**	0.3108*
	(2.39)	(2.21)	(2.06)	(1.91)
Large	0.4173**	0.4087**	0.3675**	0.3139**
	(2.49)	(2.44)	(2.17)	(2.04)
Panel C: Subperiods				
1993-2003	1.0430***	0.9626***	1.0256***	0.8151***
	(3.83)	(3.78)	(3.92)	(3.40)
2004-2014	0.3983**	0.3523**	0.3416**	0.3673**
	(2.45)	(2.17)	(2.10)	(2.27)

Table 6: **Fama-MacBeth Regressions using Morning Returns**

The table reports the estimated coefficients from Fama-Macbeth regressions of monthly stock returns on prior-month performance. The dependent variable is the monthly return from month $t+1$. The independent variables are stock performance from month t and months from $t-6$ to $t-1$. R_t is the monthly return from month t; $R_{t-6,t-1}$ is the six-month returns from month $t-6$ to $t-1$; $R_{t-12,t-7}$ is the six-month returns from month $t-12$ to $t-7$. $R^{F2H}_{t-6,t-1}$ is the accumulated first 2-hour returns from month $t-6$ to $t-1$. $R^{F2H}_{t-12,t-7}$ is the accumulated first 2-hour returns from month $t-12$ to $t-7$. $LogSize_t$ is the log firm size at the end of month t. $LogBM_t$ is the log of firm book-to-market ratio at the end of month t. $Illiq_t$ is Amihud (2002) illiquidity measure in month t. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than \$5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			R_{t+1}			
Intercept	2.5830**	2.4771*	2.6289**	2.3868*	2.4522*	2.4062*
	(2.02)	(1.82)	(2.05)	(1.82)	(1.78)	(1.84)
$Log(Size)_t$	-0.045	-0.063	-0.0523	-0.0561	-0.0541	-0.0603
	(-0.90)	(-1.16)	(-1.05)	(-1.04)	(-1.02)	(-1.12)
$Log(BM)_t$	0.1394	0.0723	0.1303	0.0746	0.083	0.066
	(0.99)	(0.47)	(0.97)	(0.52)	(0.52)	(0.46)
R_t	-0.0084*	-0.0087*	-0.0087*	-0.0087*	-0.0083	-0.0089*
	(-1.70)	(-1.74)	(-1.77)	(-1.68)	(-1.65)	(-1.72)
$R_{t-6,t-1}$	0.0046		0.0024			
	(1.37)		(0.67)			
$R^{F2H}_{t-6,t-1}$		0.0072***	0.0056***			
		(3.39)	(2.84)			
$R_{t-12,t-7}$				0.0012		-0.0006
				(0.49)		(-0.25)
$R^{F2H}_{t-12,t-7}$					0.0052***	0.0053***
					(2.61)	(3.06)
Observations	597626	597626	597626	597626	597626	597626
R^2	0.0449	0.0390	0.0472	0.0409	0.0376	0.0429

Table 7: **Momentum Strategies**

This table reports the results of time series regressions of momentum strategies' returns on the Fama-French three and four factors. Panel A presents the results of the strategies with $J = 6, K = 6$. At the end of each month, the stocks are ranked into deciles on the basis of prior 6-month performance. Skipping a month, an equally-weighted winner-minus-loser portfolio is formed and held for six months. Panel B presents the results of the strategies with $J = 6, K = 1$. At the end of each month, the stocks are ranked into deciles on the basis of prior 6-month performance. Skipping a month, an equally-weighted winner-minus-loser portfolio is formed and held for one month. Panel C presents the results of the echo strategies. At the end of month $t-1$, the stocks are ranked into deciles on the basis of 6-month performance in month $t-12$ to $t-7$. An equally-weighted winner-minus-loser portfolio is formed and held for one month. MOM strategies use close-close returns as performance measure. MOM^{F1H} strategies use accumulated first 1-hour returns as performance measure. MOM^{F2H} strategies use accumulated first 2-hour returns as performance measure. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than $5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	MOM		MOM^{F1H}		MOM^{F2H}	
Panel A: $J = 6, K = 6$						
Raw Return	0.8897 (2.16)		0.6727 (2.13)		0.8269 (2.59)	
Sharpe Ratio	0.13		0.13		0.16	
Intercept	1.1445*** (2.72)	0.1222 (0.61)	0.8612*** (3.33)	0.4711** (2.16)	1.0400*** (3.78)	0.5329** (2.59)
MKT	-0.3749*** (-3.76)	0.1268** (2.56)	-0.3505*** (-5.73)	-0.1579*** (-2.93)	-0.4006*** (-6.15)	-0.1503*** (-2.96)
SMB	0.3402** (2.54)	0.1605** (2.54)	-0.3311*** (-4.01)	-0.4012*** (-5.81)	-0.2266** (-2.58)	-0.3177*** (-4.89)
HML	-0.2988** (-2.10)	0.1349** (1.97)	0.5403*** (6.17)	0.7061*** (9.48)	0.4899*** (5.26)	0.7054*** (10.07)
UMD		1.2721*** (30.89)		0.4894*** (10.93)		0.6360*** (15.10)
R^2	0.0789	0.7974	0.3594	0.5568	0.3056	0.6248

Continued:

	(1)	(2)	(3)	(4)	(5)	(6)
	MOM		MOM^{F1H}		MOM^{F2H}	
Panel B: $J = 6, K = 1$						
Raw Return	1.1353		0.6693		0.9966	
	(2.43)		(2.16)		(3.18)	
Sharpe Ratio	0.15		0.13		0.19	
Intercept	1.3905***	0.3579	0.8829***	0.5886***	1.2402***	0.8233***
	(3.08)	(1.41)	(3.60)	(2.64)	(4.78)	(3.90)
MKT	-0.5090***	-0.0023	-0.3932***	-0.2482***	-0.4513***	-0.2458***
	(-4.77)	(-0.04)	(-6.75)	(-4.49)	(-7.34)	(-4.71)
SMB	0.5070***	0.3255***	-0.2946***	-0.3487***	-0.1945**	-0.2712***
	(3.53)	(4.07)	(-3.77)	(-4.96)	(-2.36)	(-4.08)
HML	-0.1928	0.2452***	0.5446***	0.6673***	0.4718***	0.6456***
	(-1.26)	(2.84)	(6.60)	(8.83)	(5.42)	(9.04)
UMD		1.2847***		0.3678***		0.5210***
		(24.72)		(8.08)		(12.10)
R^2	0.1078	0.7272	0.3983	0.5175	0.3465	0.5797
	$ECHO$		$ECHO^{F1H}$		$ECHO^{F2H}$	
Panel C: Echo						
Raw Return	0.6718		0.7367		0.8473	
	(1.73)		(2.15)		(2.48)	
Sharpe Ratio	0.11		0.13		0.15	
Intercept	0.8448**	0.0120	0.8770***	0.4717*	0.9988***	0.5168**
	(2.19)	(0.06)	(3.08)	(1.96)	(3.36)	(2.19)
MKT	-0.1811**	0.2494***	-0.2488***	-0.0394	-0.2812***	-0.0321
	(-1.99)	(4.69)	(-3.72)	(-0.66)	(-4.02)	(-0.55)
SMB	-0.0071	-0.1569**	-0.4420***	-0.5149***	-0.3296***	-0.4163***
	(-0.06)	(-2.31)	(-4.91)	(-6.81)	(-3.50)	(-5.63)
HML	-0.4156***	-0.0321	0.6031***	0.7897***	0.5317***	0.7536***
	(-3.19)	(-0.44)	(6.28)	(9.61)	(5.29)	(9.38)
UMD		1.0857***		0.5284***		0.6284***
		(24.51)		(10.71)		(13.03)
R^2	0.0462	0.7088	0.3399	0.5399	0.2705	0.5559

Table 8: **Size-sorted Momentum Portfolios**

This table reports the performance of momentum strategies within different size groups. The strategies are same as in Table 2.7. Panel A presents the 3-factor and 4-factor alphas of strategies with $J = 6, K = 6$. Panel B presents the alphas of strategies with $J = 6, K = 1$. Panel C presents the alphas of echo strategies. MOM strategies sort stocks on basis of close-close returns. MOM^{F2H} strategies sort stocks on the basis of accumulated first 2-hour returns. The Small Size sample includes the stocks within NYSE size deciles of 2, 3 and 4. The Mid Size sample includes the stocks within NYSE size deciles of 5, 6 and 7. The Large Size sample includes the stocks within NYSE size deciles of 8, 9 and 10. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than $5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	3-Factor Alpha		4-Factor Alpha	
	MOM	MOM^{F2H}	MOM	MOM^{F2H}
Panal A: $J = 6, K = 6$				
Small	1.1669***	1.2153***	0.1785	0.6797***
	(2.85)	(4.27)	(0.90)	(3.22)
Mid	0.9663**	0.7480**	-0.089	0.1774
	(2.16)	(2.45)	(-0.38)	(0.78)
Large	1.1021***	0.8359***	0.1449	0.4288**
	(2.79)	(3.29)	(0.77)	(2.05)
Panal B: $J = 6, K = 1$				
Small	1.5397***	1.5844***	0.5484*	1.1632***
	(3.39)	(5.85)	(1.96)	(5.17)
Mid	1.0340**	0.9642***	-0.074	0.4741*
	(2.07)	(3.03)	(-0.25)	(1.79)
Large	1.2141**	0.7613***	0.1586	0.4569*
	(2.58)	(2.86)	(0.57)	(1.86)
Panal C: Echo				
Small	0.7860**	1.0865***	-0.0426	0.6082**
	(1.99)	(3.55)	(-0.18)	(2.46)
Mid	0.8782*	0.6984*	-0.0376	0.1175
	(1.95)	(1.95)	(-0.13)	(0.41)
Large	1.0841***	1.0413***	0.3148	0.6470**
	(2.74)	(3.50)	(1.19)	(2.50)

Table 9: **Subsamples and Subperiods Results**

This table reports the performance of the momentum strategies within different subsample and subperiods. The strategies are same as in Table 2.7. MOM strategies sort stocks on the basis of close-close returns. MOM^{F2H} strategies sort stocks on the basis of accumulated first 2-hour returns. Panel A presents the results when excluding January. Panel B presents the results in subperiods of 1993-2003 and 2004-2014. Panel C presents the results when using value-weighted portfolios. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than $5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$J=6, K=6$		$J=6, K=1$		Echo	
	MOM	MOM^{F2H}	MOM	MOM^{F2H}	MOM	MOM^{F2H}
Panel A: Excluding Jan						
3-Factor	1.3996***	1.2813***	1.6645***	1.4736***	1.0958***	1.2721***
	(3.67)	(5.34)	(3.69)	(5.94)	(2.92)	(4.71)
4-Factor	0.1732	0.7376***	0.3466	1.0162***	0.0385	0.7590***
	(0.95)	(3.82)	(1.25)	(4.65)	(0.17)	(3.27)
Panel B: Subperiods						
1993-2003						
3-Factor	1.9913***	1.1430**	2.3094***	1.3881***	1.7357**	1.2838**
	(2.70)	(2.50)	(2.84)	(3.33)	(2.43)	(2.39)
4-Factor	0.2781	0.3859	0.5352	0.8224**	0.3001	0.5060
	(0.85)	(1.07)	(1.20)	(2.26)	(0.75)	(1.15)
2004-2014						
3-Factor	0.2230	0.6269**	0.4059	0.8148***	0.1323	0.5504**
	(0.56)	(2.36)	(0.91)	(2.87)	(0.36)	(2.14)
4-Factor	-0.1373	0.4164**	0.0313	0.6340***	-0.1812	0.3668**
	(-0.86)	(2.61)	(0.13)	(3.17)	(-0.96)	(2.05)
Panel C: Value Weight						
3-Factor	1.2557***	0.7589***	1.2482**	0.5949**	1.2988***	1.0407***
	(3.18)	(3.04)	(2.55)	(2.04)	(3.19)	(3.49)
4-Factor	0.3113	0.3733*	0.1527	0.2612	0.5838*	0.6841**
	(1.57)	(1.78)	(0.53)	(0.97)	(1.92)	(2.55)

Table 10: **Spanning Tests**

This table reports the results of time series regressions of MOM and MOM^{F2H} strategies' returns on the Fama-French three factors and each other. The momentum strategies are same as in Table 2.7. MOM is the strategy based on close-close returns. MOM^{F2H} is the strategy based on accumulated first 2-hour returns. The sample includes all common stocks on NYSE, AMEX, and NASDAQ from 1993 - 2014. Stocks with prices less than $5 or in the bottom NYSE size decile are excluded. Stock returns are expressed in percentage terms. T-statistics, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(5)
	$J=6, K=6$		$J=6, K=1$		Echo	
	MOM	MOM^{F2H}	MOM	MOM^{F2H}	MOM	MOM^{F2H}
Intercept	-0.0780	0.4426**	-0.0478	0.7013***	-0.1509	0.4979**
	(-0.30)	(2.56)	(-0.13)	(3.57)	(-0.60)	(2.59)
MKT	0.0972	-0.2004***	0.0284	-0.2593***	0.0993*	-0.1739***
	(1.52)	(-4.84)	(0.32)	(-5.45)	(1.66)	(-3.85)
SMB	0.5610***	-0.3872***	0.7404***	-0.3875***	0.3215***	-0.3253***
	(6.82)	(-7.06)	(6.76)	(-6.18)	(4.02)	(-5.39)
HML	-0.8978***	0.6663***	-0.7482***	0.5432***	-0.9457***	0.7781***
	(-9.89)	(11.43)	(-6.19)	(8.36)	(-10.78)	(11.87)
MOM^{F2H}	1.1601***		1.1863***		0.9969***	
	(20.29)		(14.67)		(19.53)	
MOM		0.5214***		0.3786***		0.5929***
		(20.29)		(14.67)		(19.53)
Observations	263	263	263	263	263	263
R^2	0.6339	0.7265	0.5075	0.6400	0.6100	0.7017