Intraday Patterns in the Cross-Section of Stock Returns

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Abstract

Motivated by the literature on investment flows and optimal trading, this paper examines intraday predictability in the cross-section of stock returns. We confirm a well-known return reversal commonly associated with bid-ask bounce. Notably, we also find significant continuation of returns at half-hour intervals that are exact multiples of a trading day, and this effect lasts for forty trading days. Percentage changes in volume, order imbalance, and volatility exhibit similar patterns, but do not explain the return patterns. Additionally, bid/ask spreads do not explain the return pattern. The return continuation at daily frequencies is more pronounced for, but not restricted to, the first and last half-hour periods of the day. These effects are not driven by firm size, systematic risk premia, or inclusion in the S&P500 index. The pattern is robust to controlling for a number of documented types of periodicity. Our results suggest that traders may wish to time portfolio rebalancing to account for these persistent intraday patterns.

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1. Introduction

We postulate that systematic trading and institutional fund flows lead to predictable patterns in trading volume and order imbalances among common stocks. If these patterns are fully anticipated, then they should not cause predictability in stock returns. However, we find periodic autocorrelation in the cross-section of stock returns. We study the nature of intra-day periodicity by dividing the trading day into 13 half-hour trading intervals. A stock's return over a trading interval is negatively related to its returns over recent intervals, which is consistent with the negative autocorrelation induced by bid-ask bounce. However, there is a statistically significant positive relation between a stock's return over an interval and its subsequent returns at daily frequencies (i.e., 13, 26, 39, ... interval lags). That is, knowing that the equity of XYZ, Inc. is high between 1:30 PM and 2:00 PM today has explanatory power for the return on XYZ, Inc. equity at the same time tomorrow and subsequent days. This effect is statistically significant for up to forty trading days.

Two disparate strands of literature suggest that there may be intra-day periodicity in trading volume and order imbalances. First, there is substantial evidence that fund flows to certain types of institutional investors exhibit autocorrelation. Del Guercio and Tkac (2002, Table 5) find that flows to mutual funds exhibit significant autocorrelation while flows to pension fund managers show much weaker autocorrelation. Figure 1 of Frazzini and Lamont (2008) illustrates that fund flows into mutual funds in the current quarter are related to fund flows in many future quarters (up to 18 quarters). Lou (2008) also finds very persistent fund flows in to and out of mutual funds. Blackburn, Goetzmann, and Ukhov (2007) find that the autocorrelation in mutual fund flows varies by category, with value funds exhibiting greater autocorrelation in flows than growth funds. Even without explicit autocorrelation in fund flows, there may be autocorrelation in trading by a given manager. For example, some managers rebalance individual customers' separate accounts on successive days. Campbell, Ramadorai, and Schwartz (2007) use quarterly 13-F filings and intra-day trading data from the New York Stock Exchange's Trade and Quotation (TAQ) database to estimate trading behavior of all institutional investors at a daily frequency. Their evidence indicates that institutional trading is highly persistent. That is, institutional investment managers tend to buy or sell the same stocks on successive days.

Second, there is a growing literature on trading algorithms which are designed to minimized trading costs or optimize the trade-off between trading costs and the uncertainty associated with the prices obtained over the trading program. For example, Bertsimas and Lo (1998) study the problem of minimizing the expected cost of executing an exogenously specified trade of size, X, over an exogenously given horizon. In the simplest version of their model the price impact of trade is permanent and proportional to the number of shares traded. Non-trade information causes asset prices follow a random walk. In this setting the optimal (lowest expected impact) strategy is to trade equal number of shares at every point in time. If conditional mean price changes are non-zero, then it would be optimal to either speed up, or slow down, trading relative to this base case (depending on the expected direction of price movements and the desired direction of trade).

A number of papers extend the results of Bertsimas and Lo (1998) to incorporate the risk of the trading program, in addition to the expected trading cost, for risk averse traders (e.g., Almgren and Chriss (2000), Grinold and Kahn (2000), Huberman and Stanzl (2005), and Engle and Ferstenberg (2007)). Under price dynamics similar to Bertsimas and Lo (1998) and a price impact function with permanent and transitory components, Almgren and Chriss (2000) derive an efficient frontier of optimal trading strategies that explicitly trade off execution costs with the risk of adverse price movements when traders have mean-variance utility. Linear price impact functions allow for closed form solutions. In these papers, the expected cost minimizing strategy of Bertsimas and Lo (1998) is optimal for risk neutral agents. Risk averse agents will generally liquidate the portfolio more rapidly in order to reduce the variance of the execution cost. Thus, these papers imply a trading trajectory that executes quickly at the beginning of the trading horizon and slows down as time passes. Hora (2006) uses a different preference specification which leads to an optimal trading strategy that trades rapidly at the beginning and end of the trading horizon and slowly in the middle of the period.

The horizon over which trading takes place is generally unspecified in the models and could be a day, a month, year, or some other interval. Almgren and Lorenz (2006) argue that a trading horizon of one day is consistent with the manner in which many institutions trade. Consistent with this, Breen, Hodrick, and Korajczyk (2002) find that 92.5% of a sample of institutional orders are completed the same day that trading is initiated.

The autocorrelation of fund flows and the application of trading algorithms discussed above implies the existence of daily patterns in volume and order imbalances in individual stocks. If Fund A receives fund flows today and buys stock XYZ using the Almgren and Chriss (2000) algorithm then A will trade XYZ more aggressively in the morning and less aggressively as the day progresses. Since fund flows are autocorrelated, Fund A is likely to receive fund flows tomorrow. Fund A is likely to buy XYZ tomorrow using the same trading algorithm, leading to volume and order imbalances in XYZ tomorrow at the same time as today.

More anecdotal evidence indicates that this correlation in periodicity may be likely to happen even without explicitly invoking trading algorithms. Large equity managers have demanding schedules, involving client meetings, staff meetings, compliance, and reporting. The decision to buy or sell stock may require research analysis or portfolio optimization. Then the manager must decide to use brokers or relay the transactions through a crossing network such as Island or Archipelago. These networks cross at certain times of the day, leaving unfilled orders at the end. A busy manager may find it cheap and expedient to execute these orders at specific times of the day to leave remaining time available for other trading, research, and risk management activity. Use of a trading algorithm that specifies a specific pattern of trades, such as those discussed above, would tend to strengthen this periodicity. Some types of institutional traders may have other reasons for periodicity in trading. For example index funds tend to trade at the close to reduce tracking error.

Consistent with periodicity in volume and order imbalance, there is a long literature on intra-day patterns in volume and volatility. Intra-day patterns in returns and volatility are found by Wood, McInish, and Ord (1985). Returns and volatility are higher, on average, at the beginning and end of the trading day. Harris (1986) and Andersen and Bollerslev (1997) find similar results. Jain and Joh (1988) find that volume is highest in the first hour of trading and second highest in the last hour of trading.

While intra-day patterns of volume and volatility found in Wood, McInish, and Ord (1985), Harris (1986), Jain and Joh (1988), and Pagano, Peng, and Schwartz (2008) can be justified with models of discretionary liquidity trading (e.g., Admati and Pfleiderer (1998) and Hora (2006)), predictable patterns in returns are harder to explain.

There is a long-standing literature on seasonal return patterns, say at the monthly or quarterly frequency, in stock returns (see Keim (1983), Ariel (1987), Lakonishok and Smidt (1988)). Some of this periodicity is consistent with predictable patterns of trading by investors. For example, Keim (1989) finds the turn-of-the-year trading patterns induce patterns in the probability that trades that occur at the ask price versus the bid price. He finds that this trading pattern explains the size-related turn-of-the-year effect in stock prices.

The return periodicity that we find is not due to changes in the frequency of trades occurring at the bid or ask prices, as in Keim (1989). Our relation is stronger over the first and last half-hour of the trading day, as one might expect given the patterns in volume and volatility, but remains statistically significant over the other periods of the day. Thus, the intra-day return pattern is not merely due to uniformly high returns at the beginning and end of the trading day.

Alternatively, markets may respond to news that arrives on a daily schedule. Newscasts and conference calls occur at regular times of the day, and behavioral biases may cause traders to overreact or under-react to salient news (Tversky and Kahneman (1974)) leading to return periodicity. One would expect that the availability biases, found in the psychology literature would be more pronounced in large (i.e., salient) stocks that are subject to regular media coverage instead of smaller, less liquid stocks. We find the opposite. That is, the return periodicity is larger for smaller capitalization stocks. Our observed return periodicity is also consistent with the information acquisition model of Holden and Subrahmanyam (2002) if agents tend to become informed at intervals that correspond to our observed periodicity.

Finally, if there are regular news cycles, then traders may be reluctant to hold stocks during risky times. For example, if market-wide information is released at 3:30 then high beta stocks may have a higher return premium at those times. This suggests that daily phenomena will be more pronounced among risky stocks than safe stocks. We do not find support for this hypothesis.

We show that trading volume has similar patterns to those of returns, i.e. firms that experience a relatively high change in their trading volume over a particular half-hour interval of a day typically experience a high change in their volume during the same half-hour interval during each of the next few days. Although related, the periodicity in trading volume does not completely explain the periodicity of returns. We also split volume into that due to large versus small trade size. Both measures of volume show daily periodicity, but neither explains the daily return periodicity. Oddly, the level of order imbalance (OI) does not exhibit obvious periodicity, even when partitioned into small versus large trades, e.g. Hvidkjaer (2008). However, percentage changes in order imbalance exhibit periodicity similar to returns, but that pattern in order imbalances does not explain the pattern in returns. Possibly the algorithm we use to classify buyer-initiated versus seller-initiated trades, and to calculate OI, results in error-prone estimates for our experimental design (i.e., individual stocks over short, half-hour, intervals).

Several other tests indicate that the intra-day periodicity at the daily frequency is not merely an artifact of previously shown patterns. For example, it is not concentrated in any particular weekday and, therefore, is not a manifestation of the day-of-the-week effect (see French (1980) and Smirlock and Starks (1986)). It is not concentrated in any particular month (for monthly seasonality see Heston and Sadka (2008a, b)). The effect is also not particularly related to the turn-of-the-month effect (Ariel (1987)) or the turn-of-the-quarter effect (Carhart, Kaniel, Musto, and Reed (2002)). The pattern of intra-day returns is highly persistent as it seems to last for over a month (20 trading days). It is not due to a particular market capitalization group, inclusion in the S&P500 index, nor a manifestation of intra-day movements in systematic risk. There is substantial evidence of intra-day periodicity of return volatility (Andersen and Bollerslev (1997)), which we also find in our sample. However, patterns in volatility do not explain our return periodicity.

Finally, we compare the results for the post-decimalization period to prior periods which include 1993-1997, for which the minimum price increment was one eighth of a dollar, and 1997-2000, for which the minimum price increment was one sixteenth of a dollar. We find that the strength of the intra-day periodicity is greatest in the post-decimalization period.

2. Patterns of Resilience in Intra-day Stock Returns

We begin this study by measuring intra-day persistence in the cross-section of stock returns. It is well-known that short-term stock returns are negatively autocorrelated (Lehmann (1990) and Lo and MacKinlay (1990)). While this phenomenon does not occur in the model of Glosten and Milgrom (1985), in which the spreads are due solely to adverse selection caused by informed traders, it appears in other models with bid-ask spreads (Roll (1984) and Glosten and Harris (1988)), specialist inventory effects (Stoll (1978)), or other non-adverse selection costs associated with market-making. We want to study the resilience of stock prices based on the pattern of autocorrelation over various horizons.

Our sample of firms consists of all New York Stock Exchange (NYSE) listed firms from January 2001 through December 2005. The period of study is chosen to coincide with the period of decimalization, the transition to which was completed by February 2001. We use the NYSE Trade and Quotation (TAQ) database to calculate intra-day stock returns. For each stock we calculate returns over half-hour intervals. This gives thirteen intra-day intervals per trading day from 9:30 a.m. to 4:00 p.m. This excludes after-hours trading and overnight open-close price movements. Note that settlement on stock transactions occurs after the end of the trading day. This means trades at different times do not need to earn the risk-free rate intra-day. In other words, intra-day stock returns give compensation for liquidity and risk, not for time value of money. In addition to returns, we also measure changes in volume defined as the logarithm of ratio of the number of shares traded over a half-hour interval relative to the number of shares traded in the previous half-hour interval. This gives a measure of the price and quantity movements of individual stocks throughout the day.

We analyze intra-day stock returns using the cross-sectional regression methodology of Jegadeesh (1990). For each half-hour period in our data set we run cross-sectional regressions of half-hour stock returns on lagged half-hour returns

$$r_{it} = \alpha_{tk} + \gamma_{tk} r_{i,t-k} + e_{it}, \quad (1)$$

where r_{it} is return on stock i in the half-hour interval, t. The slope coefficients γ_{tk} represent the response of returns at half-hour t to returns over a previous interval lagged by k half-hour periods. Therefore, we call them "return responses."[1] In addition to the simple regression (1), we also use a multiple regression to estimate all return responses jointly

$$r_{it} = \alpha_t + \gamma_{t1} r_{i,t-1} + \gamma_{t2} r_{i,t-2} + ... + \gamma_{t65} r_{i,t-65} + e_{it}. \quad (2)$$

Both the simple regression and the multiple regression use all firms with returns available in interval t and interval $t - k$. Presently we assume the return responses are constant at different times of the day t, and vary over different lags k. Later we shall examine intra-day variation in the magnitude of these effects. We calculate the pattern of return effects by averaging average return responses over time for half-hour lags, k. Note that using cross-sectional regression in this way is different than measuring autocorrelation of stock returns. In particular, the cross-sectional regression subtracts an overall market effect, which reduces variance and focuses on returns relative to other stocks.

Figure 1 presents the average return responses across different lags (Panel A) for lags up to one week.[2] The data are scaled so the units for $\widehat{\gamma}_k$ are basis points. With thirteen half-hour intervals per day and five trading days per week, this produces 65 lagged intervals. Consistent with previous literature, the first several return responses are negative. This means that stock returns experience a reversal period lasting several hours. Following this reversal period the returns effects are positive, peaking at a horizons of that are exact multiples of 13 half-hours, or one trading day. The figure shows clear periodicity at daily intervals. Panel B of Figure 1 plots the t-statistics of $\widehat{\gamma}_k$ as estimated in Fama and MacBeth (1973). The t-statistics show the same type of periodicity. Over the first week the smallest t-statistic at the daily frequency (lags 13, 26, 39, 52, and 65) is 9.62.

[1]Following Fama (1976), these responses have the interpretation of excess returns on costless portfolios that had excess returns of 100% in a previous half-hour interval.

[2]We use Fama and MacBeth (1973) t-statistics, which assume no autocorrelation in the coefficients of the cross-sectional regressions, because we find no evidence of significant autocorrelation in the estimates of γ_k.

Table 1 Panel A shows the simple regression return responses are highly statistically significant at almost all lags. Table 1 Panel B shows the results of the multiple regression responses are similar to the simple regression in both magnitude and statistical significance. Over the period of one calendar day these results indicate that returns are temporarily reversed but then rebound.

Looking beyond 13 lags, the return effects over half-hour intervals on subsequent days remain largely negative, with statistically significant positive effects at exact daily multiples of 13 lags, i.e., 26, 39, 52, and 65. It appears that temporary price pressure is reversed at virtually all future times except at the same time interval on subsequent days.

Since the simple regression produces results almost identical to the multiple regression, a univariate specification (1) seems adequate. By focusing on one lag at a time, we can easily examine many different lags.

The implicit portfolio weights in the portfolio returns obtained from the estimated regression coefficients, $\widehat{\gamma}_k$, could be rather extreme (Lehmann and Modest (2005). Therefore, we also study the returns to explicit long-short portfolios formed on the basis of lagged half-hour returns. We use the methodology of Jegadeesh and Titman (1993) in which we sort stocks into equal-weighted deciles based on their returns over a previous half-hour interval. Figure 2 and Table 2 present those results extending the lags to roughly two trading months (520 lags). Two months seems long enough to for any autocorrelation to decay, and allows detection of potential effects at a weekly or monthly lag.

Based on a half-hour return on one day, the average difference between the top decile of winners and the bottom decile of losers is 3.01 basis points at the same time on the next day. In terms of economic magnitude, being able to capture 3 basis points is similar in magnitude to saving a \$0.01 commission on a stock priced at \$30/share (which is in line with institutional commission rates on common stock).

The average return difference remains positive on subsequent days, albeit smaller. The difference remains positive and statistically significant for up to 40 days (520 half-hours). It appears there is a persistent and predictable pattern in intra-day stock transaction prices. When a stock goes up on one day, buyers earn a return premium by buying the stock prior to the same time interval on future days. Conversely sellers provide a discount by selling at this time when they could expect a higher average price 30 minutes later.

A. Patterns Across Past-Return Deciles

We develop and compare strategies that hold stocks over a single half hour interval to focus on the periodic pattern that relates these stock returns to past returns at different lags. Table 3 shows the performance of stock deciles ranked on their performance in previous half-hour intervals. The daily strategies sort stocks based on just one half-hour interval from a previous day, at an exact daily lag. These daily strategies match the formation period time of day to the holding time of day. For example, a daily strategy would choose to hold stocks from 2:00-2:30 based on past performance from 2:00–2:30 on a previous day. In contrast, the nondaily strategies use average returns over a previous day at all times that are not exact daily lags. Specifically they use twelve previous half-hour intervals from the twenty-four hour period that do not match the holding period. For example, for the 2:00–2:30 period, the nondaily strategies would use formation periods 9:30-10:00,..., 1:30-2:00 plus 2:30-3:00, 3:00-3:30, and 3:30-4:00 on the previous trading day. By studying the returns on these decile portfolios we can observe any nonlinearity and see whether the daily pattern is concentrated in the upper or lower performing deciles.

The table shows most of the statistical and economic significance comes from the extreme decile. For example, the worst nondaily losers over the previous day earned an average of 3.16 basis points, while the best nondaily winners lost 1.51 basis points per half hour holding period. The average returns are nearly monotonic across intermediate deciles. The signs are reversed for the daily decile strategies. For example, the worst decile of losers over the same interval of the previous day continued to lose an average of 1.35 basis points, while the best decile of daily winners earned 1.66 basis points per half hour interval. The intermediate decile average returns are monotonic, but most of the significance comes from the lowest and highest decile.

The magnitude of the daily response is most substantial on the first day. This suggests the effect may be largely explained by trading orders that get repeated on successive days, e.g., partially filled orders that get executed at the same time of day. But there is smaller persistent effect. For lags beyond one day, the average daily decile spreads remain above one basis point per half hour for lags of up to five days, i.e., one week (with t-statistics above 8.7). By contrast, the magnitude of the negative nondaily decile spreads is less than one basis point. Average decile spreads for nondaily strategies are statistically significant for lags of at least four days.

B. Time of Day

The autocorrelation pattern in Figures 1 and 2 reflects the average behavior throughout the day. Investors can pay up to 3 extra basis points to execute trades at a particular time of day. However, it is possible this effect is concentrated at certain times of the day. We first investigate whether the intra-day pattern is an artifact of biases in opening or closing prices. Overnight orders are executed at the open, and many traders (for example index funds concerned with minimizing daily tracking error) place market-at-close orders. Temporary price distortions caused by opening and closing procedures might produce predictability in stock returns that does not affect stock prices at other times of the day.

Table 4 shows the excess return of decile spread strategies during different half-hour intervals throughout the day. The daily decile spreads are sorted based on the return for lag 13, while the nondaily spreads are sorted based on the average return for lags one through twelve. The return effect is quite pronounced in the first and last half-hours of trading. The Day 1 daily decile spread earns over 11 basis points in the opening half-hour, while the Day 1 nondaily strategy loses over 8 basis points. This is a difference of 19 basis points between these strategies in the opening half-hour. Similarly the Day 1 daily decile spread earns over 8 basis points near the close of trading, while the corresponding nondaily strategy loses 11 basis points. A smaller daily effect remains during the middle of the day. The Day 1 daily strategy earn positive average excess returns in every half-hour interval from 10:00 a.m. to 3:30 p.m., averaging 1.75 basis points over this period. Meanwhile the Day 1 nondaily strategy loses over every half-hour period, losing 3.74 basis points over this period. This is a consistent pattern throughout the day. The pattern is smaller but still consistent based on previous days. When we average the second through twelfth intervals (i.e., average returns from 10:00 a.m. to 3:30 p.m.) all the daily and nondaily decile spreads are significantly different from zero at conventional levels.

Figure 3 shows the periodic daily pattern of return strategies has a similar shape throughout the day. The daily strategies earn a premium in the first half hour of trading, the last half hour, and in the intermediate intervals from 10:00 to 3:30. This evidence indicates that the intra-day patterns in the cross-section of stock returns are stronger at the beginning and end of the trading day, but seem to exist at all times. This is inconsistent with an argument that the patterns are completely driven by institutional trading at, or near, the opening or closing of the trading day.

3. Potential Cross-Sectional Explanations

The pattern of daily return continuation has different potential explanations. The biggest concern involves data error caused by thinly traded stocks. After addressing this, this section considers whether risk or size can explain the return pattern.

A. Low Price and Thin Trading

A major concern is whether the return continuation is driven by thinly traded stocks with inaccurately or irregularly measured returns. Returns on low-priced stocks are most strongly affected by discreteness. In addition, many of these stocks may not be traded throughout a half hour interval. For example, a $5 stock might trade once at 12:01, and then a second time at 12:02, without any further activity before 12:30. While it isn't clear whether this would impart a daily pattern, we want to verify that our results are not contaminated by these inaccurate or illiquid returns.

Table 5 addresses this issue by repeating the decile spread analysis of Table 3 eliminating low-priced and thinly traded stocks. We define low-priced stocks as stocks with share prices below $5. Removing the low-priced stocks diminishes the nondaily reversal effect. The average nondaily decile spread on Day 1 attenuates from -4.67 basis point per half hour in Table 3 to -1.77 basis points in Table 5. The daily continuation effect shrinks less. Table 5 shows the daily decile spread earns roughly 2 basis points (1.93) on Day 1, whereas it earns roughly 3 basis points with all stocks in Table 3. In both Table 3 and Table 5 the daily decile spread remains roughly 1 basis point per half hour on subsequent days for up to a week.

To address problems of thin trading, we eliminated stocks that did not have an average of at least 10 trades per half hour interval over the previous month. In other words we used stocks that average at least one trade every 3 minutes. This retains roughly 80 percent of stocks in our sample. The second column of Table 5 shows this restriction does not affect the results as much as eliminating the low-priced stocks. The daily decile spread earns 2.45 basis points per half hour on Day 1, while the nondaily decile spread loses 3.17 basis points. Results on subsequent days are similar to previous returns in Table 3. Overall the reversal and continuation pattern is not an artifact of mismeasurement of the return on low-priced stocks or mis-timing of returns on thinly traded stocks.

B. Beta

If high-frequency changes in risk or liquidity influence investors' demand for assets, then we might find periodicity in returns due to periodicity in risk or liquidity. For example, stocks might be riskier at certain times of the day when news is released, or they might be subject to institutional transactions that follow a business day cycle. This section explores these possibilities.

A priori, it seems unlikely for stocks to have large fluctuations in systematic risks during the day because companies do not change their financial exposures from hour to hour. On the other hand, some economic series are released at scheduled times, and firms may have exposure to systematic news released at those times. In this case traders may be reluctant to hold stocks at these risky times. To diagnose this possibility we control for risk by regressing stock returns on the equal-weighted market index. To correct for non-synchronous trading (Scholes and Williams (1977) and Dimson (1979)) we include the contemporaneous market return along with 13 leads and lags. Table 6 reports the average intercepts from these regressions. Since the intra-day interest rate is effectively zero, these intercepts have the interpretation of risk-adjusted returns.

The results of Table 6 resemble the previous results using unadjusted average returns. The average risk-adjusted return on decile spreads of previous-day winners in excess of previous-day losers is 3.03 basis points when investing at the same time of day. Yet this decile spread underperforms by 4.65 basis points at non-daily intervals. These effects are particularly pronounced in the first half-hour and last half-hour of the day, but remain statistically significant in the middle of the day.

The average risk-adjusted returns for the daily decile spreads continue to be substantial in the opening and closing half hour even when sorting on half-hour returns up to five business days previous. The Day 5 average decile spread is 4.84 basis points in the first half-hour, and 3.42 basis points in the last half hour. This indicates a substantial tendency for some stocks to persistently trade up or down at the open and close. The effect is much smaller in the middle of the day, less than 1 basis point, but remains statistically significant. Controlling for market risk does not eliminate the daily pattern.

C. Size and Transactions Costs

A concern about the nature of intra-day patterns in stock returns is market depth. If there is a return premium at certain times of the day then it may be compensation for illiquidity that makes stocks difficult to trade at efficient prices at those times. For example, Admati and Pfleiderer (1988) develop models where traders pool trades in certain periods of the day in order to take advantage of the increased liquidity of pooling. This implies a pattern primarily among smaller and less liquid stocks which face larger adverse selection problems. To the extent that firm size proxies for larger adverse selection problems, it provides a control variable.

Table 7 sorts stocks into three groups based on market capitalization. The table reports the decile spread strategies separately for these subuniverses of small-, medium-, and large-capitalization firms. The Day 1 nondaily strategy returns are larger, in absolute value, among small firms, consistent with those firms having larger proportional spreads. The Day 1 nondaily decile spread loses more than 10 basis points in the opening half-hour and more than 22 basis points in the closing half-hour, while averaging a loss of more than 8 basis points in the midday half-hour intervals. Conversely the daily decile spread strategies are more profitable with small stocks. The Day 1 daily strategy averages over 5 basis points per half-hour. In contrast these numbers are in the range of 1-3 basis points for medium and large stocks. The average excess returns for strategies based on longer daily and nondaily lags are smaller and consequently do not differ much across size categories. However almost all daily strategies maintain statistical significance at the 95% level in all size categories at the open, midday, and close. This indicates that while a liquidity/microstructure effect explanation may have merit, it is not associated exclusively with small firms.

An important consideration is the magnitude of transaction costs associated with the trading strategies implicit in the reported returns. We find predictable excess returns of several basis points within a half-hour interval based on transaction prices. However, a trader with no other motive for trade must pay the ask price or accept the offer price to get immediate execution. Larger orders also lead to larger price impacts. Table 8 reports the decile spread results for strategies that buy at the offer price and sell at the bid price. The average results are all negative for all size categories at all times of the day, indicating that the periodicity we find does not indicate a pure profit opportunity. It is important to remember that these results involve the round-trip transactions costs of two different long-short decile strategies. Therefore, they incur the average cost of a single transaction multiplied by four. For example, among small stocks the average decile spread on the Day 1 Nondaily strategy is -25.03 basis points, and the average decile spread on the Day 1 Daily strategy is -23.78 basis points. Recall Table 7 showed the Day 1 Nondaily strategy lost 9.92 basis points among small stocks while the Day 1 Daily strategy gained 5.16 basis points. Comparing the pre-transaction cost returns in Table 6 to the post-spread returns in Table 8 we see that the implied one-way spread cost is between 4 and 7 basis points. The difference between the performance of Daily and Nondaily strategies does not cover the costs of two round trips, it often compares favorably with the magnitude of one-way transaction costs. This suggests many investors have a demand for immediate execution of trades in small stocks and are not willing to shift their trades by 30 minutes to take advantage of the periodicity.

These trading strategies are not likely to be profitable for stocks with large bid/ask spreads. Therefore, the results in Table 7 exclude stocks that have a quoted relative spread of more than 10 basis points at the beginning of a given trading interval. We also condition on spreads of 5 and 25 basis points and obtain similar results. Note, very few small stocks have spreads less than 5 basis points, so there is no point conditioning on less than 5 basis points. Since our reported raw profits are not greater than 25 basis points, we do not condition on spreads greater than 25 basis points. The results suggest it is quite difficult to profit from these type of intra-day strategies without some exogenous desire to trade.

The transaction costs for medium and large stocks are substantially smaller than those for small stocks. Table 8 shows that for medium stocks the average decile spread results are roughly -20 basis points and for large stocks they are roughly -14 basis points. This corresponds to one-way trading costs of less than 5 basis points. The losses of the Nondaily and Daily strategies in Table 8 are smaller for medium and large stocks than for small stocks. In particular they do not exceed the one-way cost of the bid-offer spread. But the magnitudes are similar, and this again raises the question of why investors do not time their trades to improve execution.

4. Volume, Order Imbalance, and Related Variables

An important link the to patterns in prices is the behavior of traded quantities. If a single large trade or a collection of small trades moves prices then the excess demand may have been removed from one side of the market. This might explain the price reversal. But positive return effects on future days indicate that price pressure occurs at the same time of day. This suggests there are recurring transactions that produce price pressure at the same time of day. If the daily return effect is caused by these fluctuations in supply and demand for individual stocks, then a pattern should also manifest in the volume of stocks traded, or in related measures such as order imbalance, volatility, and bid-ask spread. This section finds common periodic daily patterns in some of these variables, but shows these variables do not subsume the pattern of return predictability.

A. Volume and Order Imbalance

To address trading-demand explanations of periodicity we repeat the cross-sectional regression using volume data

$$v_{it} = a_{tk} + g_{tk} v_{i,t-k} + u_{it}, \tag{3}$$

where v_{it} is the percentage change in volume of stock i over half-hour interval t. The means and t-statistics[3] of the time series of volume responses plotted in Panel A of Figure 4. The pattern for $\widehat{g}_t$ strongly resembles the return response pattern, $\widehat{\gamma}_t$ in Figure 1. In particular, the cross-sectional volume response effects are uniformly negative at all lags except multiples of 13, i.e., except at exact daily lags. Figure 4 shows the pattern for 65 lagged half-hour intervals corresponding to one week of calendar lags. Like the pattern of return responses, the effect of volume responses lasts much longer. Appendix Figure A1 shows the strength of daily volume responses decays with longer lags, but remains positive and statistically significant for up to 520 half-hour lags, corresponding to 40 days. Together Figures 1 and 4 (or longer-term results in Figures 2 and A1) show the intra-day cross-sections of daily return and volume display similar persistence lasting up to two months. Note that to the extent that volume and volatility are correlated, the volume pattern is consistent with the patterns in intra-day volatility documented in Andersen and Bollerslev (1997). Both returns and volume tend to be negatively autocorrelated intra-day, but display positive autocorrelation at the same time of day.

It is probable that orders of different size convey different information, and have different execution costs. Small trades are primarily generated by individual investors, whereas large trades are preponderantly institutional. To check for differential effects of volume generated by orders of different sizes, we determine, for each 30-minute interval, the volume generated by trades of less than 1,000 shares each (small trade volume) and the volume generated by trades of greater than, or equal to, 1,000 shares each (large trade volume). Appendix Figure A2 shows the volume responses separately for small trades (Panel A) and large trades (Panel B). Both percentage changes in small- and large-trade volume exhibit the same pattern of periodicity that we see in returns in Figure 1 and in overall volume Figure 4. We cannot isolate the pattern based on volume alone.

[3] These series, $\widehat{g}_{tk}$ did not display substantial autocorrelation so we did not make adjustments to the Fama-MacBeth standard errors.

It is possible that institutions disguise large trades by breaking them into smaller ones, making it difficult to detect their trades. Regardless of our ability to identify specific types of trades, price pressure is presumably caused by one-sided volume, and not balanced trading. Therefore we also look at the behavior of percentage changes in signed volume, order imbalance. Order imbalance is defined as the net signed volume over the interval where the sign is determined by a variant of the Lee and Ready (1991) trade classification algorithm.[4] For example, if a time interval had 100,000 shares transacted that were classified as buyer-initiated and 75,000 shares transacted that were classified as seller-initiated then the order imbalance for the period would be 25,000 shares (equal to 100,000 - 75,000). Panel D of Figure 4 shows that the percentage changes in order imbalance exhibit periodicity similar to, but less pronounced, than the periodicity in returns and volume.

Appendix Figure A2 indicates that the level of order imbalance does not exhibit any additional periodicity when partitioned into small versus large trades, in contrast to the momentum results of Hvidkjaer (2008). Indeed, the periodic pattern is absent in the order pattern for large trades. Perhaps trade classification algorithms for identify buyer- versus seller-initiated trades produces noisy estimates for individual stocks over short horizons such as the half-hour intervals used here.

B. Volatility and Bid-Ask Spreads

It is well documented that there is intra-day periodicity in volatility, (e.g., Wood, McInish, and Ord (1985), Harris (1986), and Andersen and Bollerslev (1997)). In particular, volatility tends to be high at the beginning and end of the trading day. In addition, Andersen and Bollerslev (1997) find high returns for the Standard and Poor's 500 (S&P 500) composite stock index futures contract at the beginning and end of the day. It might be the case that movements in volatility are driving the return periodicity we observe here. For example, movements in volatility might be related to movements in bid-ask spreads. Bid-ask bounce induces negative autocorrelation in returns and an upward bias in arithmetic returns that is more severe for high-frequency returns (Blume and Stambaugh (1983)).

Figure 4 (Panel B) shows that percentage changes in volatility (measured by the absolute value of returns) exhibit intra-day periodicity similar to that found for returns and volume.

If market activity in individual stocks has daily periodicity, then bid-ask spread might follow the same pattern. We want to examine this to distinguish changes in execution costs from changes in underlying returns. In addition, the high-frequency return bias discussed in Blume and Stambaugh

[4] Given the increased transactions volume in our sample period relative to that in Lee and Ready (1991), we do not require their 5 second minimum period between quotes and transactions.

(1983) is related to bid-ask bounce, we wish to test whether the return patterns we find are related to systematic changes in bid-ask spreads. Panel C of Figure 4 shows the t-statistics from cross-sectional regressions in which percentage changes in spreads are regressed on their lagged values. Spreads do not exhibit the type of periodicity that we observe in returns.

C. Does Periodicity in Related Variables Explain Periodicity in Returns?

We have shown that volume, order imbalance, and volatility have cross-sectional predictability with the same daily pattern as returns. This gives hope that these variables might explain the return predictability. For example, daily patterns in institutional volume might affect stock liquidity at the same time each day. News cycles might trigger volume that causes investors to demand return premiums on a daily cycle.

To control for these additional variables, we ran cross-sectional regressions of returns on lagged returns, including additional lagged regressors. The regression was

$$r_{it} = \alpha_{tk} + \gamma_{tk} r_{i,t-k} + \delta'_{tk} V_{i,t-k} + e_{it}, \tag{4}$$

where the vector $V_{i,t-k}$ includes volume (total shares traded during the lagged half-hour interval), order imbalance over the lagged time interval, volatility (absolute return over the lagged time interval), and relative bid-ask spread. If return predictability is caused by predictable market activity based on these variables, then including them should diminish or even subsume the predictability of returns based on past returns. Surprisingly, Figure 4 shows that the daily pattern of cross-sectional return predictability is unaffected by including the additional regressors. In other words volume, order imbalance, and volatility have similar patterns of intra-day predictability, but these variables do not explain daily return predictability.

As an additional refinement, we also regress returns on lagged returns, lagged small-trade volume, and lagged large-trade volume. Appendix Figure A2 reports the results. Panel C shows the coefficients and t-statistics of coefficients of returns on lagged returns. The results show that the return periodicity is not subsumed by large- or small-volume either.

D. Transactions Prices Versus Bid and Ask Prices

As mentioned in the introduction, Keim (1989) finds the turn-of-the-year trading patterns induce systematic patterns in the fractions of equity trades that occur at the ask price versus the bid price and that this trading pattern explains the size-related turn-of-the-year effect in stock prices. It might be the case that the patterns we see are an artifact of periodicity in transactions prices relative to the bid/ask prices without any periodicity in the bid and ask prices. Certainly, the pervasive negative coefficients at lags less than 13 are likely to be due to bid-ask bounce and do not imply negative autocorrelation in the bid and ask prices. To check for this we re-ran our tests using three alternatives to returns calculated using transaction prices: (a) returns calculated using bid prices only, (b) returns calculated using ask prices only, and (c) returns calculated using the midpoint of the bid-ask spread only. These return series do not suffer from bid-ask bounce, so we expect that much, if not all, of the intra-day negative autocorrelation to disappear. The results are shown in Figure 6. The figure shows that there is significant negative coefficient on last period's return (which might be indicative of temporary liquidity imbalances), generally positive coefficients at other lags, and pronounced positive coefficients at lags 13, 26, 39, 52, and 65. Thus, the pronounce periodicity in transaction price returns at the daily frequency is not solely an artifact of periodicity in where transactions occur relative to the bid and ask prices.

E. Pre-decimalization Results

We focus our analysis in this paper on the post-decimalization period. In Table 9 we compare the return spreads on daily-frequency strategies (lags 13, 26, 39, 52, and 65) over our sample period to two additional sample periods corresponding to tick sizes of one eighth and one sixteenth of a dollar. We find that the statistical significance of the intra-day periodicity is greatest in the post-decimalization period. This might be due to the increased use of trading algorithms (of the sort discussed in Almgren and Chriss (2000), Grinold and Kahn (2000), Huberman and Stanzl (2005), Hora (2006), and Engle and Ferstenberg (2007)) by institutional investors. Results during the period when the tick size is one sixteenth are quite volatile, and therefore we present additional results in Table 9, Panel B, where the returns are winsorized at the 1% level. The winsorized results do not represent implementable trading strategies, but reduce the influence of outliers. These Winsorized results with one sixteenth tick size resemble the post-decimalization results.

5. Additional Diagnostics

The previous sections have demonstrated a pattern of daily return continuation. This pattern is concentrated at the open and close, but also persists throughout the day, and lasts for at least a week. Because of the novelty of this effect, it is important to verify that we have properly characterized the pattern, and that it is pervasive and not restricted to special days. This section examines the pattern at higher frequency and in different calendar periods.

A. 5-Minute Interval Returns

Figure 1 shows that a half-hour interval seems to capture the return dynamics inside one day. Sometimes there appears to be slight spillover from one time interval to adjacent intervals. While the returns responses are most positive at exact multiples of one trading day (e.g., 13-half-hour lags), they are often slightly positive at adjacent intervals too (e.g., 12- or 14-half-hour lags). In this sense the choice of half-hour intervals seems adequate.

But it is conceivable that our choice of interval masks higher frequency phenomena. It addition, we would like to ensure that our results are not sensitive to the exact methodological choices. Therefore, we recalculate returns over 5-minute intervals and estimated the return responses of equation (1). In this case there are 78 5-minute intervals during a trading day (omitting overnight returns).

Figure 7 shows these high-frequency results. Figure 7 looks like a noisy version of Figure 1. The negative return reversal is most pronounced for the first few 5-minute lags, but persists for several days. And while there is a clear daily effect at daily multiples of 78, the leakage of the neighboring 5-minute intervals is also apparent. Overall this graph confirms the previous results and indicates the half-hour return intervals are fine enough to faithfully characterize high-frequency returns.

B. Day of Week

A potential concern is the existence day-of-the-week effects. French (1980) finds that the stock market earns different average returns on different days of the week. In particular, average returns on the day following a weekend are lower than average returns on other days. Therefore, we want to check whether our daily effect is really a weekend effect or part of some other weekly pattern.

Table A1 shows the performance of our daily and nondaily decile spread strategies on different days of the week. The effect is remarkably consistent throughout the week. The Day 1 nondaily strategy loses money at the open, midday, and close on every day. The amounts range from -3.51

basis points on Thursdays to -6.14 basis points on Mondays. Meanwhile the Day 1 daily strategy earns a positive premium when averaged over all half-hour intervals. This ranges from 2.62 basis points on Tuesdays to 3.44 basis points on Wednesdays. The results for longer lags are weaker, but they have the same sign and are usually statistically significant at the 95% level. We conclude that the daily results are not limited to a weekend effect or other weekday pattern.

C. Calendar Month and Turn-of-Month

There are well-known monthly patterns in the stock market. This includes both market-wide January effects and year-long seasonality (Rozeff and Kinney (1976), Bouman and Jacobsen (2002), and Kamstra, Kramer, and Levi (2003)) and cross-sectional performance such as the size effect at the turn-of-year (Keim (1983)). In addition to ruling out weekday effects, we want to ensure the daily pattern is not an artifact of some other monthly seasonal phenomenon.

Table A2 reports the decile spread strategies for every calendar month. Again, the results are strikingly consistent. The Day 1 nondaily strategy loses money in every calendar month, ranging from -2.88 basis points in June to -5.90 basis pints in March. And the Day 1 daily strategy makes money in every month, ranging from 1.7 basis points in March to 7.80 basis points in November. The longer lag strategies have a similar pattern, albeit smaller and less consistent. Nevertheless the Day 5 daily strategy is still profitable in every calendar month. The results are not limited to a particular time of year, and certainly not limited to the turn-of-year.

While the results are not limited to a turn-of-year seasonality, they might be driven by intra-month patterns. Ariel (1987) shows stocks earn a premium near the beginning and end of calendar months. Park and Reinganum (1986) find a similar pattern in Treasury bills. This suggests we test for a similar pattern in intra-day stock returns.

Table A3 controls for turn-of-month by separately reporting the combined results for trading days that occur on the first or last day of the month. The results are remarkably consistent. The Day 1 and Day 2 nondaily strategies lose money at the open, midday, and close both at the turn of month and middle of month, while the daily strategies make money at all these times. With few exceptions the Days 3, 4, and 5 strategies maintain this pattern. The pattern is not related to turn-of-month.

D. Index Membership

If stocks risk and fall at the same time of day then presumably there are buyers and sellers who persistently trade them at those times (with persistence in the direction of the trade). Index funds and benchmarked mutual funds are natural suspects for these actions. These funds may have large daily inflows or outflows and have an inelastic demand to invest those funds to replicate the index. To economize on trading activity they might perform "basket trades" at the open of trade, and to minimize tracking error they would have a particular motivation to trade near the close. This is consistent with previous results showing a strong effect at these times.

Table A4 separates the decile spread results for S&P500 firms and non-S&P500 firms. The results for both daily and non-daily strategies are generally stronger among the non-S&P500 stocks. For example, the average decile spread based on the previous nondaily returns loses 5.58 basis points in the non-S&P500 stocks, but loses less than 1 basis point with the S&P500 index stocks. The Day 1 daily strategy earns 3.28 basis points with the non-S&P500 stocks, but earns only 2.19 basis points with the index stocks. Naturally we would expect the non-index stocks to be smaller and less liquid. So these results are consistent with some type of daily liquidity effect and consistent with the results sorted by the market capitalization of the firm (reported above). These results are not consistent with a liquidity effect that driven by stocks indexed to the S&P 500.

6. Conclusion

We study the periodicity of cross-sectional differences in returns using half-hour observation intervals in the period from January 2001 through December 2005. We document pronounced intraday return reversals due to bid/ask bound, and these reversals last for several trading days. However, we find significant continuation of returns at intervals that are multiples of a day and this effect lasts for over forty trading days. Percentage changes in trading volume, order imbalances, and volatility exhibit similar patterns, but do not explain the return patterns. The return continuation at daily frequencies is more pronounced for the first and last half-hour periods. These effects are not driven by firm size, systematic risk premia, or inclusion in the S&P500 index (as a proxy for trading by index funds). The pattern is also not driven by particular months of the year, days of the week, or turn-of-the-month effects. The periodicity at the daily frequency is observed when we also use bid-to-bid, ask-to-ask, or midpoint-to-midpoint returns, so the periodicity is not merely due to patterns of where transactions prices occur relative to the bid and ask prices. The results are consistent with investors having a predictable demand for immediacy at certain times of the day. The pattern does not present a profit opportunity in the absence of other motives to trade, since strategies that attempt to take advantage of the daily periodicity lose money, after paying the bid/ask spread. However, traders who have other exogenous motives for trading might wish to exploit these persistent intra-day patterns and designers of algorithmic trading models may wish to incorporate this periodicity in their models of intra-day expected returns.

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Table 1

Cross-Sectional Regressions

Intraday cross-sectional simple regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$ are calculated for half-hour interval t and lag k, and where $r_{i,t}$ is return of stock i during interval t. The lagged variable $r_{i,t-k}$ is return of stock i in interval $t-k$. The regression is calculated for every half-hour interval t from January 2001 through December 2005 (16,261 intervals), and for lag k values 1 through 65 (past 5 trading days). Panel A reports the time-series averages of $\gamma_{k,t}$. Panel B calculates multiple cross-sectional regressions, including all past lags in the same regression. The analysis uses NYSE-listed stocks.

Panel A. Simple regressions

Lag	Estimate	*t*-statistic	Lag	Estimate	*t*-statistic	Lag	Estimate	*t*-statistic	Lag	Estimate	*t*-statistic	Lag	Estimate	*t*-statistic
1	-5.35	-59.22	14	0.04	0.60	27	0.05	0.74	40	0.05	0.87	53	0.19	3.13
2	-1.44	-17.96	15	-0.26	-3.97	28	-0.01	-0.11	41	-0.10	-1.65	54	0.08	1.29
3	-0.65	-8.26	16	-0.21	-3.24	29	-0.11	-1.66	42	-0.04	-0.60	55	0.00	0.01
4	-0.38	-5.02	17	-0.17	-2.49	30	-0.05	-0.81	43	-0.11	-1.65	56	-0.02	-0.31
5	-0.21	-2.73	18	-0.03	-0.42	31	-0.23	-3.51	44	-0.12	-1.83	57	-0.09	-1.36
6	-0.20	-2.58	19	-0.18	-2.68	32	-0.24	-3.63	45	-0.15	-2.30	58	-0.11	-1.65
7	-0.11	-1.44	20	-0.27	-3.92	33	-0.17	-2.57	46	-0.10	-1.58	59	-0.01	-0.08
8	0.05	0.68	21	-0.12	-1.75	34	-0.10	-1.55	47	0.01	0.10	60	-0.08	-1.31
9	0.00	-0.01	22	-0.03	-0.51	35	-0.15	-2.29	48	-0.10	-1.50	61	0.12	1.91
10	0.16	2.31	23	-0.13	-2.02	36	0.07	1.03	49	-0.05	-0.86	62	0.09	1.40
11	0.34	5.05	24	0.15	2.41	37	-0.07	-1.07	50	0.09	1.52	63	0.14	2.30
12	0.52	8.10	25	0.17	2.62	38	0.13	2.04	51	0.24	3.96	64	0.18	3.00
13	1.19	18.22	26	0.79	12.45	39	0.70	11.54	52	0.58	9.62	65	0.63	10.57

Panel B. Multiple regressions

Lag	Estimate	*t*-statistic	Lag	Estimate	*t*-statistic	Lag	Estimate	*t*-statistic	Lag	Estimate	*t*-statistic	Lag	Estimate	*t*-statistic
1	-5.01	-71.76	14	0.10	2.29	27	0.20	4.47	40	0.10	2.41	53	0.27	6.15
2	-1.32	-22.01	15	-0.16	-3.32	28	0.05	1.20	41	0.07	1.56	54	0.10	2.25
3	-0.50	-8.63	16	-0.29	-6.06	29	-0.10	-2.20	42	-0.01	-0.28	55	0.00	-0.03
4	-0.35	-6.11	17	-0.24	-4.96	30	-0.01	-0.31	43	-0.12	-2.48	56	0.04	0.89
5	-0.44	-7.95	18	-0.24	-4.86	31	-0.18	-3.71	44	-0.02	-0.33	57	-0.04	-0.94
6	-0.32	-5.72	19	-0.29	-5.89	32	-0.24	-4.91	45	-0.09	-1.75	58	-0.01	-0.24
7	-0.22	-4.04	20	-0.34	-6.89	33	-0.20	-4.23	46	-0.08	-1.70	59	0.03	0.58
8	-0.10	-1.79	21	-0.20	-4.09	34	-0.05	-1.14	47	-0.04	-0.75	60	0.00	-0.05
9	-0.02	-0.30	22	-0.12	-2.51	35	-0.18	-3.96	48	-0.04	-0.78	61	0.05	0.98
10	0.01	0.26	23	-0.07	-1.51	36	0.01	0.20	49	-0.06	-1.29	62	0.10	2.26
11	0.15	3.27	24	-0.07	-1.46	37	0.00	-0.09	50	0.08	1.88	63	0.10	2.35
12	0.34	7.46	25	0.15	3.38	38	0.13	3.03	51	0.22	5.20	64	0.18	4.24
13	1.05	22.68	26	0.71	16.21	39	0.52	12.22	52	0.49	11.69	65	0.38	8.93

Table 2

Long-Run Performance

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, Lag 65 trading strategy ranks stocks according to their return during the historical lag half-hour interval 65. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average returns (per half hour, in basis points) of the bottom and top decile portfolios, as well as their portfolio return spread, for trading strategies corresponding to each 13th lag from 13 through 520 for the period January 2001 through December 2005 (16,261 intervals) are reported below, as well as the corresponding t-statistics (in brackets). The analysis uses NYSE-listed stocks.

Strategy	1 (losers)		10 (winners)		10-1	
(lag)	Return	*t*-statistic	Return	*t*-statistic	Return	*t*-statistic
13	-1.35	-6.18	1.66	7.93	3.01	22.15
26	-0.90	-4.18	1.07	5.15	1.97	15.01
39	-0.63	-2.95	0.73	3.53	1.36	10.75
52	-0.58	-2.73	0.68	3.27	1.26	10.01
65	-0.43	-2.05	0.66	3.19	1.09	8.70
78	-0.53	-2.51	0.63	3.05	1.16	9.34
91	-0.52	-2.46	0.60	2.89	1.12	9.12
104	-0.32	-1.50	0.51	2.50	0.83	6.81
117	-0.33	-1.54	0.59	2.85	0.91	7.42
130	-0.45	-2.13	0.48	2.33	0.93	7.58
143	-0.35	-1.65	0.49	2.40	0.84	6.95
156	-0.30	-1.44	0.47	2.29	0.77	6.46
169	-0.35	-1.66	0.40	1.95	0.75	6.18
182	-0.31	-1.46	0.47	2.31	0.77	6.38
195	-0.14	-0.68	0.43	2.12	0.58	4.76
208	-0.24	-1.17	0.45	2.23	0.70	5.93
221	-0.26	-1.26	0.40	1.95	0.66	5.60
234	-0.08	-0.41	0.27	1.34	0.36	3.03
247	-0.06	-0.27	0.22	1.08	0.28	2.34
260	-0.30	-1.43	0.29	1.43	0.59	4.99
273	-0.27	-1.29	0.30	1.48	0.57	4.92
286	-0.18	-0.84	0.37	1.84	0.55	4.72
299	-0.16	-0.78	0.39	1.94	0.56	4.77
312	-0.19	-0.93	0.37	1.81	0.56	4.75
325	-0.17	-0.84	0.31	1.53	0.48	4.12
338	0.06	0.27	0.10	0.51	0.05	0.39
351	-0.21	-1.01	0.34	1.68	0.55	4.73
364	-0.04	-0.19	0.25	1.21	0.28	2.47
377	-0.05	-0.23	0.26	1.29	0.31	2.63
390	-0.18	-0.86	0.16	0.77	0.33	2.84
403	-0.02	-0.11	0.18	0.86	0.20	1.70
416	-0.09	-0.42	0.18	0.90	0.27	2.35
429	-0.16	-0.75	0.10	0.50	0.26	2.23
442	-0.13	-0.62	0.22	1.10	0.35	3.03
455	-0.13	-0.61	0.22	1.07	0.34	2.98
468	-0.07	-0.34	0.28	1.37	0.35	3.05
481	0.10	0.51	0.26	1.29	0.16	1.37
494	-0.11	-0.53	0.26	1.27	0.37	3.20
507	-0.21	-0.99	0.36	1.77	0.56	4.99
520	-0.19	-0.91	0.23	1.16	0.42	3.67

Table 3

Returns of strategies based on past performance

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average returns (per half hour, in basis points) of the various trading strategies for the period January 2001 through December 2005 (16,261 intervals) are reported below, as well as the corresponding *t*-statistics (in brackets). The analysis uses NYSE-listed stocks.

Strategy	1 (losers)	2	3	4	5	6	7	8	9	10 (winners)	10-1
Day 1											
Nondaily	3.16	0.67	0.27	0.09	-0.02	-0.17	-0.15	-0.24	-0.59	-1.51	-4.67
	[13.64]	[3.68]	[1.62]	[0.57]	[-0.13]	[-1.09]	[-0.98]	[-1.48]	[-3.40]	[-7.16]	[-28.16]
Daily	-1.35	-0.64	-0.35	-0.07	0.06	0.16	0.44	0.63	0.92	1.66	3.01
	[-6.18]	[-3.51]	[-2.05]	[-0.42]	[0.39]	[1.03]	[2.76]	[3.83]	[5.22]	[7.93]	[22.15]
Day 2											
Nondaily	0.61	0.37	0.22	0.23	0.13	0.18	0.12	0.02	-0.10	-0.31	-0.92
	[2.78]	[2.06]	[1.30]	[1.42]	[0.81]	[1.13]	[0.77]	[0.11]	[-0.58]	[-1.55]	[-6.57]
Daily	-0.90	-0.42	-0.20	-0.06	0.13	0.22	0.37	0.50	0.75	1.07	1.97
	[-4.18]	[-2.34]	[-1.15]	[-0.37]	[0.80]	[1.41]	[2.32]	[2.99]	[4.25]	[5.15]	[15.01]
Day 3											
Nondaily	0.41	0.25	0.28	0.17	0.19	0.17	0.08	0.05	0.07	-0.21	-0.62
	[1.92]	[1.41]	[1.70]	[1.07]	[1.22]	[1.09]	[0.52]	[0.29]	[0.40]	[-1.04]	[-4.62]
Daily	-0.63	-0.27	-0.05	0.03	0.08	0.23	0.31	0.40	0.54	0.73	1.36
	[-2.95]	[-1.51]	[-0.28]	[0.18]	[0.52]	[1.42]	[1.90]	[2.44]	[3.09]	[3.53]	[10.75]
Day 4											
Nondaily	0.21	0.20	0.20	0.26	0.25	0.15	0.18	0.02	0.12	-0.13	-0.34
	[0.99]	[1.13]	[1.18]	[1.61]	[1.62]	[0.98]	[1.16]	[0.10]	[0.69]	[-0.64]	[-2.60]
Daily	-0.58	-0.25	-0.11	0.05	0.07	0.19	0.21	0.38	0.50	0.68	1.26
	[-2.73]	[-1.42]	[-0.66]	[0.32]	[0.44]	[1.22]	[1.28]	[2.26]	[2.83]	[3.27]	[10.01]
Day 5											
Nondaily	0.08	0.12	0.14	0.20	0.10	0.21	0.27	0.13	0.21	0.02	-0.06
	[0.39]	[0.66]	[0.86]	[1.24]	[0.62]	[1.32]	[1.66]	[0.80]	[1.20]	[0.09]	[-0.49]
Daily	-0.43	-0.17	0.01	-0.04	0.06	0.22	0.23	0.23	0.47	0.66	1.09
	[-2.05]	[-0.94]	[0.07]	[-0.26]	[0.38]	[1.39]	[1.44]	[1.39]	[2.66]	[3.19]	[8.70]

Table 4

Returns of strategies based on past performance in different half-hour intervals of the trading day

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) for each half-hour interval of a trading day for the period January 2001 through December 2005 (there are 1,255 observations for each half-hour interval of a trading day) are reported below, as well as the corresponding t-statistics (in brackets). The analysis uses NYSE-listed stocks.

Strategy	1 (first) [9:30-10:00]	2 [10:00-10:30]	3 [10:30-11:00]	4 [11:00-11:30]	5 [11:30-12:00]	6 [12:00-12:30]	7 [12:30-13:00]	8 [13:00-13:30]	9 [13:30-14:00]	10 [14:00-14:30]	11 [14:30-15:00]	12 [15:00-15:30]	13 (last) [15:30-16:00]	2-12 [10:00-15:30]
Day 1														
Nondaily	-8.36	0.62	-1.00	-2.01	-1.96	-2.89	-4.88	-2.83	-3.38	-8.17	-5.96	-8.75	-11.24	-3.74
	[-8.80]	[0.77]	[-1.55]	[-3.61]	[-3.83]	[-5.99]	[-10.84]	[-6.38]	[-7.49]	[-16.08]	[-12.08]	[-17.27]	[-18.32]	[-22.60]
Daily	11.48	5.02	2.66	1.20	1.38	1.35	1.53	0.76	1.19	0.81	0.89	2.46	8.42	1.75
	[12.58]	[7.97]	[5.01]	[2.87]	[3.71]	[3.92]	[4.69]	[2.16]	[3.72]	[2.12]	[2.45]	[6.48]	[14.90]	[14.06]
Day 2														
Nondaily	-2.96	0.68	0.68	-0.06	-0.50	0.05	-0.42	-0.24	0.78	-1.94	-1.75	-2.58	-3.79	-0.48
	[-3.52]	[1.04]	[1.22]	[-0.13]	[-1.08]	[0.13]	[-1.10]	[-0.65]	[1.99]	[-4.88]	[-4.30]	[-6.03]	[-7.25]	[-3.44]
Daily	10.48	2.59	1.32	0.51	-0.06	0.35	0.84	0.06	0.27	0.22	1.35	1.10	6.52	0.78
	[12.32]	[4.22]	[2.67]	[1.21]	[-0.17]	[1.08]	[2.61]	[0.20]	[0.80]	[0.62]	[3.99]	[2.91]	[11.43]	[6.45]
Day 3														
Nondaily	-4.87	-0.24	0.88	-0.07	0.21	0.04	0.04	0.06	0.19	-1.31	-1.10	-0.63	-1.29	-0.17
	[-6.03]	[-0.39]	[1.59]	[-0.15]	[0.48]	[0.10]	[0.09]	[0.18]	[0.50]	[-3.33]	[-2.89]	[-1.58]	[-2.64]	[-1.31]
Daily	6.32	1.55	0.23	0.34	0.40	0.38	0.65	-0.18	0.57	0.06	1.19	0.56	5.57	0.52
	[7.59]	[2.70]	[0.46]	[0.80]	[1.06]	[1.14]	[2.07]	[-0.58]	[1.76]	[0.17]	[3.76]	[1.56]	[10.46]	[4.44]
Day 4														
Nondaily	-2.55	0.31	0.08	-0.89	0.08	-0.45	-0.58	0.34	0.28	0.00	0.27	-0.06	-1.26	-0.06
	[-3.31]	[0.51]	[0.15]	[-1.94]	[0.19]	[-1.13]	[-1.62]	[0.93]	[0.74]	[0.01]	[0.70]	[-0.14]	[-2.67]	[-0.43]
Daily	5.64	1.52	0.84	0.90	0.25	0.10	0.06	0.04	0.65	0.53	0.95	0.54	4.32	0.58
	[6.86]	[2.51]	[1.67]	[2.26]	[0.69]	[0.31]	[0.19]	[0.14]	[2.06]	[1.52]	[2.86]	[1.56]	[7.98]	[4.95]
Day 5														
Nondaily	-0.14	0.43	-0.43	-0.81	-0.28	-0.22	0.90	0.89	-0.31	-0.08	0.99	-0.49	-1.29	0.05
	[-0.18]	[0.72]	[-0.77]	[-1.76]	[-0.66]	[-0.57]	[2.44]	[2.50]	[-0.82]	[-0.21]	[2.66]	[-1.24]	[-2.83]	[0.42]
Daily	4.98	1.37	-0.68	0.89	0.18	0.45	0.34	0.88	0.64	0.62	0.25	0.78	3.50	0.52
	[6.13]	[2.34]	[-1.27]	[2.21]	[0.46]	[1.37]	[1.06]	[2.75]	[2.04]	[1.69]	[0.72]	[2.25]	[6.97]	[4.35]

Table 5

Strategies based on past performance of liquid stocks

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The portfolios are rebalanced every half hour. The average returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) for the period January 2001 through December 2005 are reported below, as well as the corresponding *t*-statistics (in brackets). The strategies are performed separately for firms of price above 5 dollars at the end of previous calendar month (returns are value weighted, using firm market capitalization at the end of the previous calendar year) and firms of at least 10 trades per half hour, on average, during the previous calendar month (equally weighted returns). The analysis uses NYSE-listed stocks.

Strategy	Stock above 5 dollars (value-weighted returns)	Stocks with at least 10 trades per half hour
Day 1		
Nondaily	-1.77	-3.17
	[-8.07]	[-19.44]
Daily	1.93	2.45
	[10.34]	[18.44]
Day 2		
Nondaily	-1.28	-1.21
	[-6.45]	[-8.65]
Daily	1.25	1.72
	[7.14]	[13.38]
Day 3		
Nondaily	-0.75	-0.56
	[-4.01]	[-4.26]
Daily	0.99	1.05
	[5.75]	[8.54]
Day 4		
Nondaily	-0.48	-0.20
	[-2.57]	[-1.58]
Daily	1.06	1.07
	[6.06]	[8.74]
Day 5		
Nondaily	0.24	0.09
	[1.32]	[0.72]
Daily	0.97	0.94
	[5.58]	[7.63]

Table 6
Controlling for Market Risk

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) for the period January 2001 through December 2005 are regressed on the equal-weighted market average return (along with its 1 through 13 leads and 1 through 13 lags). The regression intercepts and their corresponding t-statistics (in brackets) are reported below. The risk-adjusted returns are also partitioned using all half-hour intervals of a day, as well as using only the first, the last and the rest. The analysis uses NYSE-listed stocks.

Strategy	Risk-adjusted returns			
	1-13 (all)	1 (first)	2-12	13 (last)
Day 1				
Nondaily	-4.65	-8.52	-3.71	-10.79
	[-28.26]	[-8.53]	[-22.62]	[-16.96]
Daily	3.03	11.64	1.76	8.40
	[22.33]	[12.24]	[14.17]	[14.17]
Day 2				
Nondaily	-0.90	-3.25	-0.45	-3.73
	[-6.44]	[-3.64]	[-3.27]	[-6.89]
Daily	1.98	10.30	0.79	6.92
	[15.14]	[11.52]	[6.56]	[11.53]
Day 3				
Nondaily	-0.61	-4.82	-0.17	-0.85
	[-4.57]	[-5.69]	[-1.26]	[-1.66]
Daily	1.38	6.82	0.55	5.96
	[10.94]	[7.80]	[4.67]	[10.61]
Day 4				
Nondaily	-0.34	-3.21	-0.06	-0.91
	[-2.58]	[-3.94]	[-0.43]	[-1.84]
Daily	1.25	5.96	0.57	4.26
	[9.96]	[6.92]	[4.86]	[7.46]
Day 5				
Nondaily	-0.04	-0.14	0.07	-0.53
	[-0.33]	[-0.17]	[0.56]	[-1.12]
Daily	1.10	4.84	0.53	3.42
	[8.76]	[5.63]	[4.42]	[6.40]

Table 7
Controlling for Size

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) for the period January 2001 through December 2005 are reported below, as well as the corresponding *t*-statistics (in brackets). The strategies are performed separately for three equally sized groups sorted by firm market capitalization at the end of the previous calendar year. The returns are reported using all half-hour intervals of a day, as well as using only the first, the last and the rest. The analysis uses NYSE-listed stocks.

Strategy	Small				Medium				Large			
	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)
Day 1												
Nondaily	-9.92	-10.89	-8.69	-22.55	-2.98	-12.11	-1.93	-5.45	-1.15	1.18	-0.94	-5.88
	[-30.94]	[-6.33]	[-26.73]	[-18.55]	[-16.16]	[-10.55]	[-10.62]	[-9.00]	[-6.24]	[1.03]	[-5.08]	[-10.77]
Daily	5.16	20.43	3.15	11.98	2.20	9.36	1.11	7.08	1.88	6.67	0.86	8.38
	[16.71]	[11.90]	[10.26]	[9.77]	[14.47]	[8.72]	[7.90]	[12.78]	[12.43]	[6.30]	[5.95]	[20.58]
Day 2												
Nondaily	-1.04	-4.55	-0.20	-6.82	-1.05	-2.22	-0.78	-2.77	-1.28	-3.70	-0.91	-2.91
	[-3.64]	[-2.95]	[-0.70]	[-6.12]	[-6.61]	[-2.19]	[-5.09]	[-4.76]	[-7.78]	[-3.37]	[-5.66]	[-6.19]
Daily	2.87	12.06	1.51	8.70	1.72	10.01	0.55	6.30	1.36	7.78	0.29	6.65
	[9.70]	[7.52]	[5.07]	[7.38]	[11.69]	[10.01]	[4.01]	[11.86]	[9.55]	[8.00]	[2.15]	[16.80]
Day 3												
Nondaily	-0.89	-7.69	0.08	-4.78	-0.66	-3.68	-0.39	-0.53	-0.53	-3.85	-0.34	0.80
	[-3.15]	[-5.03]	[0.29]	[-4.60]	[-4.41]	[-3.92]	[-2.69]	[-1.01]	[-3.41]	[-3.83]	[-2.24]	[1.85]
Daily	2.10	7.26	1.04	8.59	1.16	6.39	0.34	5.06	0.88	4.88	0.13	5.14
	[7.01]	[4.63]	[3.41]	[7.32]	[8.07]	[6.27]	[2.52]	[9.75]	[6.34]	[5.15]	[0.94]	[14.04]
Day 4												
Nondaily	-0.72	-4.33	-0.14	-3.50	-0.13	-1.01	-0.07	0.12	-0.30	-0.75	-0.30	0.18
	[-2.59]	[-3.02]	[-0.49]	[-3.35]	[-0.85]	[-1.07]	[-0.46]	[0.24]	[-1.99]	[-0.75]	[-2.04]	[0.42]
Daily	1.67	7.03	0.75	6.41	1.01	5.29	0.39	3.57	0.94	5.05	0.28	4.07
	[5.59]	[4.20]	[2.51]	[5.49]	[7.23]	[5.61]	[2.97]	[6.71]	[6.60]	[5.12]	[2.02]	[11.22]
Day 5												
Nondaily	-0.19	0.35	-0.08	-2.00	-0.06	-0.56	0.11	-1.50	0.20	1.52	0.12	-0.25
	[-0.70]	[0.24]	[-0.28]	[-1.93]	[-0.44]	[-0.60]	[0.78]	[-3.00]	[1.33]	[1.58]	[0.80]	[-0.58]
Daily	1.86	6.46	1.13	5.27	0.78	4.65	0.19	3.40	0.80	4.06	0.24	3.61
	[6.24]	[3.76]	[3.79]	[4.70]	[5.55]	[4.82]	[1.44]	[6.78]	[5.66]	[4.22]	[1.79]	[10.10]

Table 8
Controlling for Transaction Costs

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The table reports long-short portfolio strategies: the daily strategies are calculated as top-minus-bottom-decile portfolios, while the nondaily strategies are calculated as the bottom-minus-top-decile portfolios. The average returns of the different strategies (per half hour, in basis points), after accounting for transaction costs, for the period January 2001 through December 2005 are reported below, as well as the corresponding *t*-statistics (in brackets). The strategies are performed separately for three equally sized groups sorted by firm market capitalization at the end of the previous calendar year. The post-transaction-cost return of buying a stock is calculated as the return from the first quoted offer price of a half-hour interval to its last quoted bid price. The post-transaction-cost return of selling a stock is calculated as the negative of the return from the first quoted bid price of a half-hour interval to its last quoted offer price. The returns are reported using all half-hour intervals of a day, as well as using only the first, the last and the rest. In each given interval, only firms with the first quoted relative bid/ask spread (spread divided by the midpoint of quotes) no larger than 10 basis points in a given interval are used for the calculations. The analysis uses NYSE-listed stocks.

Strategy	Small				Medium				Large			
	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)
Day 1												
Nondaily	-25.03	30.56	-24.91	-27.41	-19.67	-17.60	-19.89	-17.58	-14.77	-27.92	-14.24	-9.74
	[-27.51]	[0.90]	[-26.05]	[-9.54]	[-45.23]	[-1.81]	[-45.33]	[-13.18]	[-44.97]	[-7.92]	[-53.48]	[-13.03]
Daily	-23.78	-28.26	-23.68	-24.41	-18.58	-11.49	-19.03	-15.07	-13.25	-13.43	-13.91	-5.84
	[-28.37]	[-0.72]	[-27.43]	[-8.75]	[-49.79]	[-1.34]	[-52.11]	[-12.10]	[-46.50]	[-4.24]	[-61.05]	[-8.96]
Day 2												
Nondaily	-25.17	9.90	-24.84	-29.03	-20.52	-31.97	-20.30	-20.60	-12.98	-6.42	-13.62	-11.21
	[-30.97]	[0.22]	[-29.47]	[-10.83]	[-53.45]	[-4.16]	[-52.20]	[-18.59]	[-33.13]	[-1.22]	[-56.95]	[-16.66]
Daily	-24.49	-84.59	-24.31	-23.41	-19.38	-11.39	-19.83	-15.99	-13.46	-11.02	-14.07	-8.79
	[-29.41]	[-2.89]	[-28.20]	[-8.37]	[-53.34]	[-1.46]	[-54.83]	[-13.54]	[-49.00]	[-3.61]	[-63.68]	[-14.60]
Day 3												
Nondaily	-25.26	-59.52	-24.99	-26.72	-20.84	-35.56	-20.49	-22.03	-14.40	-13.72	-14.33	-15.72
	[-32.59]	[-2.51]	[-30.75]	[-10.54]	[-56.43]	[-4.26]	[-55.07]	[-19.55]	[-50.33]	[-4.44]	[-60.54]	[-24.69]
Daily	-24.29	-35.03	-24.61	-21.30	-20.31	-16.53	-20.64	-17.49	-13.77	-8.75	-14.48	-10.02
	[-30.68]	[-1.03]	[-30.07]	[-7.62]	[-54.89]	[-1.79]	[-57.42]	[-15.04]	[-52.27]	[-3.15]	[-65.83]	[-17.25]
Day 4												
Nondaily	-25.23	5.24	-25.06	-28.06	-20.67	-23.26	-20.53	-21.75	-14.65	-15.63	-14.53	-15.27
	[-31.85]	[0.22]	[-30.15]	[-11.15]	[-55.56]	[-2.78]	[-54.38]	[-19.32]	[-54.40]	[-5.33]	[-65.76]	[-23.97]
Daily	-23.77	-15.34	-23.44	-26.96	-20.38	-20.71	-20.43	-19.76	-14.13	-13.56	-14.50	-10.52
	[-28.87]	[-0.46]	[-27.75]	[-9.26]	[-56.52]	[-2.44]	[-57.60]	[-18.08]	[-53.48]	[-4.85]	[-65.71]	[-18.27]
Day 5												
Nondaily	-25.31	-28.62	-24.94	-28.27	-20.61	-23.79	-20.42	-22.11	-14.92	-18.84	-14.72	-14.09
	[-33.95]	[-1.40]	[-31.87]	[-12.15]	[-56.15]	[-3.15]	[-54.63]	[-20.42]	[-55.45]	[-6.65]	[-64.02]	[-21.71]
Daily	-25.92	-21.21	-25.63	-28.77	-20.27	-22.00	-20.37	-18.85	-13.66	-8.08	-14.28	-11.40
	[-32.58]	[-0.64]	[-30.95]	[-10.51]	[-56.64]	[-2.96]	[-56.85]	[-16.12]	[-35.73]	[-1.58]	[-61.98]	[-18.29]

Table 9

Returns of strategies based on past performance: Subperiod analysis

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. Three subperiods corresponding to different tick-size regimes are analyzed: January 1, 1993, through June 23,1997 (one eigth); June 24, 1997, through December 31, 2000 (one sixteenth); and January 1, 2001, through December 31, 2005 (decimal). The average returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) of the various trading strategies for are reported below, as well as the corresponding *t*-statistics (in brackets). Panel A uses the raw portfolio returns while Panel B uses portoflio returns winsorized at the top and bottom 1% of the distribution each month (across all strategies). The analysis uses NYSE-listed stocks.

Panel A. Raw portfolio returns

Strategy	January 1, 1993 - June 23, 1997 [14,190 observations)	June 24, 1997 - December 31, 2000 [11,506 observations]	January 1, 2001 - December 31, 2005 [16,261 observations]
Day 1	2.88	-10.30	3.01
[lag 13]	[4.90]	[-0.84]	[22.15]
Day 2	1.00	4.67	1.97
[lag 26]	[6.52]	[3.01]	[15.01]
Day 3	0.84	69.61	1.36
[lag 39]	[5.56]	[1.31]	[10.75]
Day 4	-0.21	-54.00	1.26
[lag 52]	[-0.21]	[-1.02]	[10.01]
Day 5	0.68	-15.15	1.09
[lag 65]	[4.44]	[-1.00]	[8.70]

Panel B. Winsorized portfolio returns (top and bottom 1%)

Strategy	January 1, 1993 - June 23, 1997 [14,190 observations)	June 24, 1997 - December 31, 2000 [11,506 observations]	January 1, 2001 - December 31, 2005 [16,261 observations]
Day 1	2.28	3.43	2.90
[lag 13]	[15.22]	[18.27]	[22.89]
Day 2	0.98	2.07	1.89
[lag 26]	[6.69]	[11.39]	[15.34]
Day 3	0.86	1.61	1.38
[lag 39]	[5.88]	[8.95]	[11.56]
Day 4	0.72	1.57	1.26
[lag 52]	[4.90]	[8.80]	[10.52]
Day 5	0.69	1.12	1.13
[lag 65]	[4.72]	[6.29]	[9.58]

Table A1

Controlling for Day of the Week

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) for the period January 2001 through December 2005 are reported below, as well as the corresponding *t*-statistics (in brackets). The returns are reported separately using half-hour intervals of each day of the week. The returns are also partitioned using all half-hour intervals of a day, as well as using only the first, the last and the rest. The analysis uses NYSE-listed stocks.

Strategy	Mondays				Tuesdays				Wednesdays				Thursdays				Fridays			
	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)
Day 1																				
Nondaily	-6.14	-10.78	-5.11	-12.89	-3.74	-5.75	-3.17	-8.10	-4.18	-5.92	-3.39	-11.15	-3.51	-7.35	-2.54	-10.29	-5.90	-12.22	-4.59	-13.98
	[-17.14]	[-4.88]	[-14.52]	[-10.42]	[-10.88]	[-3.09]	[-9.07]	[-6.25]	[-10.76]	[-2.81]	[-8.76]	[-6.71]	[-8.94]	[-3.24]	[-6.40]	[-8.34]	[-16.21]	[-5.67]	[-12.87]	[-10.49]
Daily	2.86	11.62	1.49	9.19	2.62	8.17	1.73	6.80	3.44	13.96	1.97	9.06	3.20	13.75	1.70	9.21	2.93	9.95	1.84	7.90
	[9.25]	[5.29]	[5.41]	[7.25]	[9.05]	[4.20]	[6.51]	[5.42]	[11.18]	[6.91]	[6.92]	[7.50]	[10.14]	[6.53]	[5.85]	[7.38]	[9.83]	[5.15]	[6.71]	[5.88]
Day 2																				
Nondaily	-0.68	-1.01	-0.53	-2.02	-0.95	-3.20	-0.50	-3.61	-0.88	-2.34	-0.48	-3.78	-0.94	-5.29	-0.25	-4.24	-1.15	-2.86	-0.63	-5.23
	[-2.25]	[-0.53]	[-1.78]	[-1.89]	[-3.18]	[-1.80]	[-1.69]	[-3.47]	[-2.72]	[-1.31]	[-1.48]	[-3.01]	[-2.95]	[-3.01]	[-0.77]	[-3.44]	[-3.55]	[-1.32]	[-2.04]	[-4.28]
Daily	1.95	10.13	0.84	5.88	1.40	7.58	0.45	5.77	2.28	12.94	0.95	6.28	2.28	12.59	0.96	6.47	1.92	9.17	0.70	8.20
	[6.38]	[4.69]	[3.05]	[4.97]	[5.07]	[4.16]	[1.77]	[4.39]	[7.69]	[7.01]	[3.41]	[5.15]	[7.51]	[6.32]	[3.48]	[4.84]	[6.81]	[5.46]	[2.63]	[6.27]
Day 3																				
Nondaily	-0.57	-6.48	0.03	-1.34	-0.59	-6.96	-0.06	0.05	-0.46	-5.11	0.05	-1.40	-0.53	-3.44	-0.12	-2.12	-0.97	-2.39	-0.77	-1.69
	[-1.85]	[-3.16]	[0.11]	[-1.32]	[-2.02]	[-4.11]	[-0.22]	[0.05]	[-1.49]	[-3.07]	[0.15]	[-1.21]	[-1.73]	[-1.92]	[-0.39]	[-1.81]	[-3.32]	[-1.31]	[-2.72]	[-1.53]
Daily	1.63	7.28	0.78	5.34	1.00	4.73	0.19	6.21	1.56	6.76	0.64	6.47	1.20	6.92	0.29	5.53	1.41	6.01	0.74	4.21
	[5.49]	[3.43]	[2.85]	[5.08]	[3.84]	[2.97]	[0.77]	[5.74]	[5.43]	[3.66]	[2.39]	[5.06]	[4.18]	[3.78]	[1.08]	[4.18]	[5.06]	[3.11]	[2.90]	[3.57]
Day 4																				
Nondaily	0.24	-3.20	0.66	-0.98	-0.48	-3.52	-0.30	0.59	0.02	-1.59	0.24	-0.74	-0.49	-3.68	-0.07	-2.00	-0.97	-0.81	-0.78	-3.24
	[0.80]	[-1.67]	[2.27]	[-0.89]	[-1.67]	[-2.14]	[-1.03]	[0.60]	[0.07]	[-0.95]	[0.77]	[-0.68]	[-1.69]	[-2.31]	[-0.23]	[-2.01]	[-3.39]	[-0.45]	[-2.81]	[-2.98]
Daily	1.53	7.44	0.55	6.34	1.16	5.05	0.59	3.53	1.11	6.47	0.43	3.19	1.23	4.52	0.78	2.85	1.28	4.84	0.54	5.88
	[5.39]	[3.75]	[2.16]	[5.18]	[4.25]	[2.93]	[2.26]	[3.14]	[3.84]	[3.62]	[1.57]	[2.58]	[4.40]	[2.55]	[2.97]	[2.25]	[4.60]	[2.49]	[2.15]	[4.97]
Day 5																				
Nondaily	-0.33	0.28	-0.28	-1.48	0.02	-0.58	0.15	-0.82	0.01	-1.22	0.32	-2.20	0.17	-0.60	0.26	-0.10	-0.20	1.46	-0.21	-1.86
	[-1.14]	[0.16]	[-0.97]	[-1.56]	[0.06]	[-0.36]	[0.53]	[-0.81]	[0.03]	[-0.69]	[1.01]	[-2.17]	[0.59]	[-0.36]	[0.92]	[-0.10]	[-0.69]	[0.78]	[-0.73]	[-1.78]
Daily	1.50	6.90	0.90	2.72	0.82	3.59	0.32	3.59	0.93	5.12	0.40	2.60	1.31	2.97	0.82	4.99	0.93	6.48	0.18	3.57
	[5.24]	[3.35]	[3.43]	[2.51]	[3.15]	[2.16]	[1.29]	[3.27]	[3.14]	[2.76]	[1.37]	[2.36]	[4.67]	[1.70]	[3.03]	[4.63]	[3.35]	[3.67]	[0.69]	[2.85]

Table A2

Controlling for Calendar Month

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) for the period January 2001 through December 2005 are reported below, as well as the corresponding *t*-statistics (in brackets). The returns are reported separately for each calendar month (using all half-hour intervals in each calendar month). The analysis uses NYSE-listed stocks.

Strategy	January	February	March	April	May	June	July	August	September	October	November	December
Day 1												
Nondaily	-4.74	-5.37	-5.90	-5.07	-3.79	-2.88	-4.71	-4.88	-3.32	-6.14	-3.74	-5.27
	[-6.98]	[-9.36]	[-10.20]	[-9.17]	[-7.71]	[-5.87]	[-7.82]	[-9.57]	[-5.20]	[-9.21]	[-6.72]	[-10.48]
Daily	3.82	3.40	1.70	2.52	2.45	2.95	3.07	3.02	3.25	3.38	3.80	2.90
	[7.14]	[7.27]	[3.64]	[5.23]	[5.79]	[7.24]	[6.50]	[7.16]	[6.88]	[6.27]	[7.80]	[6.44]
Day 2												
Nondaily	0.18	-1.23	-1.12	0.24	-1.11	-0.91	-1.56	-0.47	-0.77	-1.72	-1.16	-1.43
	[0.34]	[-2.43]	[-2.26]	[0.48]	[-2.53]	[-2.04]	[-3.03]	[-1.08]	[-1.53]	[-3.10]	[-2.31]	[-3.55]
Daily	2.58	2.58	2.22	1.55	2.06	1.14	1.46	2.07	2.09	2.44	2.05	1.38
	[5.27]	[5.57]	[4.92]	[3.38]	[5.05]	[2.89]	[3.15]	[4.99]	[4.49]	[4.59]	[4.46]	[3.28]
Day 3												
Nondaily	-0.98	-0.56	-0.57	-0.14	-0.37	-0.92	0.04	-0.32	-0.38	-1.21	-1.25	-0.80
	[-1.86]	[-1.16]	[-1.17]	[-0.30]	[-0.89]	[-2.09]	[0.07]	[-0.81]	[-0.82]	[-2.35]	[-2.55]	[-1.99]
Daily	1.41	1.30	1.50	0.94	1.87	1.48	1.60	0.95	1.66	1.26	1.24	1.08
	[2.94]	[3.00]	[3.51]	[2.04]	[4.67]	[3.91]	[3.57]	[2.43]	[3.64]	[2.52]	[2.64]	[2.89]
Day 4												
Nondaily	-0.88	0.20	-0.08	-0.27	0.04	-0.30	-0.80	-0.69	-0.82	-1.34	0.40	0.56
	[-1.74]	[0.42]	[-0.17]	[-0.58]	[0.11]	[-0.76]	[-1.70]	[-1.70]	[-1.69]	[-2.61]	[0.86]	[1.45]
Daily	1.98	1.33	1.53	1.46	0.92	0.94	1.18	1.36	1.07	0.99	0.88	1.45
	[4.21]	[2.86]	[3.21]	[3.18]	[2.51]	[2.40]	[2.58]	[3.53]	[2.54]	[2.06]	[2.06]	[3.62]
Day 5												
Nondaily	0.45	-0.10	-0.99	-0.53	-0.78	0.08	-0.04	0.36	0.56	-0.08	0.27	0.10
	[0.92]	[-0.22]	[-1.98]	[-1.20]	[-1.92]	[0.20]	[-0.08]	[0.90]	[1.22]	[-0.15]	[0.59]	[0.25]
Daily	1.44	1.22	1.63	2.19	0.74	1.00	0.79	0.78	1.12	0.82	0.92	0.49
	[2.96]	[2.86]	[3.60]	[5.04]	[1.90]	[2.55]	[1.81]	[1.88]	[2.68]	[1.59]	[2.16]	[1.25]

Table A3
Controlling for Turn-of-Month

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) for the period January 2001 through December 2005 are reported below, as well as the corresponding *t*-statistics (in brackets). The returns are reported separately using half-hour intervals during turn-of-month trading days (first and last trading day of the month) and non-turn-of-month days. The returns are also partitioned using all half-hour intervals of a day, as well as using only the first, the last and the rest. The analysis uses NYSE-listed stocks.

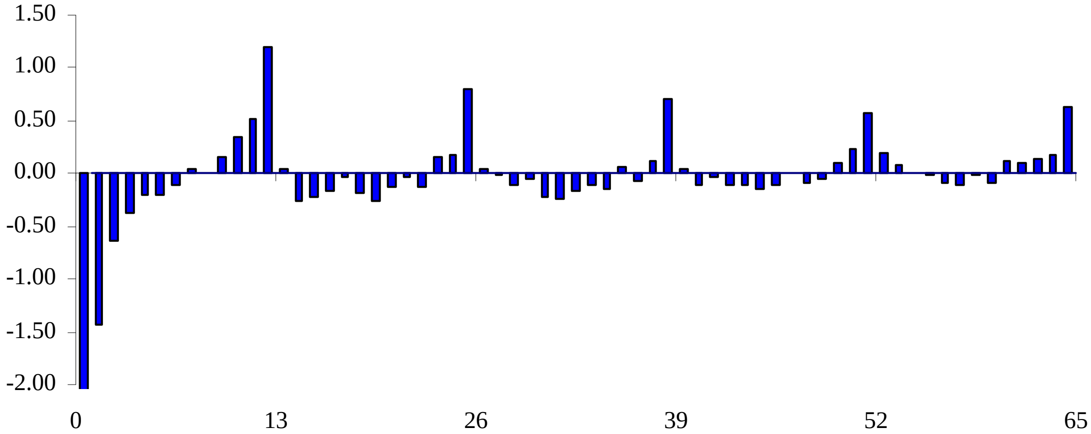
Strategy	Non-turn-of-month trading days				Turn-of-month trading days			
	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)
Day 1								
Nondaily	-4.57	-8.38	-3.65	-10.84	-5.62	-8.10	-4.55	-14.97
	[-25.92]	[-8.25]	[-20.76]	[-16.86]	[-11.79]	[-3.19]	[-9.62]	[-7.45]
Daily	3.12	12.06	1.79	8.90	1.95	5.97	1.41	3.84
	[21.81]	[12.49]	[13.63]	[15.35]	[4.50]	[2.19]	[3.52]	[1.77]
Day 2								
Nondaily	-0.87	-2.74	-0.42	-3.99	-1.44	-5.11	-1.07	-1.83
	[-5.85]	[-3.05]	[-2.83]	[-7.36]	[-3.34]	[-2.15]	[-2.50]	[-0.97]
Daily	2.05	10.77	0.83	6.74	1.16	7.73	0.27	4.33
	[14.80]	[11.88]	[6.53]	[11.22]	[2.93]	[3.29]	[0.72]	[2.41]
Day 3								
Nondaily	-0.61	-5.11	-0.14	-1.28	-0.69	-2.53	-0.46	-1.40
	[-4.32]	[-5.96]	[-1.02]	[-2.52]	[-1.69]	[-1.11]	[-1.13]	[-0.80]
Daily	1.44	6.45	0.60	5.68	0.54	5.12	-0.24	4.50
	[10.84]	[7.29]	[4.87]	[10.20]	[1.36]	[2.12]	[-0.64]	[2.49]
Day 4								
Nondaily	-0.34	-2.78	-0.02	-1.42	-0.34	-0.40	-0.39	0.31
	[-2.47]	[-3.40]	[-0.15]	[-2.89]	[-0.84]	[-0.18]	[-0.97]	[0.20]
Daily	1.26	5.85	0.58	4.15	1.23	3.68	0.58	5.94
	[9.53]	[6.76]	[4.69]	[7.36]	[3.07]	[1.39]	[1.58]	[3.13]
Day 5								
Nondaily	-0.06	-0.65	0.12	-1.40	-0.10	4.68	-0.52	-0.25
	[-0.44]	[-0.79]	[0.83]	[-2.93]	[-0.24]	[2.14]	[-1.29]	[-0.16]
Daily	1.15	5.15	0.57	3.45	0.57	3.42	0.00	3.99
	[8.67]	[6.05]	[4.53]	[6.60]	[1.44]	[1.25]	[-0.00]	[2.23]

Table A4

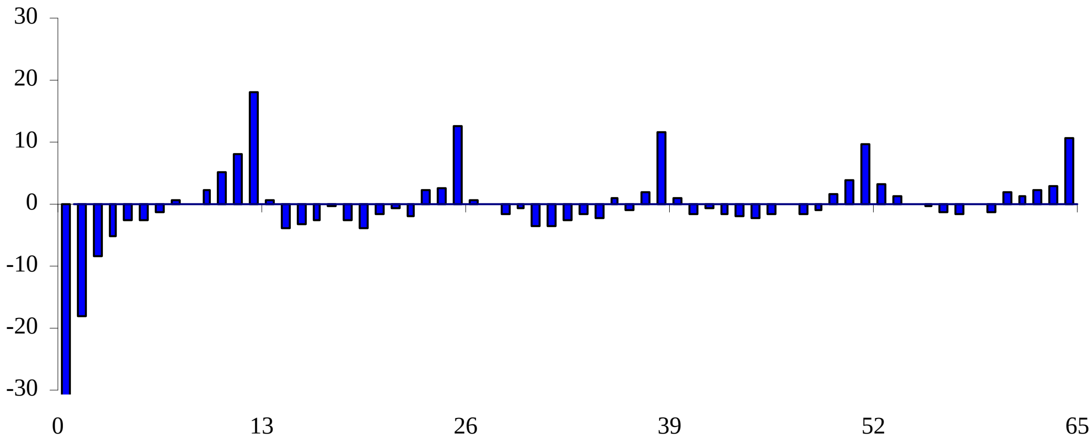
Controlling for Inclusion in the S&P500 Index

Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the Day 1 trading strategy that is formed based on a daily frequency ranks stocks according to their return during the historical lag half-hour interval 13, while the nondaily strategy ranks stocks according to their average returns over the lag half-hour intervals 1 through 12. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average returns of the top-minus-bottom-decile portfolios (per half hour, in basis points) for the period January 2001 through December 2005 are reported below, as well as the corresponding *t*-statistics (in brackets). The returns of the long-short portfolios are partitioned into the parts attributed to firms that are included in the S&P500 Index and those that are not included in the index. The returns are also partitioned using all half-hour intervals of a day, as well as using only the first, the last and the rest. The analysis uses NYSE-listed stocks.

Strategy	Non-S&P500-Index stocks				S&P500-Index stocks			
	1-13 (all)	1 (first)	2-12	13 (last)	1-13 (all)	1 (first)	2-12	13 (last)
Day 1								
Nondaily	-5.58	-10.43	-4.48	-12.84	-0.72	1.32	-0.54	-4.81
	[-31.53]	[-10.58]	[-25.37]	[-18.62]	[-2.96]	[0.83]	[-2.26]	[-6.19]
Daily	3.28	12.95	1.93	8.56	2.19	8.23	0.98	9.42
	[22.18]	[13.25]	[14.07]	[14.13]	[10.93]	[6.74]	[5.17]	[10.43]
Day 2								
Nondaily	-0.86	-3.41	-0.37	-3.78	-1.10	-1.61	-0.77	-4.29
	[-5.71]	[-3.98]	[-2.43]	[-6.31]	[-5.00]	[-1.07]	[-3.60]	[-6.59]
Daily	2.09	10.93	0.90	6.37	1.81	9.58	0.52	8.27
	[14.66]	[12.09]	[6.69]	[10.70]	[9.25]	[8.11]	[2.81]	[8.66]
Day 3								
Nondaily	-0.65	-4.94	-0.15	-1.86	-0.52	-5.15	-0.24	1.00
	[-4.41]	[-5.84]	[-1.00]	[-3.32]	[-2.46]	[-3.56]	[-1.16]	[1.51]
Daily	1.47	6.67	0.63	5.56	1.19	5.44	0.26	7.09
	[10.62]	[7.42]	[4.80]	[9.80]	[6.18]	[4.62]	[1.44]	[8.08]
Day 4								
Nondaily	-0.37	-3.39	0.01	-1.44	-0.21	0.71	-0.25	-0.74
	[-2.56]	[-4.20]	[0.04]	[-2.73]	[-1.01]	[0.49]	[-1.24]	[-1.14]
Daily	1.29	5.93	0.62	4.04	1.07	5.00	0.49	3.58
	[9.42]	[6.78]	[4.76]	[7.03]	[5.59]	[4.28]	[2.67]	[4.05]
Day 5								
Nondaily	-0.16	-0.53	0.00	-1.55	0.20	0.90	0.16	-0.02
	[-1.09]	[-0.64]	[0.03]	[-2.97]	[0.95]	[0.61]	[0.78]	[-0.03]
Daily	1.17	5.14	0.61	3.39	0.60	3.35	0.13	2.97
	[8.56]	[6.01]	[4.58]	[6.33]	[3.08]	[2.83]	[0.70]	[3.40]

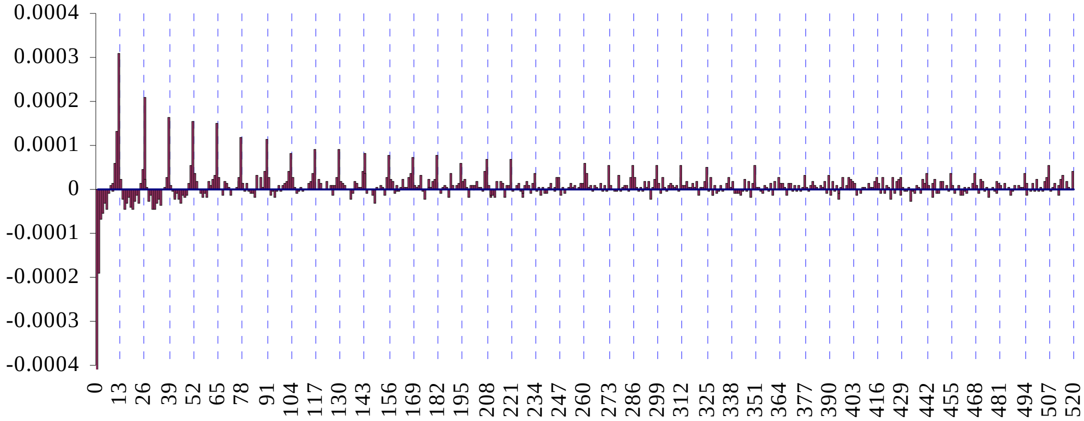


Panel A. Estimates of cross-sectional regressions

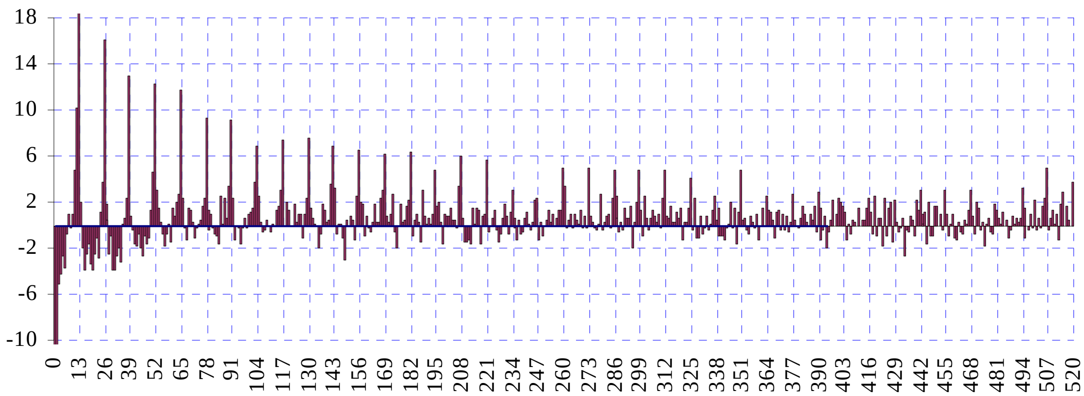


Panel B. *t*-statistics of cross-sectional regression estimates

Figure 1. Cross-sectional regressions of half-hour-interval returns. Intraday cross-sectional simple regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$ are calculated for half-hour interval *t* and lag *k*, and where $r_{i,t}$ is return of stock *i* during interval *t*. The lagged variable $r_{i,t-k}$ is return of stock *i* in interval *t–k*. The regression is calculated for every half-hour interval *t* from January 2001 through December 2005 (16,261 intervals), and for lag *k* values 1 through 65 (past 5 trading days). Panel A plots the time-series averages of $\gamma_{k,t}$ (in percent). Panel B plots the respective *t*–statistics. The analysis uses NYSE-listed stocks.



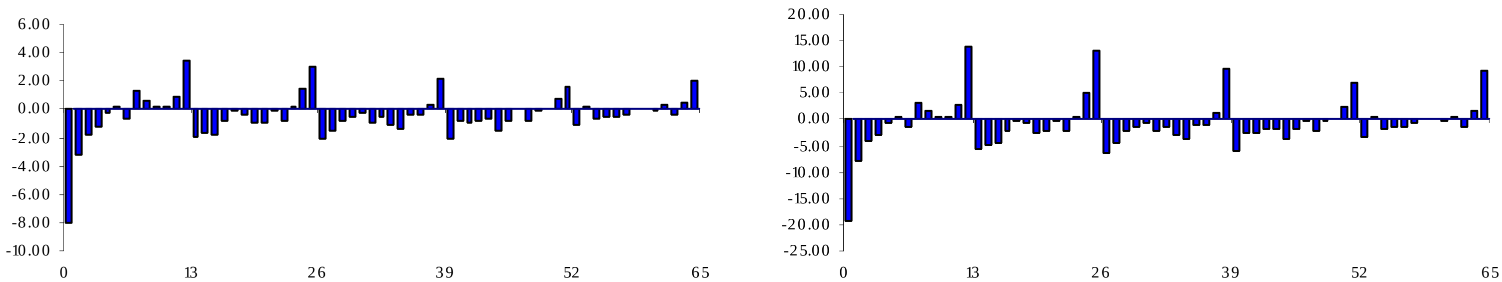
Panel A. Average decile portfolio spread returns



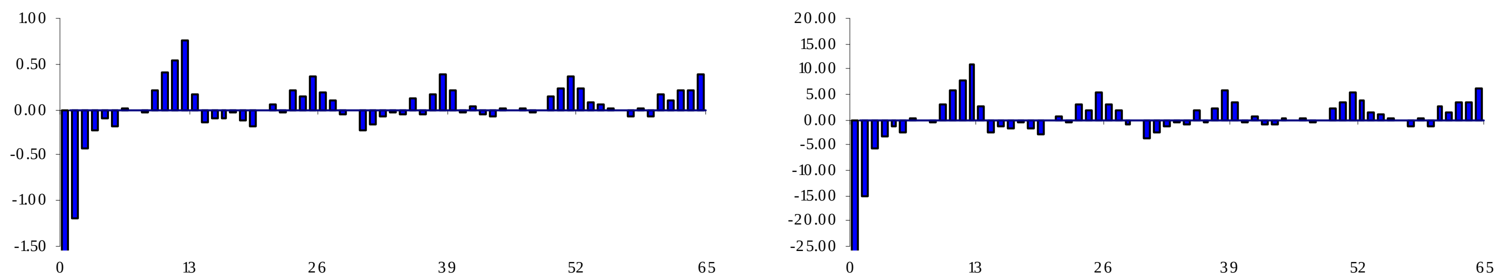
Panel B. *t*-statistics

Figure 2. Half-hour-interval returns for decile portfolio spreads. Every half-hour interval stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, Lag 65 trading strategy ranks stocks according to their return during the historical lag half-hour interval 65. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced every half hour. The average return (per half hour, in basis points) of the top-minus-bottom decile portfolios for trading strategies corresponding to lags 1 through 520 for the period January 2001 through December 2005 (16,261 intervals) are reported below, as well as the corresponding t-statistics (in brackets). The analysis uses NYSE-listed stocks.

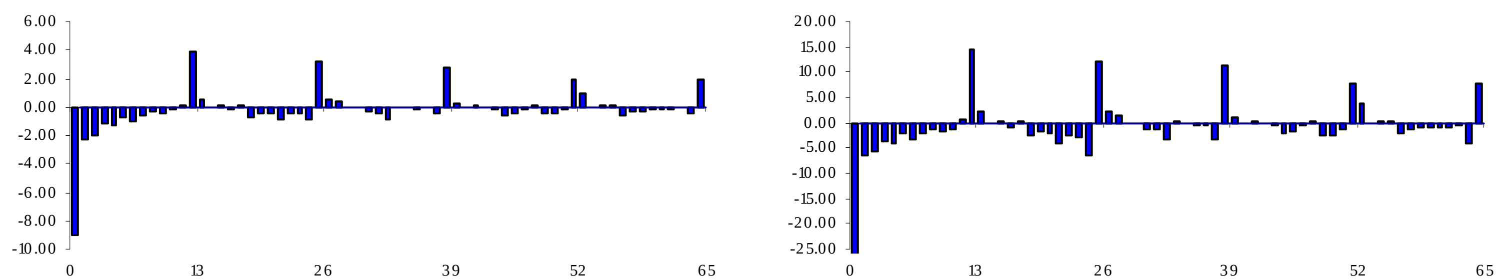
Half-hour interval 9:30–10:00



Half-hour intervals 10:00–15:30



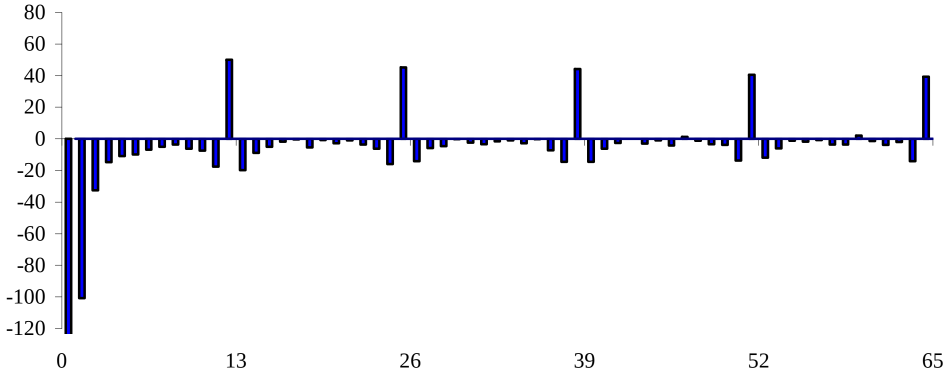
Half-hour interval 15:30–16:00



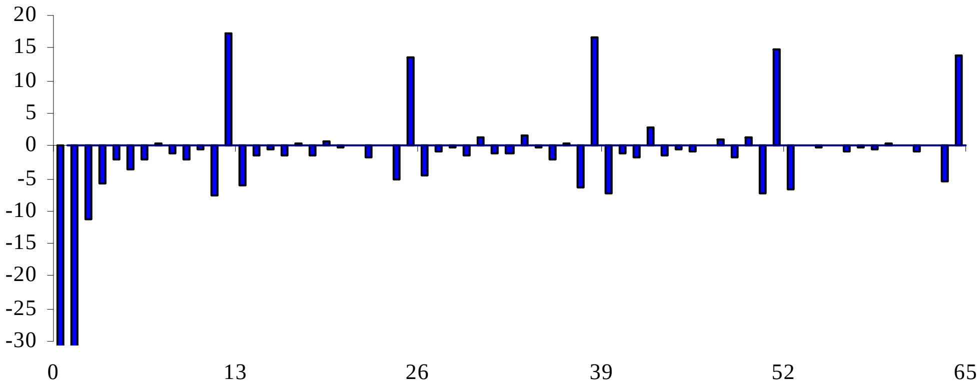
Panel A. Estimates of cross-sectional regressions

Panel B. *t*-statistics of cross-sectional regression estimates

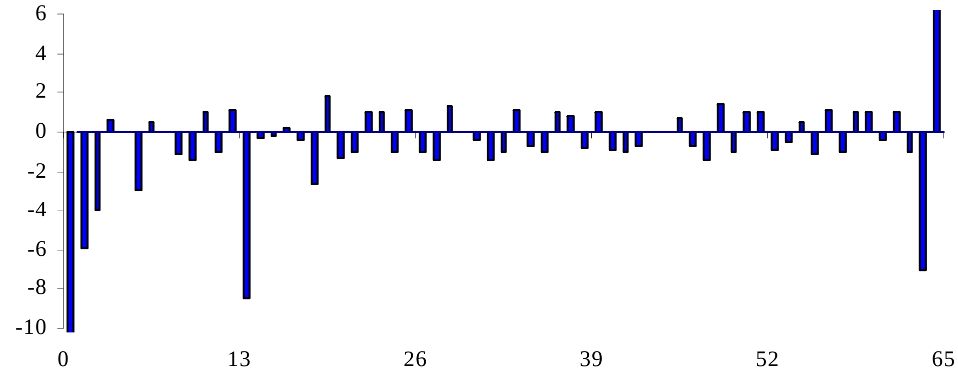
Figure 3. Cross-sectional regressions of half-hour-interval returns per interval. Intraday cross-sectional simple regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$ are calculated for half-hour interval *t* and lag *k*, and where $r_{i,t}$ is return of stock *i* during interval *t*. The regression is calculated for every half-hour interval *t* from January 2001 through December 2005 (16,261 intervals), and for lag *k* values 1 through 65 (past 5 trading days). Panel A plots the time-series averages of $\gamma_{k,t}$ (in percent) separately for the first and last half-hour intervals of a trading day, as well as pooling the rest of the intervals. Panel B plots the respective *t*–statistics. The analysis uses NYSE-listed stocks.



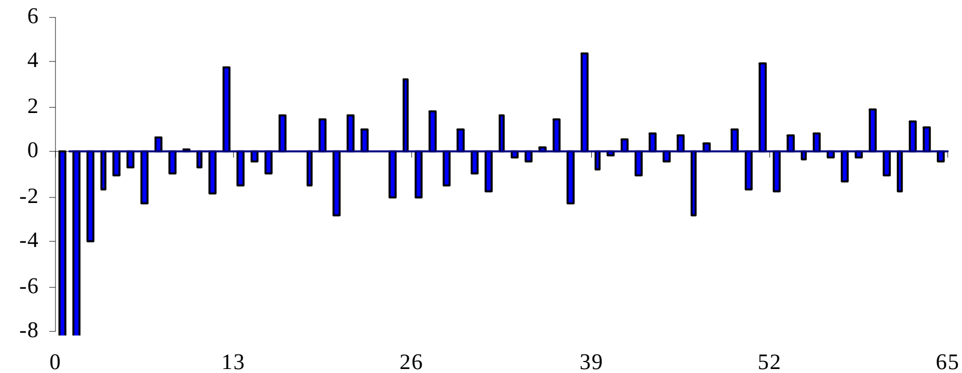
Panel A. Volume regressed on lagged volume



Panel B. Volatility regressed on lagged volatility

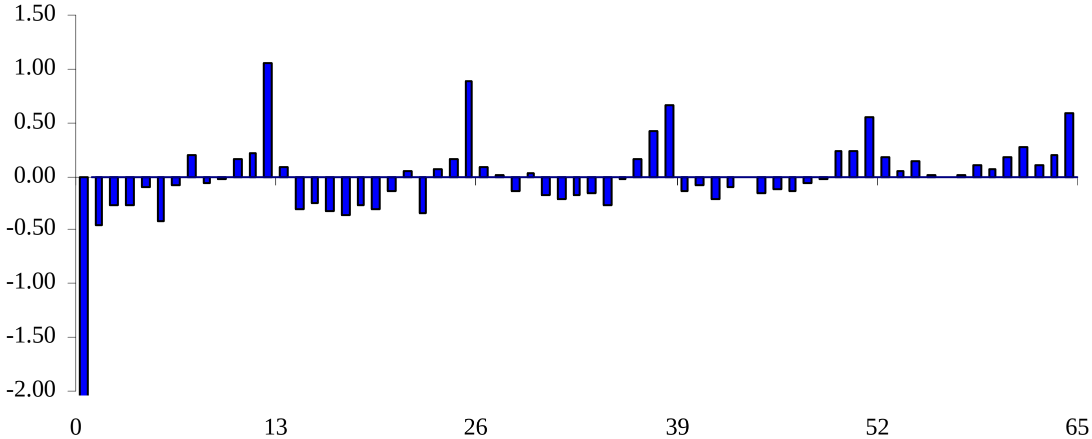


Panel C. Spread regressed on lagged spread

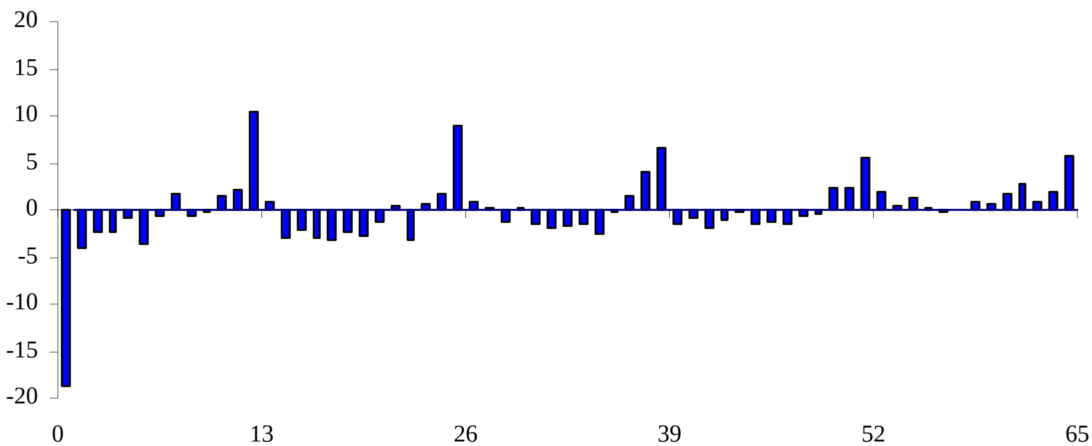


Panel D. Imbalance regressed on lagged imbalance

Figure 4. Cross-sectional regressions of half-hour interval volume, volatility, relative bid/ask spreads, and order imbalances (*t*-statistics). Monthly cross-sectional regressions of the following form are calculated for each month *t* and lag *k*: $v_{i,t} = \alpha_{k,t} + \gamma_{k,t} v_{i,t-k} + u_{i,t}$, where $v_{i,t}$ is either volume (total shares traded during the half-hour interval), volatility (the absolute value of the half-hour return), the quoted relative bid/ask spread (spread divided by the midpoint of the bid and ask; using the first quotes in each time interval), or the order imbalance over the time interval (buyer-initiated volume minus seller-initiated volume divided by their sum). For the analysis, volume, volatility, and spread are measured as the logarithm of the ratio of each and its prior one lag value, while first differences are used for order imbalance. The regressions are calculated for every half-hour interval *t* from January 2001 through December 2005 (16,261 intervals), and for lag *k* values 1 through 65 (past 5 trading days), using all firms with relative bid/ask spread of no more than 25 basis points at the beginning of the interval. All panels plot the *t*-statistics of the time-series averages of the regression coefficients. The analysis uses NYSE-listed stocks.



Panel A. Estimates of cross-sectional regressions



Panel B. *t*-statistics of cross-sectional regression estimates

Figure 5. Cross-sectional regressions of half-hour-interval returns controlling for various variables. Intraday cross-sectional simple regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + \delta_{k,t}`v_{i,t-k} + u_{i,t}$ are calculated for half-hour interval *t* and lag *k*, where $r_{i,t}$ is return of stock *i* during interval *t* and $r_{i,t-k}$ is return of stock *i* in interval *t–k*. The vector $v_{i,t-k}$ includes four lagged control variables: Volume (total shares traded during the half-hour interval), volatility (the absolute value of the half-hour return), quoted relative bid/ask spread (spread divided by the midpoint of the bid and ask; using the first quotes in each time interval), and order imbalance over the time interval (buyer-initiated volume minus seller-initiated volume divided by their sum). The variables volume, volatility, and spread are measured as the logarithm of the ratio of each and its prior one lag value, while first differences are used for order imbalance. The regression is calculated for every half-hour interval *t* from January 2001 through December 2005 (16,261 intervals), and for lag *k* values 1 through 65 (past 5 trading days). Panel A plots the time-series averages of $\gamma_{k,t}$ (in percent). Panel B plots the respective *t*–statistics. The analysis uses NYSE-listed stocks.

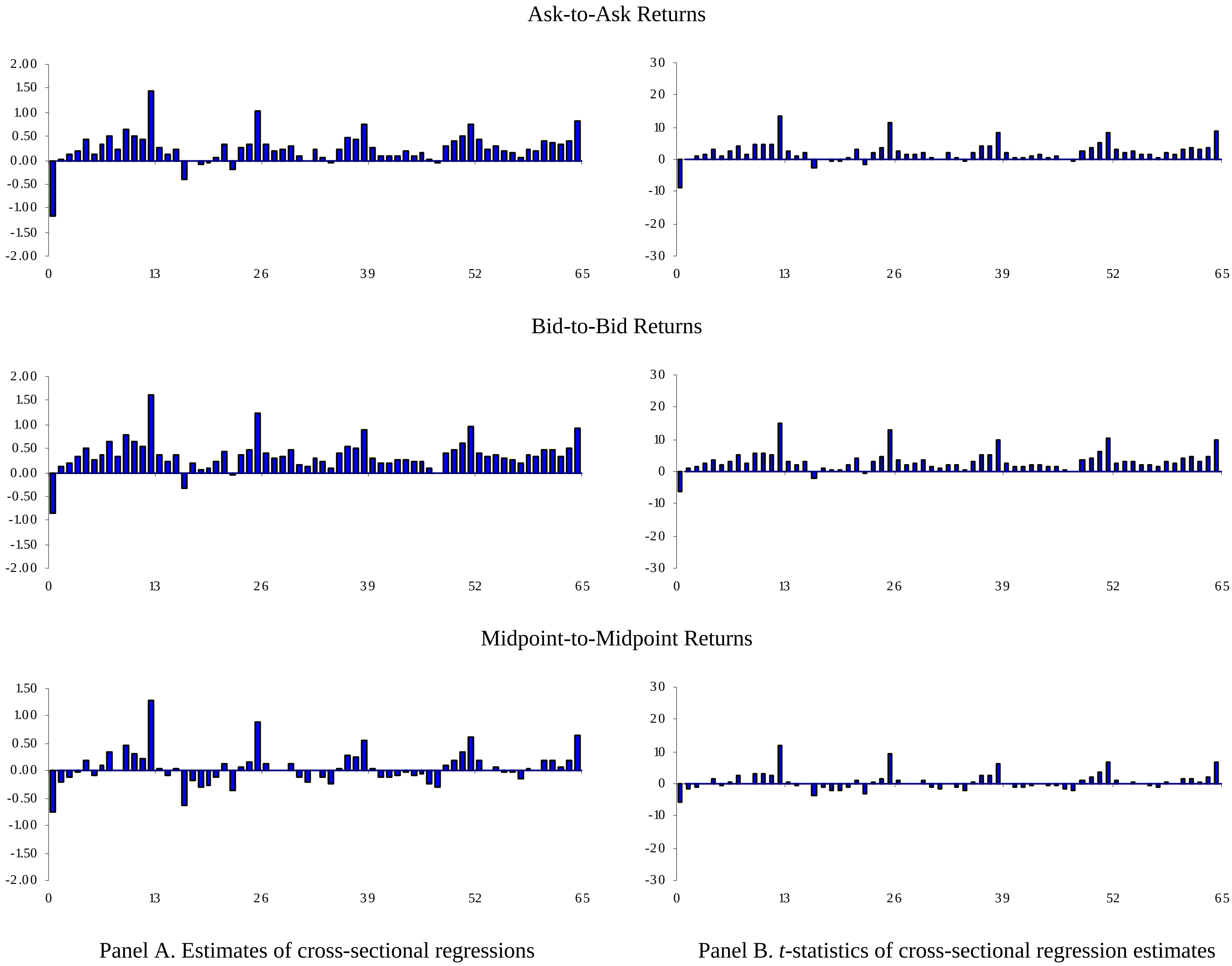
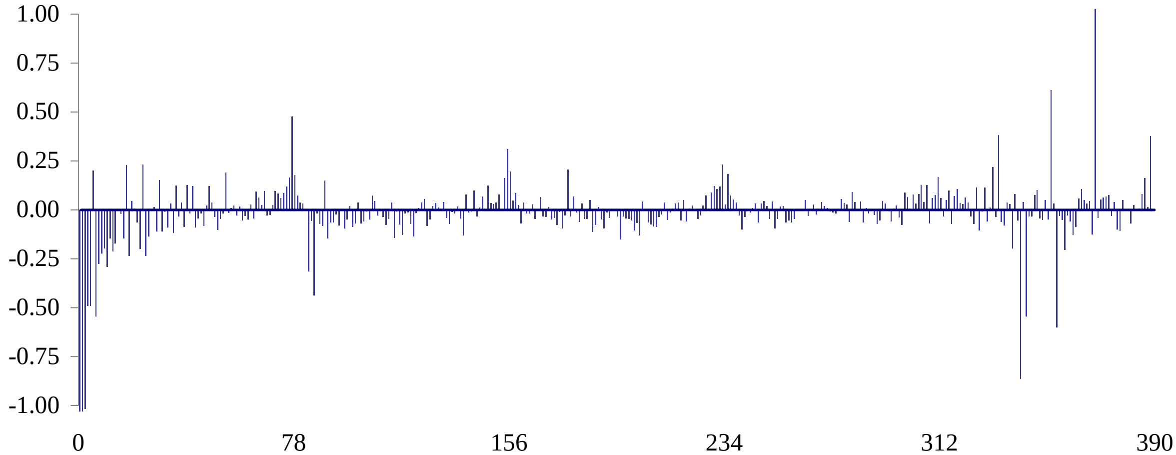
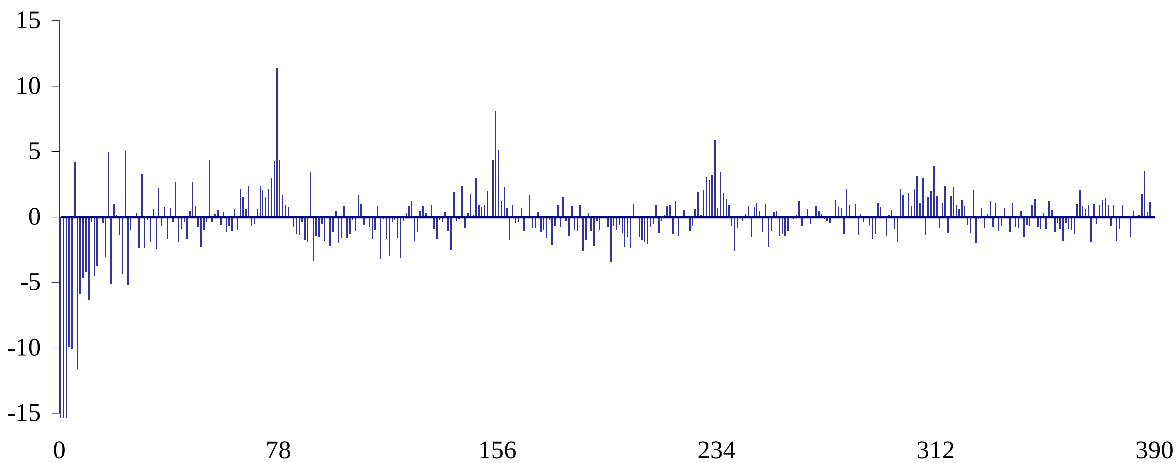


Figure 6. Cross-sectional regressions using different return measures over half-hour intervals. Intraday cross-sectional simple regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$ are calculated for half-hour interval t and lag k, and where $r_{i,t}$ is return of stock i during interval t. The lagged variable $r_{i,t-k}$ is return of stock i in interval t–k. The regression is calculated for every half-hour interval t from January 2001 through December 2005 (16,261 intervals), and for lag k values 1 through 65 (past 5 trading days). Return is measured using either ask prices, bid prices, or the bid-ask midpoint prices. Panel A plots the time-series averages of $\gamma_{k,t}$ (in percent). Panel B plots the respective t–statistics. The analysis uses NYSE-listed stocks.

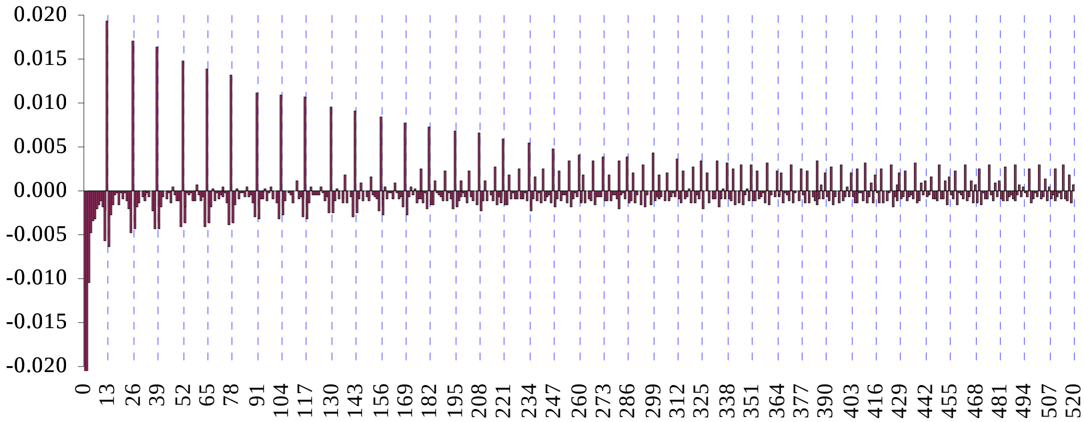


Panel A. Estimates of cross-sectional regressions

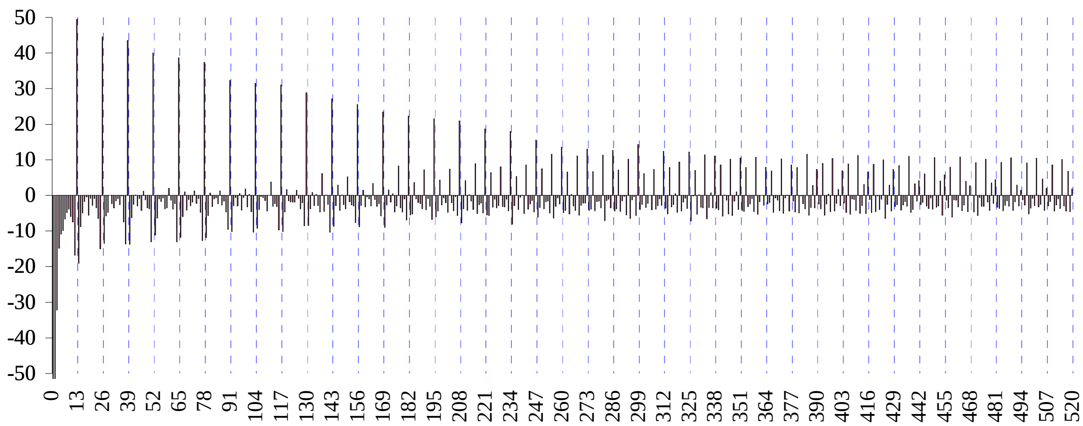


Panel B. *t*-statistics of cross-sectional regression estimates

Figure 7. Cross-sectional regressions of five-minute-interval returns. Intraday cross-sectional simple regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$ are calculated for five-minute interval *t* and lag *k*, and where $r_{i,t}$ is return of stock *i* during interval *t*. The lagged variable $r_{i,t-k}$ is return of stock *i* in interval *t*–*k*. The regression is calculated for every five-minute interval *t* from January 2004 through December 2005 (39,244 intervals), and for lag *k* values 1 through 390 (past 5 trading days; 78 intervals per trading day). Panel A plots the time-series averages of $\gamma_{k,t}$ (in percent). Panel B plots the respective *t*–statistics. The analysis uses NYSE-listed stocks.

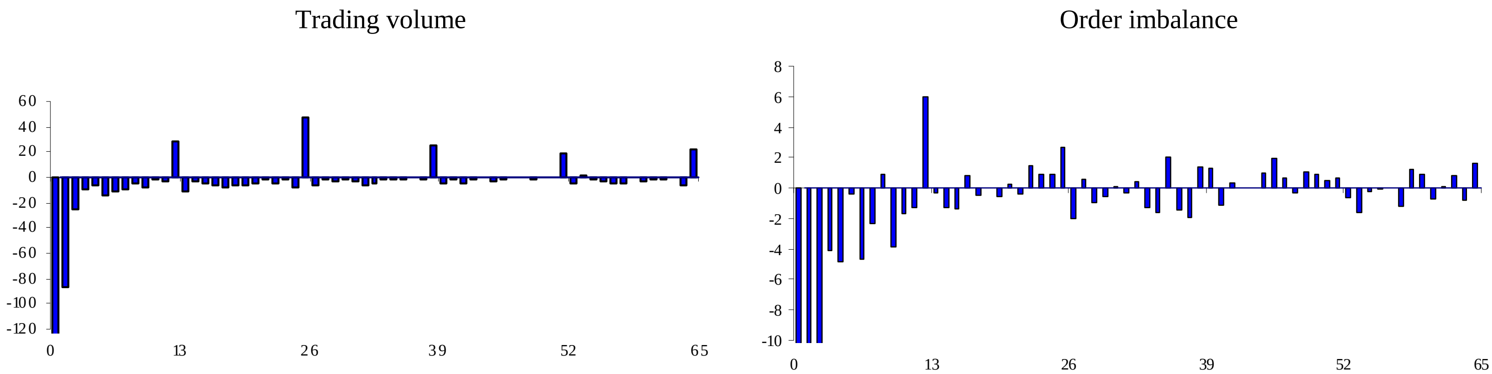


Panel A. Estimates of cross-sectional regressions

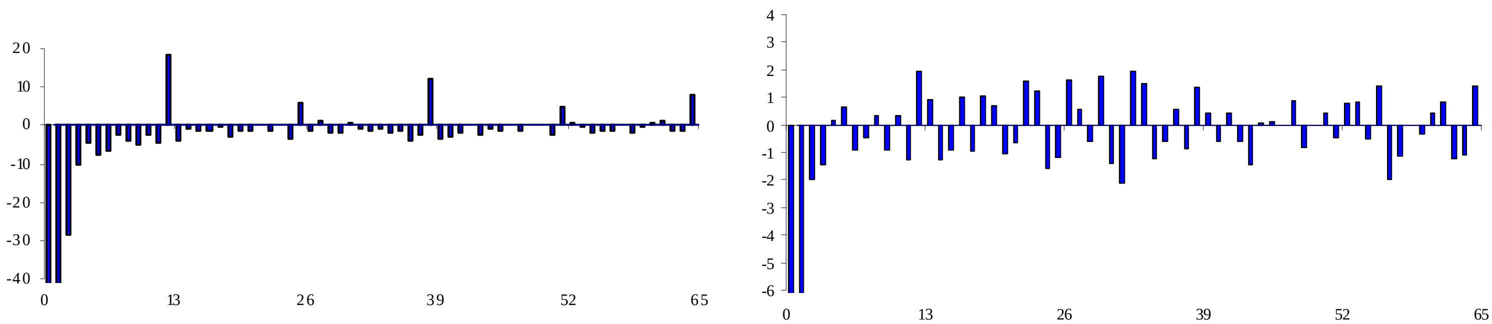


Panel B. *t*-statistics of cross-sectional regression estimates

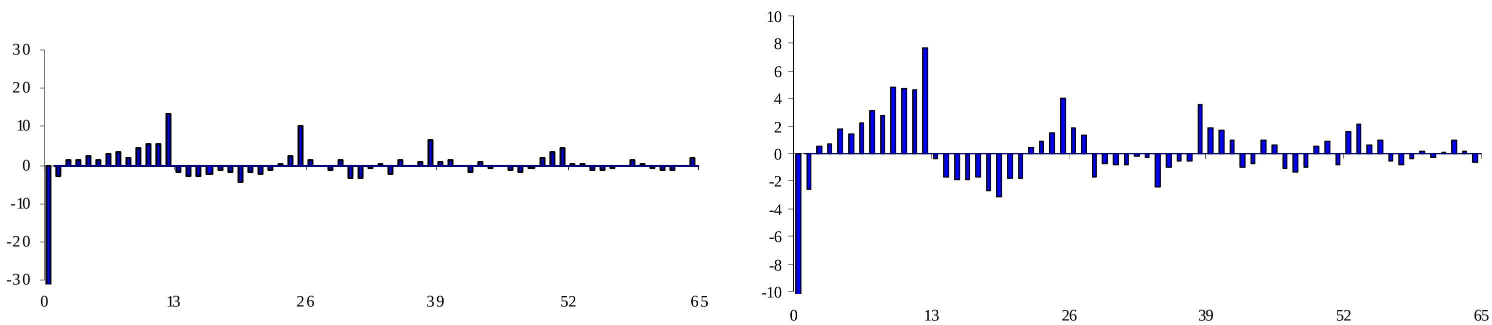
Figure A1. Cross-sectional regressions of half-hour interval volume. Monthly cross-sectional simple regressions of the form $v_{i,t} = \alpha_{k,t} + \gamma_{k,t} v_{i,t-k} + u_{i,t}$ are calculated for each month *t* and lag *k*, and where $v_{i,t}$ is volume of stock *i* during interval *t*. Volume is defined as the number of shares traded. For the analysis, volume is the logarithm of the ratio of volume and its prior one lag value. The lagged variable $x_{i,t-k}$ is either volume or return of stock *i* in month *t*–*k*. The regression is calculated for every half-hour interval *t* from January 2001 through December 2005 (16,261 intervals), and for lag *k* values 1 through 520 (past 40 trading days). Panel A plots the time-series averages of $\gamma_{k,t}$. Panel B plots the respective *t*–statistics. The analysis uses NYSE-listed stocks.



Panel A. Small trades regressed on small trades



Panel B. Large trades regressed on large trades



Panel C. Return regressed on lagged return and lagged small and large trades (lagged return coefficient)

Figure A2. Cross-sectional regressions of half-hour interval returns and small- and large-trade volume and order imbalance (*t*-statistics). Monthly cross-sectional regressions of the following forms are calculated for each month t and lag k: $sv_{i,t} = \alpha_{k,t} + \gamma_{k,t} sv_{i,t-k} + u_{i,t}$ (Panel A), $lv_{i,t} = \alpha_{k,t} + \gamma_{k,t} lv_{i,t-k} + u_{i,t}$ (Panel B), and $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + \delta_{k,t} sv_{i,t-k} + \eta_{k,t} lv_{i,t-k} + u_{i,t}$ (Panel C), where $sv_{i,t}$ and $lv_{i,t}$ are small- and large-trade volume (shares traded during the half-hour interval) or order imbalance (buyer-initiated volume minus seller-initiated volume divided by their sum) and $r_{i,t}$ is the return of stock i during interval t. Small trades are trades below 1,000 shares, and large trades those above or equal to 1,000 shares. For the analysis, each volume measure is the logarithm of the ratio of volume and its prior one lag value, while first differences are used for order imbalances. The regressions are calculated for every half-hour interval t from January 2001 through December 2005 (16,261 intervals), and for lag k values 1 through 65 (past 5 trading days). All panels plot the t-statistics of the time-series averages of the regression coefficients. The analysis uses NYSE-listed stocks.