



LUND UNIVERSITY
School of Economics and Management

Master Essay II

**The Intraday Dynamics of Stock
Returns and Trading Activity:
Evidence from OMXS 30**

Supervisors:

Hossein Asgharian

Bjorn Hansson

Authors:

Veronika Lunina

Tetiana Dzhumurat

June 2011

Abstract

In this study we analyze the intraday behaviour of stock returns and trading volume using the data on OMXS 30 stocks. We find that returns follow a reverse J-shaped pattern with the peak at the beginning of the trading day, while trading volume attains its maximum towards at the market closure. The highest volatility and kurtosis are observed at 09:30-10:00, and 11:30-12:00, when the macroeconomic news are released. Cross-sectional autoregressions reveal that both returns and volumes are significantly and positively affected by their own past realizations at daily frequencies. However, periodicity in volumes does not explain periodicity in returns. Return continuation at daily frequencies is confirmed by analyzing stocks' performance in the long run. Our results are not affected by decreasing the sampling frequency from 15 to 30 minutes.

Key words: intraday periodicity, return responses, trading volume

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1 Introduction

Extensive research has documented the existence of intraday regularities in stock returns, volatility, and key financial market variables, such as trading volumes, bid-ask spreads, order imbalances etc. The earlier studies generally provide the proof of the U-shaped intraday return pattern. For example, Wood, McInish and Ord (1985), Harris (1986), and Jain and Joh (1988) find that average returns on the New York Stock Exchange (NYSE) stocks are high at the beginning of the trading day, decline during the middle, and rise towards the market closure. The similar patterns were reported for trading volumes and bid-ask spreads in a number of studies (Brock and Kleidon (1992), McInish and Wood (1990)). The intraday data allows to reveal the information which cannot be traced using the data of lower frequency, and gain new perspective on the financial markets' behaviour. However, higher informational content comes at the cost of aggravating the impact of market microstructure frictions, such as non-synchronous trading bias, bid-ask bounce, reporting errors etc.

Traditionally, most of the papers examine the US stock market behaviour. More recently, studies of the intraday periodicities on the European equity markets have been developed, though they are still rare. Harju and Hussain (2006) document the reverse J-shaped pattern of the intraday return volatility for four main European stock market indices, namely FTSE 100, XDAX 30, SMI and CAC 40. According to Hussain (2009), the aggregate trading volume of XDAX 30 (the German blue chip index) follows the L-shaped pattern, while individual stocks display the reverse J-shaped pattern.

There are a number of explanations of the observed periodicities in trading activity and market liquidity variables. The intraday regularities on stock markets are usually attributed to the specifics of trading mechanisms, the impact of information flow, liquidity preferences of traders and spillover effects. The two main theoretical models, which imply the existence of predictable intraday patterns in bid-ask spreads, volumes and volatility, are the liquidity trading model of Admati and Pfleiderer (1988), and the market closure model of Brock and Kleidon (1992). The former grounds on the behaviour of the so called liquidity traders, who do not have any private information and execute their trades in a way that minimizes trading costs. The latter relates trading strategies to the ability to trade and liquidity demands at different times during the trading day. These models can justify the intraday periodicities in volumes and volatility. There is also

substantial empirical evidence that institutional fund flows are persistently autocorrelated. Campbell, Ramadorai, and Schwartz (2009) find that institutional traders tend to trade the same stocks on successive days, which leads to regular patterns in trading volumes.

Predictability in returns, on the other hand, is harder to explain. Heston, Korajczyk and Sadka (2010) examine the intraday patterns in the cross-section of NYSE stock returns. For each stock they compute 13 half-hour returns per trading day. By regressing the returns on their own past values, they confirm that the first several responses are negative, which is consistent with the well-proved fact that returns are negatively autocorrelated in the short term. The reversal period lasts several hours, after which the responses are positive. The important result is that a stock's return at a given time period is positively and significantly related to its subsequent returns at daily frequencies (lags 13, 26, 39 ...). Heston, Korajczyk and Sadka show that this continuation pattern lasts persistently for 40 trading days and is not induced by the previously discovered patterns, such as the day-of-the-week effect (French (1980)), or the turn-of-the-month effect (Ariel (1987)). Additional diagnostics reveal that it is not affected by firm's market capitalization, index membership or fluctuations in exposure to systematic risk. The authors conclude that trading costs may be reduced by timing buys (sells) in accordance with the daily recurrence of the recent intraday low (high) prices. Another finding is that trading volumes, return volatility and bid-ask spreads follow the same patterns, but do not subsume the predictability of returns.

The objective of this study is twofold. Firstly, it examines the intraday regularities of stock returns and trading activity on the Stockholm Stock Exchange. Secondly, it explores whether return patterns are explained by the patterns in trading volumes. Research in this area is relevant for the following reasons. First of all, existing studies focus primarily on the US equity market, and it would be of interest to get more empirical evidence from the Swedish market. Further, if there exists any predictability in the financial market variables, it can be utilized to develop the optimal trading schedule allowing to minimize execution costs.

Our data set comprises the intraday 15-minute observations on the transaction prices and trading volumes of the stocks included into the OMX Stockholm 30 index (OMXS 30), for the period Jul 1, 2010 through Dec 30, 2010. OMXS 30 measures the performance of 30 companies most traded on the Stockholm Stock Exchange. This data reveals the price and quantity movements of stocks during the trading day. Following suggestions in Heston, Korajczyk and Sadka (2010), we conduct our analysis using the cross-sectional autoregressive methodology.

Regressions are estimated both for 15-minute and for 30-minute returns. We are interested in the sign and significance of the slope coefficients, which represent return responses to their own previous realizations.

To assess the magnitude of the found periodicities we analyze the equally-weighted long-short strategies with the holding period of one time interval, as suggested in Heston, Korajczyk and Sadka (2010). Based on the past performance, we group the stocks into portfolios, and for each lag we find the average return on the strategy which goes long in the portfolio of winning stocks and short in the portfolio of losing stocks. The magnitude and significance of this top-minus-bottom return indicates the extent to which stock returns are affected by their previous realizations of a particular lag length.

Further, we repeat the cross-sectional regression procedure for percentage changes in trading volumes. We proceed with testing if periodicity in trading volumes explains periodicity in stock returns. This is done by including lags of trading volumes as additional explanatory variables into the cross-sectional autoregressive model of returns. If return patterns stem from the predictable trading activity, then including these additional regressors should decrease or even subsume regularities of returns based merely on their own past values. Statistically, this will result in the insignificance of the lagged returns.

The rest of the study is organized in the following way. Section 2 presents the theoretical premises behind the intraday behaviour of the key financial market variables, and briefly reviews the previous research in this area. Section 3 outlines the empirical methodology and the data used. Empirical analysis is described in Section 4. Section 5 summarizes the major findings and suggests the practical implications of the obtained results, as well as the ideas for future research.

2 Theoretical Background

2.1 General Stock Trading Patterns

Periodicities in financial time series have always been of academic and practical interest. That is why there are so many studies focused both on the individual patterns in the financial market variables, and their comovements. Among the most common findings of the last 20 years are the monthly, turn-of-the-year, turn-of-the-month and day-of-the-week effects in the dynamics of stock returns.

Several studies including Roze and Kinney (1976), Bouman and Jacobsen (2002) confirm the presence of the so called “January effect”. Stock returns appear to be statistically significantly larger during the first month of the year compared to the rest of the year. French (1980), Keim and Stambaugh (1984), using weekly data from the NYSE, found that on average stock returns tend to be lower when the markets open on Mondays, and higher at the close on Fridays. Later, in 1986, Harris examined the intraday patterns in returns and found significant price drop on Mondays and further increase in prices as the market evolves during the rest of the week.

Over the recent years, lots of studies employing the high frequency data emerged. The intraday data allows to reveal the patterns in financial markets’ activity, which can be hardly traced with the data of lower frequency. The two distinctive features empirically proved so far are the long memory in returns (slow U-shaped decay of volatility) and the strong intraday seasonality (opening/closing times, news announcements etc.).

With the increased availability of high frequency data more and more studies examine financial markets other than the American. This allows to analyze the interactions between different markets. In this paper we aim to extend the knowledge of the intraday stock trading patterns on the Swedish stock market.

2.2 Explanations for the Intraday Patterns in the Financial Market

Variables

The common hypothesis about asset prices is that they follow a Geometric Brownian Motion process. According to this hypothesis, asset return is considered to be a random variable

that follows a continuous time stochastic process where extremes are rare, though if a shock occurs, the value of return may change significantly in the short period of time. Stock prices are affected by the news announcements throughout the day. If the efficient market hypothesis holds, markets should respond immediately to the arrival of new information, and the present prices should fully reflect all the history. This means, that there is supposed to be no return continuation, since all the past news has already been incorporated in the current price.

However, when the studies employing the high frequency data emerged, a number of patterns were discovered that contradict the randomness of the stock price behaviour. The obvious benefit of the higher sampling frequency is that it allows to retain more information. However, there is a tradeoff between the informational content of the data and its exposure to a wide range of market microstructure frictions. According to Goodhart and O'Hara (1997), there is a difficulty even in defining the intraday returns, as there might be periods when no trades occur. The incorrect reporting and notation of bid-ask spreads during such short intervals often lead to measurement errors, and therefore, inconsistent estimates. Non-synchronous trading is another factor, which complicates analysis of high frequency data. All these frictions create statistical noise, which contaminates the price signal.

Historically, the choice of sampling frequency has been based on the availability of data. Now that the intraday databases are widely available, this choice becomes a question of the specifics of the analyzed assets, and the methodology used. For example, more liquid assets are less subject to the microstructure noise, because they are frequently traded and have lower bid-ask spreads.

Let us have a closer look at the important factors which justify the presence of the intraday variations in stock returns, return volatilities, volumes and bid-ask spreads.

- Firstly, certain intraday periodicities stem from the **institutional features of trading markets** (market microstructure). The dealer markets, such as NASDAQ, and the organized exchanges have different trading mechanisms. According to Stoll and Whaley (1990), NYSE opening procedures provide specialists with some market power at the beginning of a day, since they have private information about order imbalances. As Brock and Kleidon (1992) note, this market power, together with the inelastic demand of

investors to trade, allows specialists to widen the bid-ask spreads at the beginning and the close of trading sessions.

- Secondly, the intraday patterns may be caused by traders' **liquidity management** decisions. Liquidity risk tends to rise closer to the end of a trading day and increase volatility of returns. In order to maintain optimal portfolios, and not to be left with unhedged assets, the overnight traders tend to widen spreads prior to the closing time. Liquidity concern also causes high volatilities at the beginning of a trading day, as the new information arrives to the market. Speculators, who have taken their risk premium for holding assets overnight, need to get rid of the assets before the information, which can significantly influence the price, is revealed. Vijh (1988) documents that trades which occur before the closing hour are intended either to affect the price, or to sell the unwanted items and the associated uncertainty.
- Thirdly, the **information flow** is considered to be one of the important factors affecting returns. Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) have developed two main private information microstructure models. Both models attribute patterns in trading volumes and returns to changes in the information advantage of the informed traders. In particular, this advantage is reduced when the information is publicly released, and when market makers draw inferences from the movements in the order flow. Foster and Viswanathan claim that an informed trader has the greatest advantage at the market opening, when the volume of liquidity trading is the highest. They state that weekend closing of the market leads to significant information advantage on Mondays, which can possibly explain the negative Monday returns on assets. There are also studies which focus on the impact of seasonalities in news announcements on the intraday periodicities. For instance, Harvey and Huang (1991) document that during the first hour of trading on Friday in the US foreign exchange markets, volatility is extremely large for all currencies. They relate it to the fact that lots of macroeconomic announcements (e.g. producer price index, unemployment etc) are released on Friday mornings. Another example is Yadav and Pope (1992), who show that on average in the first hour of the day good news are more common than bad news.

- Further, **information spillovers** cause the contagion effect between different markets. It has been proven that price behaviour on one market can drive prices on the related markets, as traders often link volatilities of the observed market movements. King and Wadhvani (1990) examine these effects on the example of the US and UK Stock Exchanges (SE). One of the evidence they document, is a higher volatility on the UK SE at the time when the US market opens.
- Finally, **market microstructure frictions** (such as non-synchronous trading, price discreteness, bid-ask reporting inaccuracies etc) lead to measurement errors, which in turn result in noisy estimates. Conrad and Kaul (1993) document spurious returns caused by measurement errors. Therefore, the choice of when and how to measure variables is of fundamental importance in the analysis of high frequency data.

To sum up, the vast empirical evidence on the intraday periodicities in financial market movements is explained by a number of different factors. These include, but are not limited to, specifics of trading mechanisms, liquidity management, information flow, market contagion effects and market microstructure frictions.

2.3 Previous Research

There is an extensive amount of studies investigating the intraday patterns in stock returns, volatilities, trading volumes and bid-ask spreads. One of the most recent papers on the subject is Heston, Korajczyk and Sadka (2010). They find significant stock return continuation at the time intervals which are exact multiples of the trading day, and this effect lasts persistently for 40 trading days. Additional diagnostics reveal that the found patterns are not affected by the firm's market capitalization, index membership or exposure to systematic risk. The authors also confirm that trading volume, volatility, bid-ask spreads, and order imbalance exhibit the same patterns, though they do not subsume periodicities in returns.

The following table summarizes some of the previous studies of the intraday patterns in financial markets.

Table 1: Summary of the previous research

Authors	Data	Results
Wood, McInish and Ord (1985)	NYSE (minute-by-minute)	1. On average the highest significant positive returns appear during the first and last 30 min of a trading day 2. U-shaped volatility
Harris (1986)	NYSE	1. Significant positive returns during the first 45 min and the last 15 min of a trading day 2. Significant price drop on Mondays
Jain and Joh (1988)	NYSE	Significant U-shaped pattern in trading volumes, i.e. volume reaches maximum at the beginning of a trading day, decreases up to the lunch time and increases again at the close, though not to the level of the market opening
Brock and Kleidon (1992)	NYSE	Volume and bid-ask spread follow the U-shaped pattern during the trading day
Handa (1992)	NYSE, AMEX	The U-shaped pattern in bid-ask spreads (significant increase at the opening and sharp decline at the close)
Niemeyer and Sandås (1995)	SSE (20 min)	1. High volatility after the opening but no increase towards the close of the SE 2. No evidence of intraday patterns in returns
Harju and Hussain (2006)	FTSE100, XDAX30, SMI and CAC40 (5 min)	The intraday return volatility follows a reverse J-shaped pattern
Hussain (2009)	XDAX30 (5 min)	1. The aggregate trading volume follows the L-shaped pattern 2. Individual stocks display the reverse J-shaped pattern
Campbell, Ramadorai, and Schwartz (2009)	NYSE (30 min)	The institutional traders tend to trade the same stocks on successive days, which leads to regular patterns in trading volumes
Heston, Korajczyk and Sadka (2010)	NYSE (30 min)	1. Stock returns at a given time period are positively and significantly related to their subsequent returns at daily frequencies (continuation pattern) 2. Trading volume, volatility, bid-ask spreads and order imbalance exhibit the same pattern but do not explain periodicities in returns

To sum up, the existence of intraday patterns in stock returns and the related financial market variables has been documented in a number of independent studies for various markets and using different sampling frequencies. Most researchers find U-shaped, reverse J-shaped or L-shaped patterns in the intraday behaviour of stock returns. That is, returns appear to be positive, statistically significant and the highest at the opening of the market, decline during the lunch time when trading activity is lower, and rise again towards the market closure. The same intraday movements have been noticed in return volatility, and order flow variables. Furthermore, there is an evidence of return continuation at daily frequencies, which means that stock returns at a certain time interval during a trading day are influenced by the past returns at the same time but previous trading days. Existence of the intraday periodicities in the financial markets is largely explained by the specifics of trading mechanisms, liquidity demands of traders, information flow and spillover effects.

3 Methodology

The data used in the current study was obtained from the Stockholm Stock Exchange. It consists of the 15-minute intraday observations on the transaction prices and trading volumes of the OMXS 30 constituents, covering the period from Jul 1, 2010 to Dec 30, 2010, which corresponds to 130 trading days. OMXS 30 consists of the 30 stocks most traded on the Stockholm Stock Exchange, and is revised twice a year. Based on the information available, we divide each trading day into 30 successive 15-minute time intervals, starting 08:00 and finishing 15:15 CET (Central European Time). On Nov 5, 2010 trading session at the Stockholm Stock Exchange closed at 12:00, and we have 16 time intervals for this day, instead of 30 for all the other days. This makes our sample consist of 3 886 trading periods in total. There are periods when not all the stocks were traded, which means that returns cannot be defined at those periods. Though, as long as most of the stocks were traded at all time periods within the sample, we choose not to interpolate the missing observations, and simply exclude them from analysis. In total, we have 40 missing observations out of 116 610 on each variable (i.e. 3 886 time intervals multiplied by 30 stocks).

We perform empirical testing both on the 15-minute and 30-minute returns in order to investigate whether return behaviour is affected by data aggregation. The continuously compounded returns are calculated as follows:

$$r(i, t) = 100 \times [\ln(P_{i,t}) - \ln(P_{i,t-1})] \quad (1)$$

where $P_{i,t}$ is the close price of stock i at time interval t .

We analyze the intraday dynamics of stock returns using the cross-sectional autoregressive methodology. For each time interval t (15 minute and 30 minute) and lag k we estimate the simple cross-sectional regression using OLS:

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}, \quad (2)$$

where $r_{i,t}$ is the logreturn on stock i at time t , and $r_{i,t-k}$ is the logreturn on stock i lagged by k time intervals. These regressions are run for all combinations of time interval t and lag k ,

with values up to 5 trading days, which is 150 lags for 15-minute data, and 75 lags for half-hour data. Each cross-sectional regression includes all stocks with data available at times t and $t-k$. That is, if stock i was not traded at time interval t , then it is excluded from those regressions which involve return at time interval t either as dependent variable or regressor.

The slope coefficients $\gamma_{k,t}$ indicate the response of return at time t to return at time $t-k$, and are of particular interest. Significance of the slope coefficients indicates the presence of return continuation. Using the Fama-MacBeth (1973) methodology, we define the unconditional return responses $\bar{\gamma}_k$ as the time-series averages of $\gamma_{k,t}$ for each lag k . We test the null hypothesis that $\bar{\gamma}_k = 0$ using the t-test. The t-statistics of the average parameter is given by the following formula:

$$\text{t-stat}(\bar{\gamma}_k) = \frac{\bar{\gamma}_k}{\sqrt{\frac{1}{T} \times \frac{1}{T-1} \times (\widehat{\gamma}_{kt} - \bar{\gamma}_k)^2}} \sim t(T-1), \quad (3)$$

where T is the total number of time intervals for which the response to return of lag k is estimated from the cross-sectional regressions as in equation (2). As long as we have 3 885 time observations on returns, there will be $3\,885 - k$ cross-sectional regressions for lag k .

To assess the magnitude of the found periodicities, we analyze the equally-weighted strategies with a holding period of one time interval, as suggested in Heston, Korajczyk and Sadka (2010). Every time period, we group our stocks into 5 portfolios based on their returns during the previous intervals of lags k , which are of interest. We calculate the equally-weighted returns on the portfolios consisting of 6 stocks (i.e. 20%) which had the highest returns at time period $t-k$ (“winners”), and 6 stocks which had the lowest returns (“losers”). Then, for each lag k we compute the average return on the strategy, which is long in the portfolio of winners and short in the portfolio of losers. The magnitude of this average top-minus-bottom difference and its t-statistics are additional indicators of how stock returns are affected by their previous values at a particular lag.

The volume data is used to study the intraday dynamics of the trading activity. We define $v_{i,t}$ as the natural logarithm of the number of shares of stock i traded over time interval t minus

the natural logarithm of the number of shares of stock i traded over the interval $t-1$. For each combination of lag $k \in [1, 150]$ and time period t we run the following cross-sectional regression:

$$v_{i,t} = \alpha_{k,t} + \beta_{k,t}v_{i,t-k} + u_{i,t} \quad (4)$$

By the same methodology, we compute the time-series averages of the slope coefficients $\beta_{k,t}$ for each lag k , and calculate the Fama-MacBeth t-statistics. Thus, we get the pattern of volume responses for 150 consecutive 15-minute lags, which corresponds to 5 trading days.

To analyze if periodicity in trading volumes explains periodicity in stock returns, we repeat the cross-sectional regressions as in equation (2) including the lagged trading volume as the additional regressor:

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + \beta_{k,t}v_{i,t-k} + u_{i,t} , \quad (5)$$

where $r_{i,t}$ is the logreturn on stock i at time t , $r_{i,t-k}$ is the logreturn on stock i lagged by k time intervals, and $v_{i,t-k}$ is the natural logarithm of the percentage change in trading volume of stock i from $t-k-1$ to $t-k$.

If return patterns stem from the predictable trading activity, then including this additional regressor should decrease or even subsume regularities of returns based merely on their own past values. Statistically, this will result in the insignificance of the lagged returns. On the contrary, if the time-series average of $\gamma_{k,t}$ from equation (5) turns out to be significant, this will indicate the presence of return responses to their past realizations after controlling for the effect of past trading activity.

4 Empirical Analysis

4.1 Descriptive Statistics

15-minute Returns

Table A1 in the Appendix presents descriptive statistics of the 15-minute stock returns. To obtain the mean return, we first find the average return on the OMXS 30 stocks for each time period, and then take time series averages for each time of a trading day from 08:00 to 15:15. The highest positive and statistically significant average return (0,0675%) is observed over the first trading interval. During the market opening the influence of microstructure frictions, information flow and liquidity concerns of the traders is the most pronounced. Returns have the highest range during the first trading interval, varying from -8,82% to 9,74%, which indicates high volatility of the market at the opening. The return series is leptokurtic during the whole day, with extremely high probability of large deviations during the opening of the trading sessions and the lunch hours. The series is also skewed (mostly negatively), confirming non-normality of the set distribution. Figure 1 below demonstrates the movements of the 15-minute mean returns for the OMXS 30 index during a trading day on the Stockholm Stock Exchange.

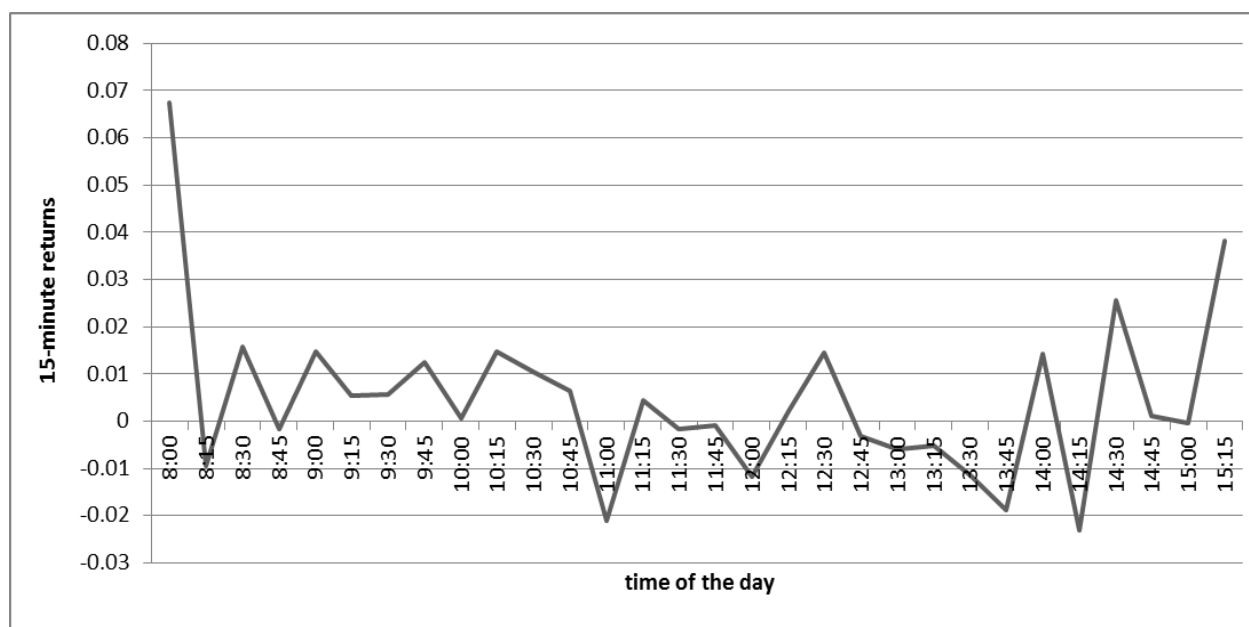


Figure 1: 15-minute average returns on the OMXS 30 stocks over the period Jul 1, 2010 – Dec 30, 2010

As the graph above indicates, the average 15-minute returns reach their maximum at the opening hours, decline towards the middle of a trading day being mostly negative between 11:00 and 14:00, and rise at the end, though do not attain the morning level. Our results are in line with the previous findings.

30-minute Returns

Since the sampling frequency can significantly affect the results, we decide to compare the behaviour of 15-minute returns with that of more aggregated, 30-minute returns.

As we can see in Table 2A, the highest positive statistically significant mean return (0,107%) is still observed during the first time interval. Range of about 19% and kurtosis of 8,1 at 08:00 are an additional evidence that opening hours are extremely subject to a number of idiosyncratic factors, which cause higher variation in stock returns. Return series is leptokurtic and skewed. The average 30-minute return movements are displayed on Figure 2 below.

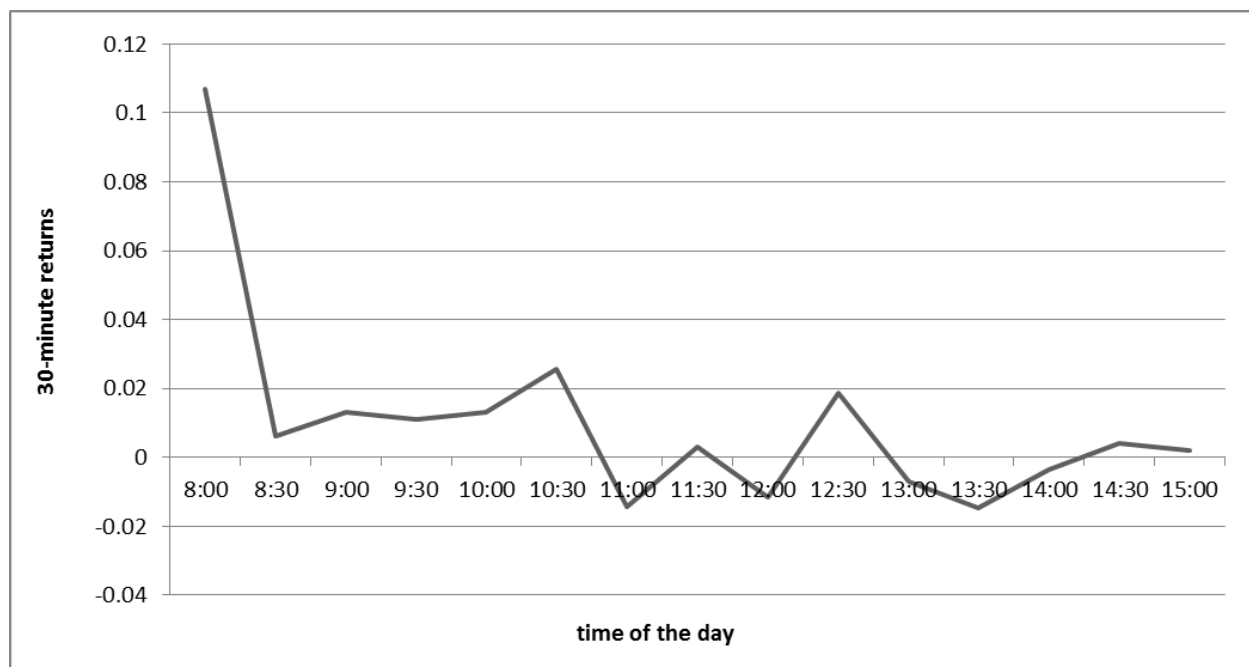


Figure 2: 30-minute average returns on the OMXS 30 stocks over the period Jul 1, 2010 – Dec 30, 2010

We can see that 30-minute returns do not rise towards market closure, as 15-minute returns do. This may be explained by the loss of information, as stocks are traded until 15:15, but the last 30-minute return is defined for 15:00. Aggregation also results in higher average returns at 08:00 (0,107% compared to 0,068% for 15-minute returns), as prices at 15:00, which are used to calculate half-hour returns, tend to be smaller than prices at 15:15, used for 15-minute returns. Another result is that both 15-minute and 30-minute returns exhibit extremely high kurtosis (13-80), as well as standard deviation, during the periods 09:30-10:00 and 11:30-12:00. This may be connected to the macroeconomic news releases in Sweden at 10:00 and 11:00, which increase volatility and lead to the frequent occurrence of extreme values.

Niemeyer and Sandås (1995), who also did research on the OMXS 30 index, have not found any clear patterns in stock returns. However, they use 1-minute sampling frequency, which is extremely subject to market microstructure noise that can distort the price signal. The more noisy the process is, the more complicated it gets to reveal any periodicities.

Trading Volume

Table 3A in the Appendix presents descriptive statistics of the 15-minute trading volume for the OMXS 30 index. As we can see, the series is characterized by very high kurtosis indicating the frequent occurrence of large deviations from the mean during the whole trading day. The highest kurtosis values are reported at 10:00, 11:15 and 12:45-13:00, which can be attributed to the macroeconomic news announcements, as in the case of returns. Trading volume is positively skewed at all time periods, which means that most of the observations lie to the left of the mean. In fact, we can see that median values are about twice smaller than means. This indicates that during some trading days the volumes are extremely large, so that they drive the mean so far to the right from the median.

Figure 3 below plots the relative share of the average trading volume at a particular time period in the average total trading volume during a trading day. We can see that higher proportion of shares is traded at the opening and closing hours, and that trading volume is relatively small around the lunch hours.

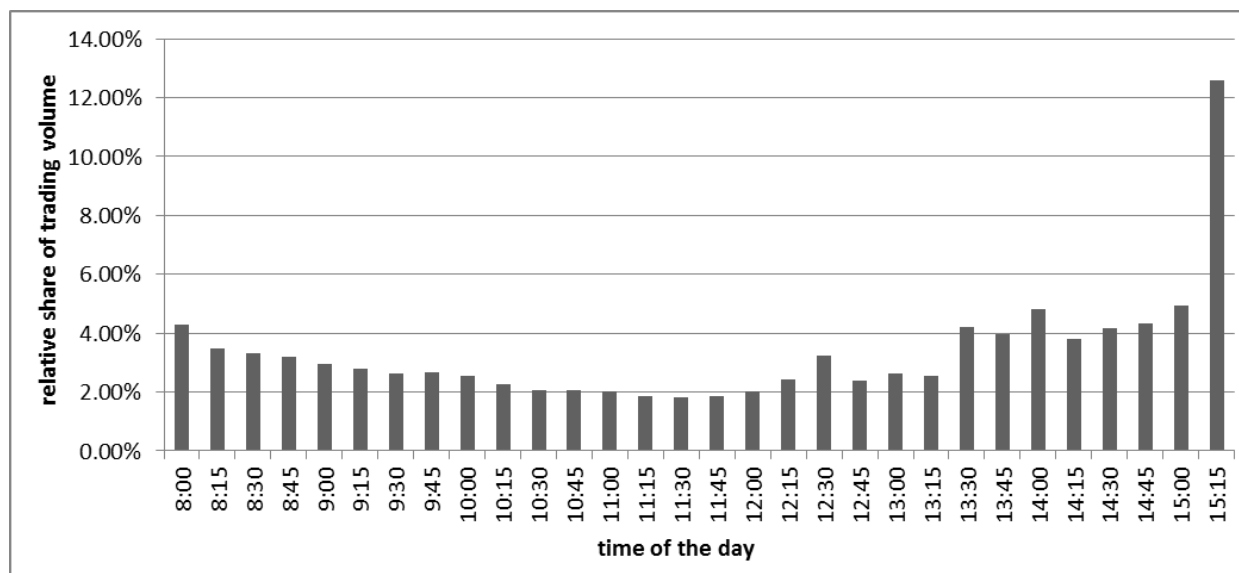


Figure 3: Distribution of the average trading volume for the OMXS 30 index throughout a trading day

Our evidence is consistent with the previous research involving the data on NYSE stocks (e.g. Jain and Joh (1988)) but we have different results as for the peak of trading. Most studies find trading volume to be the highest at the opening hours, decay during the lunch time and rise again at the closing period but not to the level of the opening hours. Our results, supporting the previous research on the Stockholm Stock Exchange by Niemeyer and Sandås (1995), show extremely high trading volume at the closing 15-minute interval. It is three times larger than at 08:00. Such a difference might come from the specifics of liquidity management demands of traders at various markets. Probably, traders on the Stockholm Stock Exchange are more unwilling to stay with unhedged assets overnight and start selling them at the end of the trading day. Unfortunately, we do not have information on the order imbalance to check if sells indeed dominate at the close of the trading sessions. This question might be of interest for speculators who buy stocks overnight expecting a high risk premium.

4.2 Cross-Sectional Regressions of Stock Returns

To investigate how the intraday stock returns are affected by their past values we use cross-sectional autoregressive methodology, as described in Section 3. The following graph plots $\overline{\gamma}_k$ from equation (2), which are the average estimated 15-minute return responses to their past realizations up to a trading week. With 30 15-minute intervals per day and 5 trading days per week, that gives 150 subsequent lags. $\overline{\gamma}_k$ are presented in percent. Lags that are multiples of 30 represent daily frequencies, and are of special interest. The exact values of the estimated coefficients and their p-values can be found in Table 4A in the Appendix.

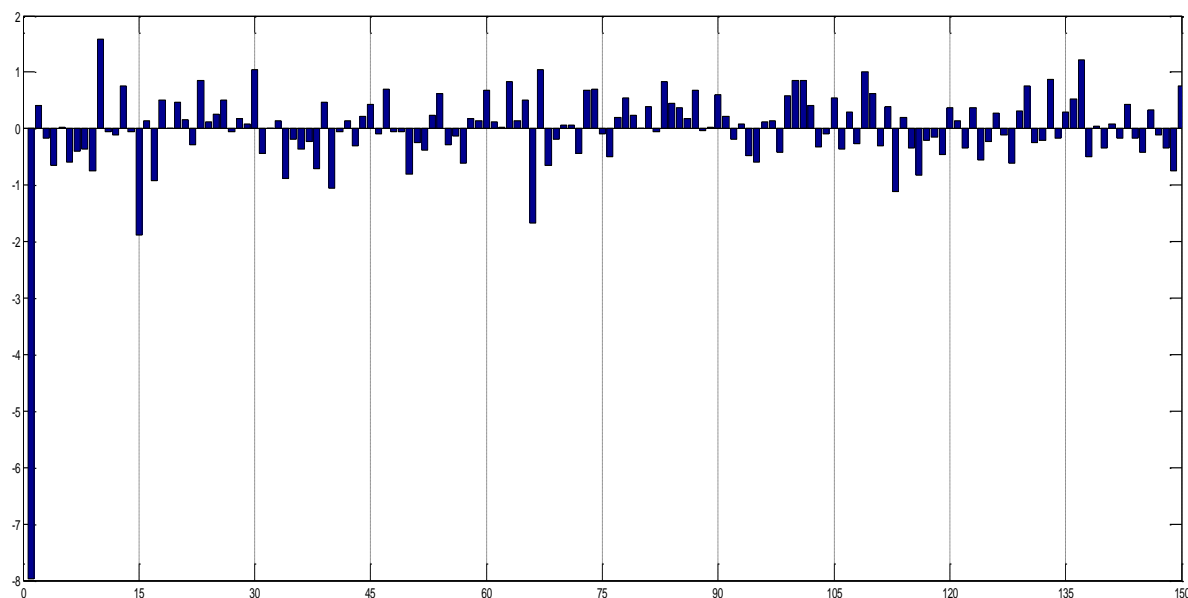


Figure 4: Average 15-min return responses from equation (2) in %

As we can see from Figure 4, except for lags 2 and 5, the first 9 coefficients are negative. However, we cannot make reliable conclusions as for the length of return reversal, since the next significant¹ lag after the first one is lag 10, which corresponds to 2,5 hours (see Figure 5 below).

¹ Hereafter, we refer to significance at 5% level unless specified differently

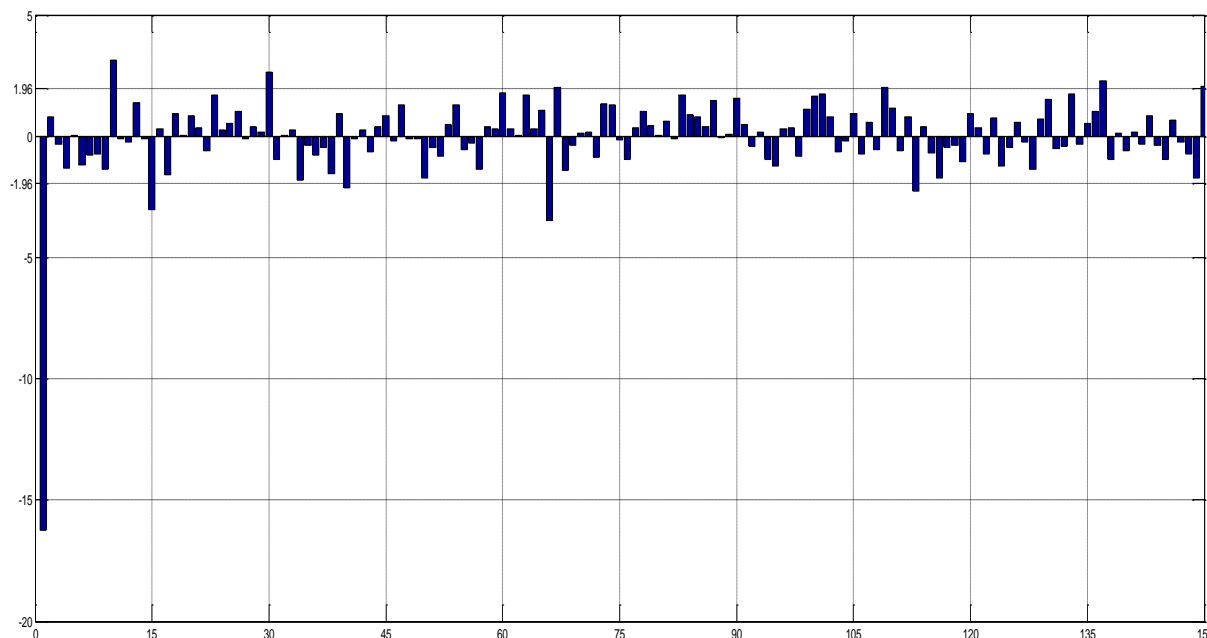


Figure 5: t-statistics of the average 15-min return responses

We do confirm positive and significant return responses at lags 30 and 150. This means that stock returns at a particular 15-minute time interval are positively affected by returns at the same time interval previous trading day, and 5 trading days ago (a trading week ago). Lag 60 has a p-value of 7,8% and can also be considered significant. Using 15-minute observations, we do not find the clear periodicity in return responses. According to Heston, Korajczyk and Sadka (2010), return effects beyond the first trading day remain mostly negative, except the significant positive spikes at daily frequencies. As Figure 4 displays, our coefficients are fluctuating around 0. Furthermore, they are generally insignificant. Except for lags 1, 30, 60 and 150 mentioned above, we find only six significant responses.

Choosing the appropriate data frequency has always been a question of the tradeoff between the amount of information, which can be inferred, and the noise it contains. Higher sampling frequency allows to keep more information from the raw data, but this comes at the cost of aggravating the impact of market microstructure high frequency frictions. Non-synchronous trading, bid-ask bounces, differences between trade sizes and the informational content of price changes are not the full list of frictions implicit in the trading process. These frictions create statistical noise which distorts the fundamental price signal. The noise component cannot be

easily removed because it is not directly observed. As a result, observed prices are no longer efficient, which leads to biased estimates. Intuitively, the data on more liquid assets, which are frequently traded and have lower bid-ask spreads, tends to contain less microstructure noise.

Since OMXS 30 is the index of the most traded stocks on the Stockholm Stock Exchange, we consider it appropriate to use 15-minute sampling frequency. However, to determine if data aggregation will affect the results, we repeat the same testing procedure for half-hour returns. Now that we divide each trading day into 15 half-hour intervals, a trading week corresponds to 75 lags. The following figure presents $\overline{\gamma_k}$ estimated for 30-minute returns, and the corresponding t-statistics. The estimated coefficients and the associated p-values are reported in Table 5A.

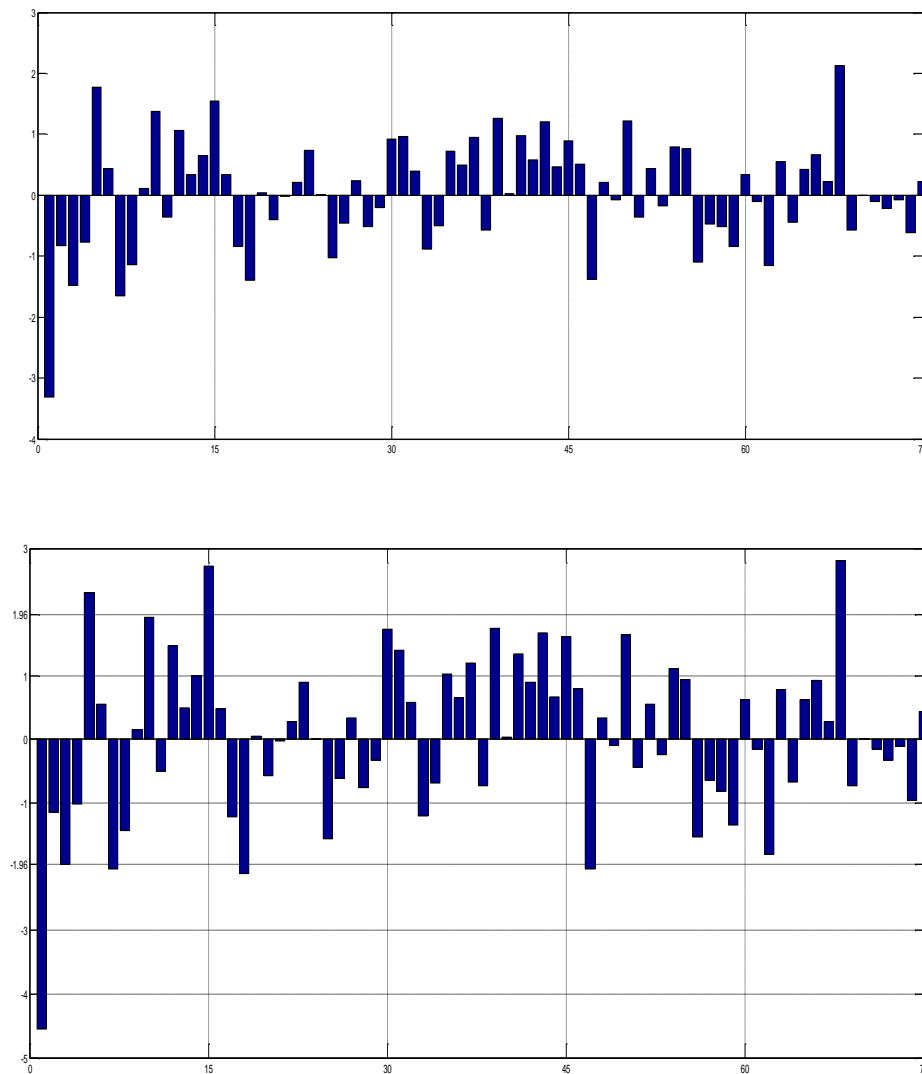


Figure 6: Average 30-min return responses from equation (2) in % (above) and the associated t-statistics (below)

Regressions involving 30-minute data contain less missing observations, which reduces the non-synchronous trading bias. However, we can see that responses of 30-minute returns are very similar to those of 15-minute, only smoother. The first four lags have negative coefficients, with return reversal lasting for about 2 hours. The following table summarizes the estimated coefficients and the corresponding t-statistics for daily frequencies of 15-minute and 30-minute data.

Table 2: Regression results from equation (2)

Lag (in trading days)	15-min data		30-min data	
	$\bar{\gamma}_k$ (in %)	t-stat	$\bar{\gamma}_k$ (in %)	t-stat
1	1,04	2,65*	1,54	2,72*
2	0,68	1,8**	0,93	1,73**
3	0,61	1,57	0,9	1,62
4	0,37	0,94	0,34	0,62
5	0,75	2,06*	0,22	0,43

Note: * denotes statistical significance at 5% level

** denotes statistical significance at 10% level

We can see that both for 15-minute and half-hour returns the first daily frequency is significant at 5% level, and the second one is significant at 10%. Coefficients, though, are larger for the more aggregated data. That means, using half-hour observations, we find that stock returns are more affected by their previous realizations. Another difference is that with half-hour data $\bar{\gamma}_k$ is decaying both in its magnitude and significance, while 15-minute data reveals significant coefficient of lag 150 (i.e. 5 trading days ago). If we treat the modelling of asset prices as the modelling of the arrival of new information, then higher frequency data should produce more reliable results. Taking into account that we do not have many missing observations, the noise component in our 15-minute data should not be significant. Nevertheless, to verify if there is return continuation at daily frequencies, we study performance of stock returns in the long run.

4.3 The Long-Run Performance of Stock Returns

To explore the stock returns dynamics in the long run we estimate the returns on the portfolios formed on the basis of stocks' past performance. This allows to find out whether the portfolio of stocks that had high returns k periods ago, yields significantly larger return at present than the portfolio of stocks that had low returns k periods ago.

First, for each time period we define 6 stocks (i.e. 20%) which had the highest returns k periods ago, and 6 stocks which had the lowest returns. We further refer to them as “winners” and “losers”. As we are particularly interested in the impact of the daily frequencies, we take only those lags, which are exact multiples of a trading day, i.e. 30, 60, 90... for 15-minute returns and 15, 30, 45... for 30-minute returns. We extend our analysis from 5 to 30 trading days. For each lag k , we calculate the time-series averages of returns on the portfolios of winners and losers. Then, for each lag we compute the equally-weighted return on a strategy which is long in the portfolio of winners and short in the portfolio of losers. The results are reported in Tables 6A and 7A in the Appendix.

All the top-minus-bottom spreads are positive and statistically significant, and decrease as long as we extend the lag length. Moreover, our returns on the long-short strategies are much higher than Heston et al. (2010) report. For instance, our average spread for 30-minute returns based on lag 15 is 0,68% compared to 3,01 basis points (i.e. 0,0301%) in Heston et al. (2010). The same holds for all the other lags. We expect this result to come from significant difference in the samples. Heston et al. (2010) use the data on 1 715 stocks, while we have only 30 stocks. Therefore, our estimations are extremely subject to the presence of outliers. As Tables 1A and 2A indicate, returns at all time intervals have a very high range compared to the mean value. Considering that our winning and losing portfolios consist of only 6 stocks, we obtain high spreads.

To conclude, assessing strategies based on stocks' past performance has proved that returns are positively and significantly related to their previous realizations at daily frequencies. Although Heston et al. state that these periodicities do not create opportunities for arbitrage, they do allow to reduce the transaction costs.

4.4 Cross-Sectional Regressions of Trading Volumes

Further, we explore the intraday dynamics of trading activity using the cross-sectional autoregressive methodology. Figure 7 below presents $\bar{\beta}_k$, which are the time-series averages of the 15-minute volume responses to their previous realizations as in equation (4), and the corresponding t-statistics. The graphs exclude the first lag, which has $\bar{\beta}$ of -44,37% and t-stat of 121,05. The exact values of lags 2 through 150 can be found in Table 8A.

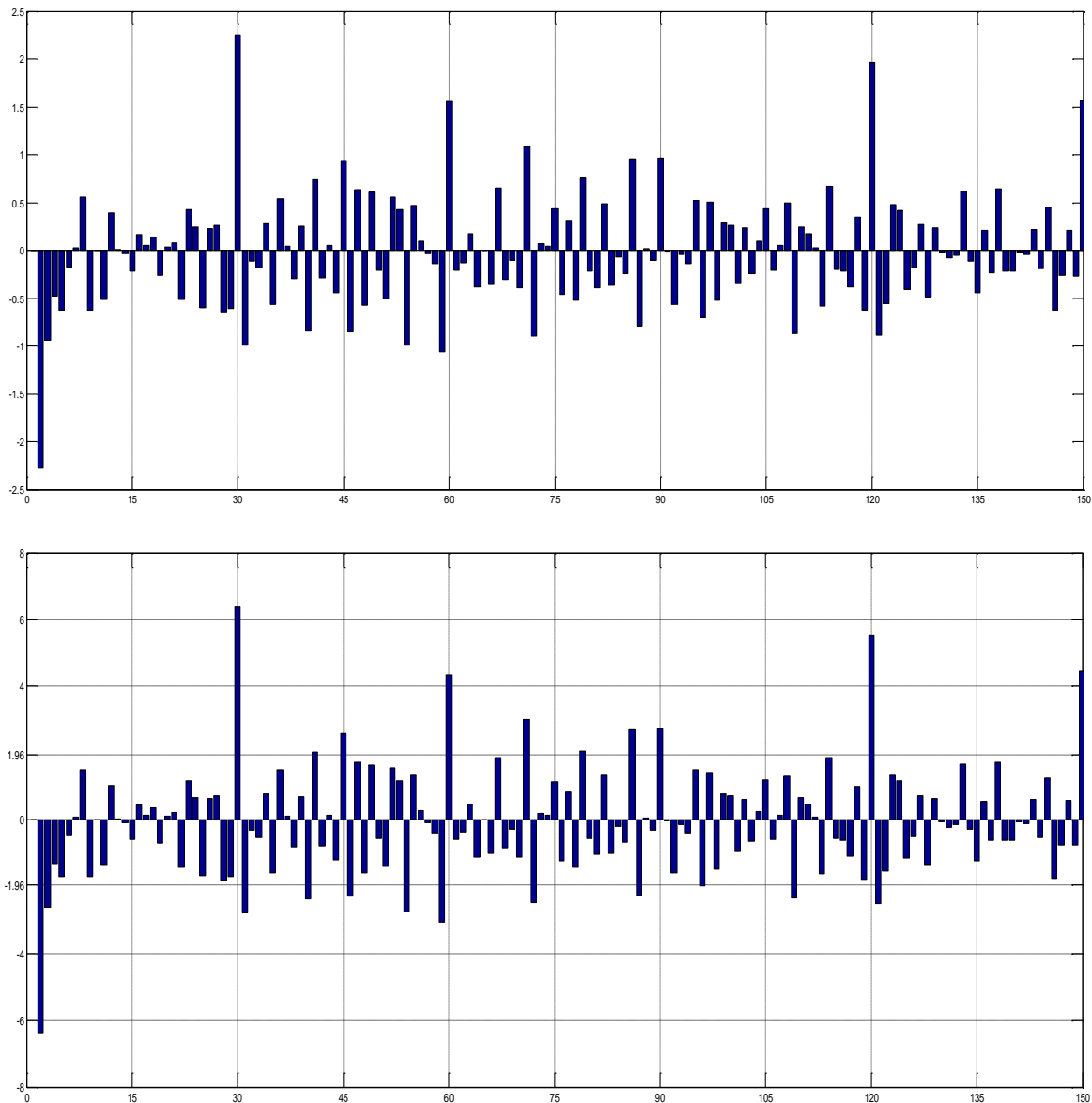


Figure 7: Average 15-min volume responses from equation (4) in % (above) and the associated t-statistics (below), excluding lag 1

In case of trading volumes we confirm the presence of much more pronounced effect at daily frequencies. Figure 7 above displays significant spikes of the coefficients and t-statistics at lags 30, 60, 90, 120 and 150. In general, we do not find the response patterns of 15-minute returns and percentage changes in trading volumes to be very similar (see Figure 4 and Figure 7). The first several responses are negative for both variables, but further, return coefficients exhibit more of a clustering behaviour. We can see on Figure 4 that starting from lag 18 and up to lag 120, positive return responses tend to be followed by 5-6 positive ones and vice versa. On the contrary, volume responses change sign at almost each lag (see Figure 7). Except for the first 6 negative coefficients, we find at most three coefficients of the same sign in a row, and these cases are rare.

On the whole, there is no clear evidence that percentage changes in trading volumes respond to their previous values in the same way as returns do. However, we should not rely on the patterns induced by insignificant responses. Instead, let us compare those lags which have significant coefficients for both variables.

Table 3: Significant responses for returns and trading volumes (10% significance level)

Lag	$\bar{\gamma}_k$ (in %)	$\bar{\beta}_k$ (in %)
1	-7,98	-44,37
30	1,04	2,25
40	-0,84	-1,05
60	0,68	1,56
67	1,04	0,66
150	0,75	1,57

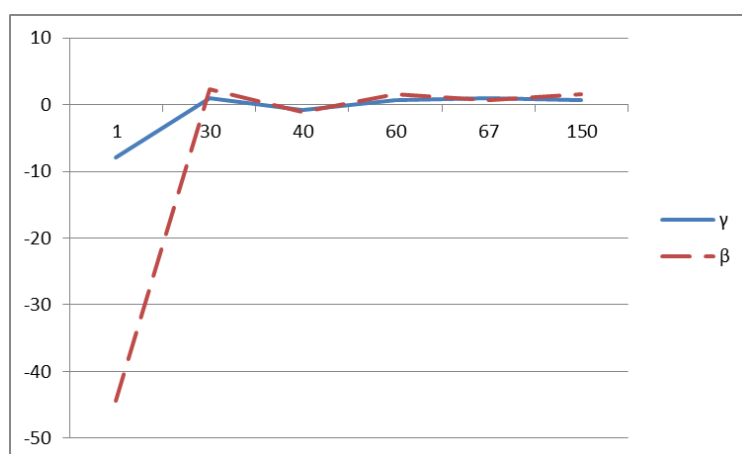


Figure 8: Significant responses for returns and trading volumes (10% significance level)

As Table 3 and Figure 8 indicate, significant lags display similar dynamics. Therefore, we check for existence of the lead-lag effect between percentage changes in trading volumes and returns using the multiple regression analysis.

4.5 Multiple Cross-Sectional Regressions

Multiple regression analysis allows to explore whether periodicity in stock returns is related to periodicity in trading activity. We regress the returns on their past values, and past percentage changes in trading volumes of the same lag simultaneously (see equation (5)). Firstly, we are interested if the lagged returns are still significant in the presence of lagged volume as an additional regressor. Figures 9 and 10 below plot $\bar{\gamma}_k$ from equation (5) estimated for 15-minute data, i.e. the average return responses to their past realizations of different lag length, and the associated t-statistics. Tables 9A and 10A present the estimated coefficients and p-values of lagged returns and lagged volumes, accordingly.

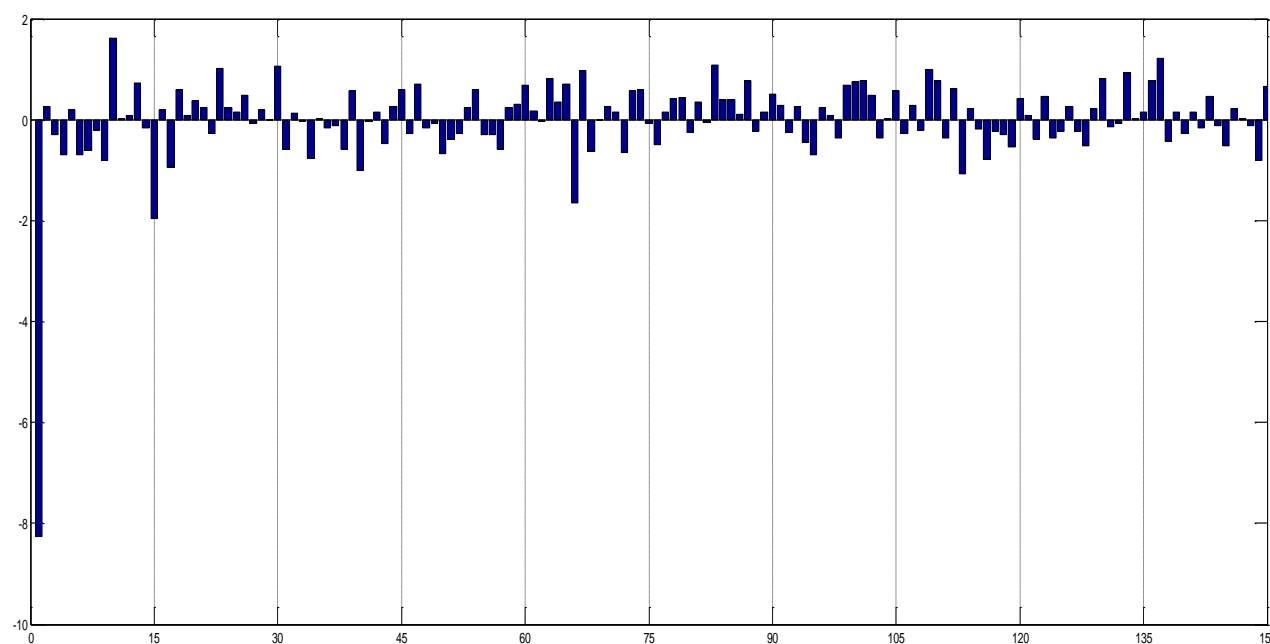


Figure 9: Average 15-min return responses from equation (5) in %

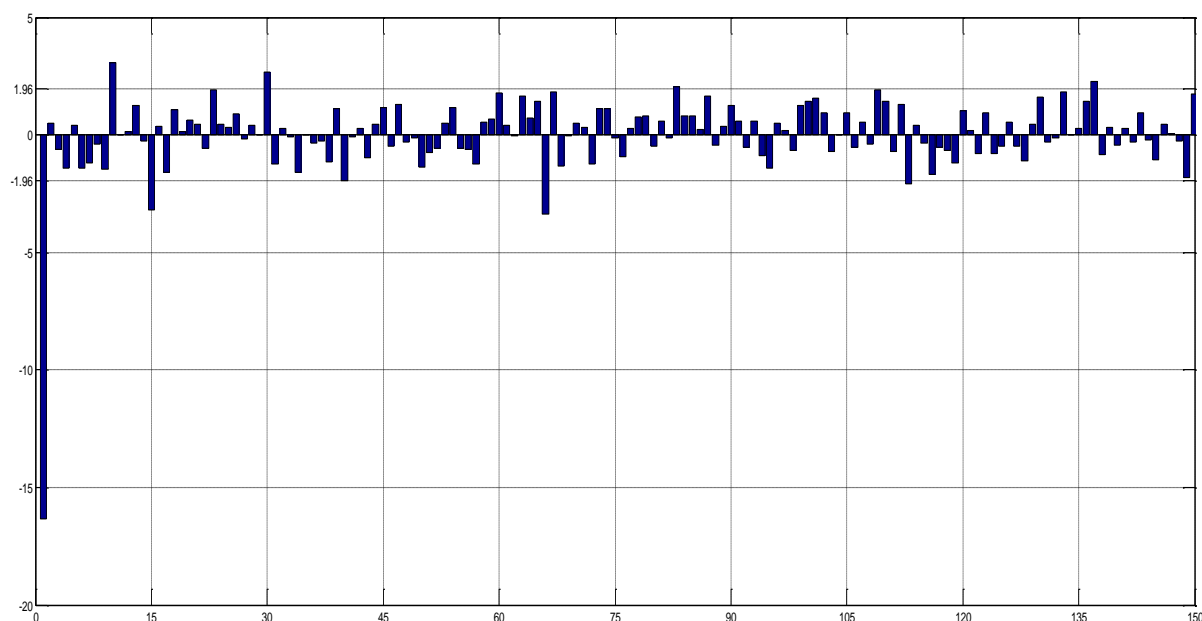


Figure 10: t-statistics of the average 15-min return responses from equation (5)

It can be easily verified that controlling for the effect of percentage change in trading volume does not affect the pattern of return responses to their own past lags. Those lags which were significant in equation (2) remain significant in equation (5), and have coefficients of the same sign and similar magnitude (see Tables 4A and 9A). Moreover, $v_{i,t-k}$ is insignificant at almost all lags, including the daily frequencies (see Table 10A). Our results suggest that periodicity in 15-minute trading volumes not only does not subsume periodicity in 15-minute returns, but does not explain it at all.

To address the issue further, we repeat the procedure using half-hour observations. We find that data aggregation does not change the results. The pattern of return responses to their lagged realizations in multiple regressions is almost identical to that in univariate regressions. The only difference from the 15-minute regression results is that lagged volume remains significant at lags 30 and 150 (see Tables 11A and 12A for the regression results on half-hour data).

To conclude, we are able to confirm the finding of Heston et al. (2010) that the intraday periodicity in stock returns is neither subsumed nor affected by the periodicity in trading volumes.

5 Conclusion

In this study we examine the intraday dynamics of stock returns and trading volume on the Swedish stock market. We employ 15-minute and 30-minute sampling frequency using the data on the OMXS 30 constituents over the period from Jul 1, 2010 to Dec 30, 2010, which corresponds to 130 trading days.

In line with the previous studies, we find that stock returns are the highest at the opening of the trading day, decline during the middle, and rise again towards the market closure, though do not attain the morning level. The first trading interval is also the period of the largest range in returns, as well as high volatility and kurtosis. This indicates that during the market opening the influence of microstructure frictions, information flow and liquidity preferences of the traders is the most pronounced. We can observe that extreme values are most frequent at 09:30-10:00 and 11:30-12:00, when macroeconomic news are announced. Further, consistently with Niemeyer and Sandås (1995), we find that average trading volume reaches its peak at the end of the trading day, unlike returns, which are higher at the opening. Roughly 20% of the whole trading occurs during the last 45 minutes. This might be caused by liquidity concerns of the traders who are not willing to stay with unhedged assets overnight and start selling them at the end of the trading day.

Decreasing sampling frequency from 15-minute to 30-minute does not have significant impact on the results. This indicates that our estimates are not seriously contaminated by market microstructure noise, which is often a problem with high frequency data.

Cross-sectional autoregressions reveal that both returns and volumes are significantly and positively affected by their own past realizations at daily frequencies. Both for 15-minute and 30-minute observations, the first several return responses are negative, with return reversal lasting for about 2,5 hours. Afterwards, we find only a few significant coefficients. In order to verify the presence of return continuation at daily frequencies, we study the long run performance of stock returns. Similarly to Heston, Korajczyk and Sadka (2010), we document significant returns on the long-short strategies based on stocks' past performance during up to 30 trading days.

Results of the multiple regression analysis allow us to conclude that the intraday periodicity in stock returns is neither subsumed nor affected by the periodicity in trading volumes.

To conclude, the observed intraday patterns in stock returns indicate the possibility to predict investors' liquidity demand during the day. As additional diagnostics, it would be reasonable to compare the behaviour of the OMXS 30 index with other stocks listed on the Stockholm Stock Exchange to check whether results are affected by index membership. It might be also of interest to examine different days of week separately. Further research of the intraday dynamics on the Swedish stock market will contribute to the development of trading algorithms allowing to minimize transaction costs.

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Appendix

Table 1A: Descriptive Statistics 15-minute returns

We divide a trading day into thirty 15-minute time intervals. For each interval we compute the mean, median, standard deviation, minimum, maximum, kurtosis, skewness and t-statistics of the returns (in %) on the constituents of the OMXS 30 index. The analysis covers the period from Jul 1, 2010 through Dec 30, 2010, which corresponds to 130 trading days. T-statistics of the average returns are calculated using Fama-MacBeth (1973) methodology. Time intervals which have statistically significant (at 5% level) returns are marked in bold.

Time interval	Mean	Median	Standard Deviation	Kurtosis	Skewness	Min	Max	t-stat
8:00	0.0675	0.0746	0.3841	8.6124	-0.0119	-8.8210	9.7394	2.0037
8:15	-0.0095	0.0000	0.1948	24.1543	-1.3118	-5.4067	1.8789	-0.5564
8:30	0.0158	0.0000	0.1535	39.9534	2.1740	-1.1445	5.3159	1.1721
8:45	-0.0017	0.0000	0.1359	1.6487	-0.0749	-1.1373	1.2567	-0.1402
9:00	0.0148	0.0000	0.1347	1.6888	0.0049	-1.3693	0.9756	1.2565
9:15	0.0053	0.0000	0.1289	8.7752	0.4919	-1.1236	2.8746	0.4663
9:30	0.0057	0.0000	0.1318	18.5132	-0.7781	-3.4356	2.2595	0.4914
9:45	0.0124	0.0000	0.1262	3.0673	-0.1998	-1.1919	0.9728	1.1197
10:00	0.0006	0.0000	0.1202	25.1288	7.1209	-3.9067	7.7558	0.0604
10:15	0.0148	0.0000	0.1224	3.2776	0.0898	-1.5504	1.1370	1.3751
10:30	0.0105	0.0000	0.1012	2.6420	0.4268	-0.8889	1.1940	1.1835
10:45	0.0064	0.0000	0.1056	3.7822	0.3529	-0.8143	1.6189	0.6909
11:00	-0.0210	0.0000	0.1039	10.9257	-0.8772	-2.1298	1.3023	-2.3066
11:15	0.0045	0.0000	0.1122	3.5269	-0.0898	-1.3793	0.8951	0.4572
11:30	-0.0016	0.0000	0.1083	10.2519	-1.0178	-2.0983	1.0565	-0.1710
11:45	-0.0008	0.0000	0.0914	2.6421	-0.0795	-1.0437	0.8446	-0.1015
12:00	-0.0117	0.0000	0.1219	26.5830	0.9333	-1.5631	3.4060	-1.0900
12:15	0.0022	0.0000	0.1158	3.1866	0.3062	-0.9235	1.5631	0.2155
12:30	0.0145	0.0000	0.2197	5.1272	-0.0632	-1.6043	1.6197	0.7548
12:45	-0.0031	0.0000	0.1160	1.8784	-0.0355	-0.9497	0.9162	-0.3090
13:00	-0.0059	0.0000	0.1202	4.6338	-0.5115	-1.5972	1.3483	-0.5598
13:15	-0.0052	0.0000	0.0946	1.8944	-0.0298	-1.0396	0.9824	-0.6214
13:30	-0.0114	0.0000	0.1941	2.4366	-0.2020	-2.0488	1.2350	-0.6716
13:45	-0.0189	0.0000	0.1903	1.7307	-0.1889	-1.2579	1.2806	-1.1345
14:00	0.0143	0.0000	0.2638	4.6057	-0.1588	-2.3942	1.8984	0.6191
14:15	-0.0232	0.0000	0.1666	3.0698	-0.2344	-1.5389	1.6246	-1.5848
14:30	0.0255	0.0000	0.1871	2.7911	-0.2764	-1.6221	1.2375	1.5552
14:45	0.0010	0.0000	0.1566	1.0107	0.0563	-1.0447	1.0582	0.0718
15:00	-0.0005	0.0000	0.1422	1.3358	0.1979	-0.9945	1.1985	-0.0365
15:15	0.0381	0.0000	0.1567	1.3025	0.1849	-1.4293	1.2749	2.7729

Table 2A: Descriptive Statistics 30-minute returns

We divide a trading day into 15 half-hour time intervals. For each interval we compute the mean, median, standard deviation, minimum, maximum, kurtosis, skewness and t-statistics of the returns (in %) on the constituents of the OMXS 30 index. The analysis covers the period from Jul 1, 2010 through Dec 30, 2010, which corresponds to 130 trading days. T-statistics of the average returns are calculated using Fama-MacBeth (1973) methodology. Time intervals which have statistically significant (at 5% level) returns are marked in bold.

Time interval	Mean	Median	Standard Deviation	Kurtosis	Skewness	Min	Max	t-stat
8:00	0.1070	0.1071	0.4236	8.1029	0.0158	-9.0602	10.0679	2.8800
8:30	0.0063	0.0000	0.2692	1.6730	0.1409	-1.8193	2.1353	0.2657
9:00	0.0132	0.0000	0.1965	1.6282	-0.1121	-1.5504	1.5896	0.7651
9:30	0.0110	0.0000	0.1722	24.6592	1.0105	-3.3210	5.1340	0.7252
10:00	0.0131	0.0000	0.1710	79.8903	2.4795	-3.9068	7.2661	0.8711
10:30	0.0255	0.0000	0.1565	2.9980	0.3027	-1.8112	1.8833	1.8585
11:00	-0.0145	0.0000	0.1418	7.9858	-0.0090	-2.1298	2.7168	-1.1675
11:30	0.0029	0.0000	0.1331	13.7192	-1.1730	-3.0900	1.1873	0.2463
12:00	-0.0116	0.0000	0.1549	9.0061	-0.0509	-1.4498	3.0669	-0.8551
12:30	0.0187	0.0000	0.2617	4.6187	0.4661	-1.7633	2.1277	0.8152
13:00	-0.0072	0.0000	0.1728	3.3126	-0.5063	-1.9508	1.4389	-0.4743
13:30	-0.0147	0.0000	0.2091	2.6064	-0.3072	-2.2584	1.7036	-0.8004
14:00	-0.0035	-0.0002	0.3352	4.9306	0.3151	-1.2872	1.4949	-0.1186
14:30	0.0042	0.0000	0.2409	1.5086	-0.0521	-1.6817	1.4065	0.2007
15:00	0.0020	0.0000	0.2144	0.9898	-0.0149	-1.3223	1.4354	0.1072

Table 3A: Descriptive Statistics Trading Volume

We divide a trading day into thirty 15-minute time intervals. For each interval we compute the mean, median, standard deviation, minimum, maximum, kurtosis, skewness and t-statistics of the trading volumes of the constituents of the OMXS 30 index. Trading volume is defined as the total number of shares bought and sold over a time interval. The mean is found by, first, averaging over the stocks for each time interval, and then averaging over trading days for the same times of the day. The analysis covers the period from Jul 1, 2010 through Dec 30, 2010, which corresponds to 130 trading days. T-statistics of the average volumes are calculated using Fama-MacBeth (1973) methodology. The first and the last time intervals are marked in bold for the sake of visibility.

Time interval	Mean	Median	Standard Deviation	Kurtosis	Skewness	Min	Max	t-stat
8:00	111,088.30	57,367.00	16,895.20	73.9	5.9	717	3,425,884.00	75.252
8:15	89,737.90	47,470.50	12,932.20	98.1	7.1	100	2,788,437.00	78.672
8:30	86,102.90	45,381.00	12,620.60	153.5	7.9	96	3,497,090.00	77.532
8:45	82,345.10	42,502.00	13,619.70	63.2	5.6	12	2,367,800.00	68.411
9:00	76,704.90	40,992.00	11,482.70	40.7	4.5	345	1,852,220.00	76.392
9:15	72,220.90	37,942.00	11,274.80	33.4	4.4	151	1,499,537.00	72.971
9:30	67,971.10	36,104.50	11,459.30	45.4	5.1	69	1,646,963.00	67.27
9:45	68,618.50	34,146.00	11,271.60	50.7	5.1	100	1,891,949.00	69.551
10:00	65,838.30	33,072.00	10,149.10	170.6	10.1	102	2,762,704.00	74.111
10:15	58,251.70	29,602.00	8,643.80	51.1	5.5	10	1,452,583.00	76.392
10:30	53,302.30	28,369.00	8,360.20	19.6	3.6	10	774,544.00	72.971
10:45	53,551.50	27,692.00	6,985.80	28.6	4.2	50	985,592.00	87.794
11:00	52,589.00	26,836.50	6,688.20	52	5.2	7	1,381,478.00	90.074
11:15	47,805.10	26,404.00	6,308.50	163	8.2	10	1,927,246.00	86.653
11:30	47,031.30	25,752.00	7,676.60	50.9	5.3	14	1,230,400.00	69.551
11:45	48,448.70	24,997.50	7,626.80	53.2	5.8	20	1,197,904.00	72.971
12:00	52,100.70	28,032.00	6,423.70	32.9	4.4	38	955,367.00	92.354
12:15	62,637.40	33,782.00	10,891.90	49.3	5.3	20	1,421,819.00	66.13
12:30	83,813.40	39,891.00	18,926.30	36.5	4.7	67	2,008,829.00	50.168
12:45	61,507.30	32,266.50	7,630.30	166.9	8.7	10	2,528,463.00	92.354
13:00	67,785.40	34,994.00	12,947.30	269.7	12	49	3,578,061.00	59.289
13:15	66,058.00	35,351.00	9,552.60	85.5	6.2	50	2,150,335.00	78.672
13:30	108,667.40	61,363.00	22,315.10	78.9	5.8	40	3,314,115.00	55.869
13:45	102,779.70	57,147.00	22,890.50	24.1	3.7	357	1,969,463.00	51.308
14:00	124,133.00	66,061.00	28,048.90	23	3.8	63	2,105,928.00	50.168
14:15	98,709.80	55,246.00	21,615.80	14.7	3.2	139	1,262,345.00	52.448
14:30	107,946.10	61,708.00	17,556.40	26.9	3.8	166	2,173,039.00	69.551
14:45	111,440.20	62,875.00	18,946.50	17.7	3.4	346	1,447,164.00	67.27
15:00	127,279.60	74,567.00	22,935.00	11.6	2.8	385	1,575,167.00	62.71
15:15	325,420.80	177,825.50	101,487.50	11.8	3	385	4,829,086.00	36.486

Table 4A: Univariate cross-sectional regressions for 15-minute returns

We divide a trading day into thirty 15-minute time intervals starting 08:00 and finishing 15:15. For each time interval t and lag k , we run a simple cross-sectional regression of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ is the logreturn on stock i at time t . Regressions are estimated for all combinations of 15-minute interval t , from Jul 1, 2010 to Dec 30, 2010 (3 885 intervals), and lag k , with values 1 through 150 (past 5 trading days). The table presents time-series averages of $\gamma_{k,t}$ in %, and the associated p-values. The analysis is done for OMXS 30 stocks.

Lag	Estimate	P- value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value
1	-7.977	0.000	31	-0.436	0.256	61	0.124	0.383	91	0.219	0.356	121	0.145	0.378
2	0.408	0.292	32	0.007	0.399	62	0.026	0.398	92	-0.183	0.368	122	-0.346	0.307
3	-0.162	0.377	33	0.135	0.387	63	0.831	0.094	93	0.076	0.393	123	0.363	0.301
4	-0.642	0.166	34	-0.873	0.076	64	0.140	0.380	94	-0.472	0.257	124	-0.552	0.190
5	0.018	0.399	35	-0.181	0.374	65	0.513	0.223	95	-0.599	0.185	125	-0.223	0.358
6	-0.589	0.195	36	-0.363	0.294	66	-1.668	0.001	96	0.130	0.382	126	0.284	0.335
7	-0.395	0.294	37	-0.217	0.359	67	1.037	0.051	97	0.147	0.378	127	-0.111	0.388
8	-0.351	0.308	38	-0.716	0.123	68	-0.652	0.146	98	-0.423	0.283	128	-0.616	0.160
9	-0.753	0.155	39	0.473	0.257	69	-0.186	0.374	99	0.580	0.220	129	0.321	0.316
10	1.591	0.003	40	-1.047	0.042	70	0.059	0.396	100	0.860	0.101	130	0.750	0.124
11	-0.046	0.397	41	-0.056	0.396	71	0.068	0.395	101	0.845	0.088	131	-0.235	0.351
12	-0.113	0.389	42	0.133	0.387	72	-0.439	0.274	102	0.401	0.290	132	-0.205	0.365
13	0.758	0.153	43	-0.306	0.325	73	0.672	0.165	103	-0.317	0.329	133	0.870	0.088
14	-0.058	0.397	44	0.215	0.371	74	0.693	0.169	104	-0.086	0.393	134	-0.162	0.380
15	-1.878	0.004	45	0.425	0.280	75	-0.086	0.395	105	0.550	0.260	135	0.287	0.349
16	0.146	0.384	46	-0.095	0.393	76	-0.503	0.251	106	-0.351	0.308	136	0.531	0.242
17	-0.928	0.116	47	0.692	0.179	77	0.195	0.375	107	0.287	0.336	137	1.223	0.029
18	0.505	0.254	48	-0.058	0.396	78	0.548	0.233	108	-0.273	0.344	138	-0.502	0.248
19	0.007	0.399	49	-0.056	0.397	79	0.233	0.363	109	0.999	0.054	139	0.054	0.397
20	0.471	0.279	50	-0.804	0.093	80	0.008	0.399	110	0.625	0.204	140	-0.348	0.330
21	0.168	0.378	51	-0.245	0.355	81	0.383	0.331	111	-0.297	0.333	141	0.091	0.394
22	-0.281	0.336	52	-0.388	0.281	82	-0.048	0.397	112	0.385	0.287	142	-0.167	0.377
23	0.859	0.095	53	0.239	0.354	83	0.828	0.098	113	-1.112	0.032	143	0.422	0.277
24	0.125	0.387	54	0.626	0.178	84	0.455	0.271	114	0.197	0.371	144	-0.169	0.374
25	0.247	0.350	55	-0.283	0.342	85	0.375	0.291	115	-0.333	0.317	145	-0.427	0.257
26	0.513	0.242	56	-0.135	0.382	86	0.173	0.372	116	-0.820	0.090	146	0.326	0.319
27	-0.048	0.397	57	-0.612	0.162	87	0.676	0.132	117	-0.208	0.358	147	-0.101	0.389
28	0.174	0.368	58	0.172	0.369	88	-0.028	0.398	118	-0.152	0.375	148	-0.337	0.303
29	0.080	0.392	59	0.139	0.380	89	0.035	0.398	119	-0.456	0.232	149	-0.739	0.087
30	1.039	0.012	60	0.681	0.078	90	0.609	0.116	120	0.368	0.257	150	0.749	0.048

Table 5A: Univariate cross-sectional regressions for 30-minute returns

We divide a trading day into 15 half-hour time intervals starting 08:00 and finishing 15:00. For each time interval t and lag k , we run a simple cross-sectional regression of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ is the logreturn on stock i at time t . Regressions are estimated for all combinations of 30-minute interval t , from Jul 1, 2010 to Dec 30, 2010 (1 942 intervals), and lag k , with values 1 through 75 (past 5 trading days). The table presents time-series averages of $\gamma_{k,t}$ in %, and the associated p-values. The analysis is done for OMXS 30 stocks.

Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value
1	-3.308	0.000	16	0.339	0.355	31	0.960	0.149	46	0.509	0.290	61	-0.108	0.394
2	-0.824	0.209	17	-0.843	0.191	32	0.394	0.338	47	-1.376	0.051	62	-1.158	0.079
3	-1.478	0.059	18	-1.393	0.044	33	-0.883	0.194	48	0.217	0.378	63	0.552	0.295
4	-0.763	0.239	19	0.032	0.398	34	-0.506	0.315	49	-0.079	0.397	64	-0.447	0.318
5	1.779	0.028	20	-0.407	0.340	35	0.718	0.236	50	1.216	0.103	65	0.424	0.327
6	0.440	0.342	21	-0.021	0.399	36	0.494	0.324	51	-0.358	0.361	66	0.659	0.259
7	-1.644	0.050	22	0.210	0.384	37	0.947	0.194	52	0.444	0.341	67	0.220	0.384
8	-1.138	0.144	23	0.738	0.267	38	-0.573	0.306	53	-0.172	0.388	68	2.131	0.008
9	0.118	0.394	24	0.008	0.399	39	1.264	0.086	54	0.792	0.217	69	-0.568	0.307
10	1.370	0.064	25	-1.020	0.119	40	0.025	0.399	55	0.765	0.256	70	-0.001	0.399
11	-0.362	0.353	26	-0.450	0.330	41	0.976	0.161	56	-1.093	0.123	71	-0.104	0.394
12	1.063	0.136	27	0.243	0.377	42	0.585	0.267	57	-0.476	0.323	72	-0.210	0.379
13	0.344	0.353	28	-0.515	0.300	43	1.198	0.098	58	-0.507	0.287	73	-0.070	0.397
14	0.645	0.241	29	-0.201	0.378	44	0.465	0.318	59	-0.847	0.160	74	-0.607	0.254
15	1.540	0.010	30	0.926	0.089	45	0.898	0.107	60	0.336	0.329	75	0.225	0.363

Table 6A: Long-run performance of 15-min returns

We divide the trading day into thirty 15-minute time intervals starting 08:00 and finishing 15:15. We assess the equally-weighted long-short strategies with a holding period of one time interval. Every 15 minutes, we group the stocks into 5 portfolios of 6 stocks each, based on their returns k periods ago. We analyze lags k that correspond to daily frequencies up to 30 trading days. The portfolio of 6 stocks (20%) which had the highest returns k periods ago is referred to as “winners”, while the portfolio of 6 stocks (20%) which had the lowest returns k periods ago is referred to as “losers”. The table reports time-series averages of the returns in % on “losers”, “winners” as well as the spread between them (“winners - losers”), and the corresponding Fama-MacBeth (1973) t-statistics. The analysis is done for OMXS 30 stocks over the period Jul 1, 2010 – Dec 30, 2010.

Losers					Winners				Winners-Losers	
Lag	return	t-statistics		return	t-statistics		Return	t-statistics		
30	-0.2360	-62.13		0.2488	58.81		0.4849	94.61		
60	-0.2338	-61.20		0.2463	57.90		0.4801	92.80		
90	-0.2312	-60.34		0.2438	57.24		0.4750	91.10		
120	-0.2287	-59.56		0.2408	56.62		0.4696	89.52		
150	-0.2256	-58.83		0.2382	55.79		0.4638	87.85		
180	-0.2225	-58.27		0.2349	55.29		0.4574	86.33		
210	-0.2196	-57.65		0.2320	54.56		0.4516	84.70		
240	-0.2167	-56.98		0.2293	53.73		0.4460	83.45		
270	-0.2140	-56.17		0.2267	53.16		0.4407	82.28		
300	-0.2114	-55.30		0.2241	52.40		0.4355	80.88		
330	-0.2089	-54.56		0.2211	51.59		0.4301	79.49		
360	-0.2063	-53.84		0.2186	50.96		0.4249	78.19		
390	-0.2041	-53.24		0.2157	50.33		0.4198	76.92		
420	-0.2013	-52.55		0.2128	49.78		0.4142	75.66		
450	-0.1980	-51.97		0.2102	49.23		0.4083	74.70		
480	-0.1953	-51.38		0.2079	48.54		0.4032	73.61		
510	-0.1930	-50.67		0.2051	47.83		0.3981	72.38		
540	-0.1909	-50.03		0.2024	47.29		0.3933	71.29		
570	-0.1883	-49.29		0.1992	46.64		0.3876	70.08		
600	-0.1861	-48.73		0.1959	46.01		0.3821	68.79		
630	-0.1841	-48.03		0.1928	45.39		0.3769	67.71		
660	-0.1820	-47.28		0.1903	44.76		0.3723	66.48		
690	-0.1792	-46.56		0.1882	44.19		0.3674	65.43		
720	-0.1768	-45.97		0.1860	43.52		0.3627	64.25		
750	-0.1752	-45.32		0.1837	42.89		0.3589	63.15		
780	-0.1733	-44.60		0.1814	42.17		0.3547	61.94		
810	-0.1708	-43.98		0.1795	41.68		0.3502	60.86		
840	-0.1686	-43.37		0.1775	41.19		0.3461	59.77		
870	-0.1666	-42.67		0.1757	40.55		0.3422	58.67		
900	-0.1648	-42.06		0.1735	39.92		0.3383	57.65		

Table 7A: Long-run performance of 30-min returns

We divide the trading day into 15 half-hour time intervals starting 08:00 and finishing 15:00. We assess the equally-weighted long-short strategies with a holding period of one time interval. Every 30 minutes, we group the stocks into 5 portfolios of 6 stocks each, based on their returns k periods ago. We analyze lags k that correspond to daily frequencies up to 30 trading days. The portfolio of 6 stocks (20%) which had the highest returns k periods ago is referred to as “winners”, while the portfolio of 6 stocks (20%) which had the lowest returns k periods ago is referred to as “losers”. The table reports time-series averages of the returns in % on “losers”, “winners” as well as the spread between them (“winners - losers”), and the corresponding Fama-MacBeth (1973) t-statistics. The analysis is done for OMXS 30 stocks over the period Jul 1, 2010 – Dec 30, 2010.

Losers			Winners			Winners-Losers	
Lag	return	t-statistics	return	t-statistics	Return	t-statistics	
15	-0.3279	-44.95	0.3546	42.28	0.6825	71.72	
30	-0.3258	-44.33	0.3515	41.63	0.6773	70.29	
45	-0.3229	-43.69	0.3489	41.25	0.6717	69.01	
60	-0.3199	-43.15	0.3460	40.72	0.6658	67.73	
75	-0.3164	-42.58	0.3427	40.06	0.6591	66.46	
90	-0.3133	-42.06	0.3386	39.53	0.6519	65.07	
105	-0.3101	-41.70	0.3356	38.98	0.6456	63.82	
120	-0.3071	-41.11	0.3323	38.42	0.6394	62.68	
135	-0.3036	-40.51	0.3289	37.87	0.6325	61.59	
150	-0.3003	-39.90	0.3258	37.36	0.6262	60.54	
165	-0.2968	-39.38	0.3219	36.76	0.6187	59.47	
180	-0.2935	-38.81	0.3186	36.31	0.6121	58.39	
195	-0.2903	-38.36	0.3145	35.82	0.6048	57.38	
210	-0.2863	-37.87	0.3105	35.44	0.5968	56.42	
225	-0.2812	-37.35	0.3070	35.03	0.5883	55.59	
240	-0.2768	-36.83	0.3038	34.57	0.5806	54.67	
255	-0.2739	-36.30	0.3000	34.04	0.5739	53.66	
270	-0.2716	-35.86	0.2965	33.65	0.5681	52.86	
285	-0.2690	-35.32	0.2932	33.23	0.5621	51.96	
300	-0.2662	-34.86	0.2893	32.75	0.5554	51.07	
315	-0.2635	-34.33	0.2838	32.42	0.5473	50.32	
330	-0.2601	-33.77	0.2805	32.01	0.5406	49.42	
345	-0.2560	-33.23	0.2769	31.78	0.5329	48.72	
360	-0.2526	-32.80	0.2738	31.29	0.5264	47.85	
375	-0.2502	-32.47	0.2703	30.98	0.5206	46.98	
390	-0.2469	-31.92	0.2667	30.45	0.5135	46.02	
405	-0.2426	-31.61	0.2633	30.29	0.5058	45.18	
420	-0.2393	-31.18	0.2598	29.88	0.4990	44.28	
435	-0.2364	-30.70	0.2569	29.51	0.4933	43.49	
450	-0.2343	-30.30	0.2527	29.04	0.4870	42.68	

Table 8A: Univariate cross-sectional regressions for 15-minute trading volume

We divide a trading day into thirty 15-minute time intervals starting 08:00 and finishing 15:15. For each time interval t and lag k , we run a simple cross-sectional regression of the form $v_{i,t} = \alpha_{k,t} + \beta_{k,t}v_{i,t-k} + u_{i,t}$, where $v_{i,t}$ is the natural logarithm of the percentage change in the volume of stock i from $t-k$ to t . Regressions are estimated for all combinations of 15-minute interval t , from Jul 1, 2010 to Dec 30, 2010 (3 885 intervals), and lag k , with values 1 through 150 (past 5 trading days). The table presents time-series averages of $\beta_{k,t}$ in %, and the associated p-values. The analysis is done for OMXS 30 stocks.

Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value
1	-44.369	0.000	31	-0.989	0.008	61	-0.205	0.337	91	-0.007	0.399	121	-0.889	0.018
2	-2.279	0.000	32	-0.109	0.379	62	-0.128	0.372	92	-0.564	0.113	122	-0.553	0.123
3	-0.939	0.013	33	-0.185	0.344	63	0.170	0.355	93	-0.047	0.395	123	0.480	0.161
4	-0.476	0.168	34	0.278	0.294	64	-0.386	0.218	94	-0.135	0.371	124	0.416	0.203
5	-0.627	0.092	35	-0.564	0.113	65	0.002	0.399	95	0.525	0.130	125	-0.409	0.205
6	-0.170	0.358	36	0.538	0.126	66	-0.357	0.240	96	-0.702	0.058	126	-0.183	0.350
7	0.028	0.398	37	0.040	0.397	67	0.656	0.070	97	0.507	0.147	127	0.266	0.308
8	0.555	0.131	38	-0.297	0.289	68	-0.301	0.282	98	-0.526	0.136	128	-0.487	0.166
9	-0.628	0.096	39	0.256	0.312	69	-0.103	0.383	99	0.287	0.294	129	0.237	0.322
10	-0.003	0.399	40	-0.846	0.025	70	-0.393	0.214	100	0.262	0.307	130	-0.017	0.398
11	-0.516	0.161	41	0.741	0.051	71	1.090	0.004	101	-0.345	0.257	131	-0.082	0.389
12	0.390	0.234	42	-0.289	0.294	72	-0.897	0.018	102	0.233	0.330	132	-0.050	0.395
13	0.011	0.399	43	0.051	0.395	73	0.070	0.392	103	-0.240	0.324	133	0.619	0.100
14	-0.033	0.397	44	-0.440	0.194	74	0.047	0.396	104	0.092	0.386	134	-0.109	0.383
15	-0.218	0.338	45	0.942	0.014	75	0.432	0.208	105	0.433	0.194	135	-0.446	0.191
16	0.168	0.362	46	-0.848	0.030	76	-0.464	0.187	106	-0.206	0.339	136	0.207	0.342
17	0.049	0.396	47	0.637	0.090	77	0.314	0.284	107	0.054	0.395	137	-0.231	0.329
18	0.137	0.372	48	-0.576	0.116	78	-0.523	0.143	108	0.493	0.171	138	0.641	0.088
19	-0.261	0.313	49	0.607	0.103	79	0.754	0.048	109	-0.869	0.025	139	-0.222	0.332
20	0.038	0.397	50	-0.205	0.341	80	-0.214	0.340	110	0.247	0.316	140	-0.218	0.330
21	0.078	0.390	51	-0.508	0.150	81	-0.395	0.233	111	0.172	0.357	141	-0.017	0.398
22	-0.517	0.145	52	0.558	0.119	82	0.487	0.163	112	0.028	0.398	142	-0.040	0.397
23	0.429	0.202	53	0.422	0.201	83	-0.366	0.244	113	-0.583	0.109	143	0.219	0.333
24	0.240	0.320	54	-0.991	0.009	84	-0.067	0.392	114	0.668	0.070	144	-0.193	0.346
25	-0.601	0.101	55	0.472	0.166	85	-0.241	0.318	115	-0.198	0.342	145	0.453	0.183
26	0.228	0.327	56	0.097	0.384	86	0.954	0.010	116	-0.218	0.330	146	-0.627	0.085
27	0.263	0.306	57	-0.032	0.397	87	-0.789	0.032	117	-0.384	0.218	147	-0.259	0.303
28	-0.641	0.078	58	-0.139	0.369	88	0.016	0.398	118	0.349	0.242	148	0.210	0.335
29	-0.611	0.092	59	-1.059	0.004	89	-0.104	0.381	119	-0.624	0.083	149	-0.270	0.299
30	2.252	0.000	60	1.557	0.000	90	0.961	0.010	120	1.961	0.000	150	1.568	0.000

Table 9A: Multivariate cross-sectional regressions for 15-minute returns. Return coefficients

We divide a trading day into thirty 15-minute time intervals starting 08:00 and finishing 15:15. For each time interval t and lag k , we run a multiple cross-sectional regression of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + \beta_{k,t}v_{i,t-k} + u_{i,t}$, where $r_{i,t}$ is the logreturn on stock i at time t , and $v_{i,t-k}$ is the natural logarithm of the percentage change in trading volume of stock i from $t-k-1$ to $t-k$. Regressions are estimated for all combinations of 15-minute interval t , from Jul 1, 2010 to Dec 30, 2010 (3 885 intervals), and lag k , with values 1 through 150 (past 5 trading days). The table presents time-series averages of $\gamma_{k,t}$ in %, and the associated p-values. The analysis is done for OMXS 30 stocks.

Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value
1	-8.262	0.000	31	-0.575	0.186	61	0.177	0.368	91	0.273	0.335	121	0.084	0.392
2	0.264	0.352	32	0.123	0.384	62	-0.026	0.398	92	-0.245	0.348	122	-0.390	0.289
3	-0.304	0.330	33	-0.038	0.398	63	0.809	0.102	93	0.264	0.335	123	0.462	0.262
4	-0.690	0.147	34	-0.751	0.116	64	0.344	0.304	94	-0.461	0.268	124	-0.356	0.295
5	0.196	0.371	35	0.013	0.399	65	0.703	0.145	95	-0.706	0.145	125	-0.234	0.355
6	-0.698	0.150	36	-0.157	0.377	66	-1.658	0.001	96	0.230	0.351	126	0.255	0.349
7	-0.612	0.200	37	-0.129	0.385	67	0.971	0.075	97	0.083	0.392	127	-0.236	0.355
8	-0.199	0.369	38	-0.585	0.201	68	-0.620	0.166	98	-0.354	0.317	128	-0.515	0.216
9	-0.815	0.138	39	0.580	0.212	69	-0.013	0.399	99	0.679	0.182	129	0.219	0.357
10	1.606	0.003	40	-1.004	0.059	70	0.266	0.350	100	0.753	0.143	130	0.812	0.111
11	0.013	0.399	41	-0.034	0.398	71	0.141	0.382	101	0.775	0.118	131	-0.151	0.379
12	0.073	0.395	42	0.158	0.383	72	-0.649	0.182	102	0.474	0.257	132	-0.073	0.395
13	0.719	0.183	43	-0.464	0.252	73	0.565	0.215	103	-0.368	0.310	133	0.916	0.074
14	-0.167	0.384	44	0.251	0.363	74	0.594	0.219	104	0.007	0.399	134	0.011	0.399
15	-1.957	0.003	45	0.594	0.208	75	-0.077	0.396	105	0.560	0.262	135	0.154	0.383
16	0.202	0.372	46	-0.267	0.355	76	-0.498	0.258	106	-0.273	0.346	136	0.767	0.142
17	-0.949	0.116	47	0.703	0.176	77	0.155	0.384	107	0.280	0.343	137	1.211	0.031
18	0.586	0.226	48	-0.159	0.380	78	0.416	0.297	108	-0.207	0.367	138	-0.436	0.282
19	0.077	0.395	49	-0.073	0.395	79	0.435	0.293	109	0.994	0.063	139	0.155	0.382
20	0.362	0.325	50	-0.662	0.158	80	-0.245	0.357	110	0.759	0.149	140	-0.263	0.359
21	0.238	0.362	51	-0.381	0.305	81	0.357	0.339	111	-0.356	0.311	141	0.155	0.385
22	-0.282	0.334	52	-0.277	0.337	82	-0.063	0.396	112	0.619	0.175	142	-0.153	0.381
23	1.012	0.063	53	0.239	0.355	83	1.069	0.048	113	-1.078	0.045	143	0.467	0.256
24	0.226	0.360	54	0.589	0.200	84	0.399	0.292	114	0.209	0.369	144	-0.109	0.389
25	0.149	0.381	55	-0.293	0.339	85	0.397	0.288	115	-0.185	0.373	145	-0.509	0.222
26	0.472	0.269	56	-0.286	0.329	86	0.103	0.390	116	-0.793	0.098	146	0.215	0.363
27	-0.084	0.393	57	-0.581	0.183	87	0.759	0.106	117	-0.232	0.350	147	0.024	0.398
28	0.182	0.368	58	0.242	0.344	88	-0.233	0.361	118	-0.294	0.321	148	-0.121	0.385
29	0.000	0.399	59	0.297	0.320	89	0.156	0.375	119	-0.542	0.193	149	-0.799	0.076
30	1.066	0.011	60	0.672	0.083	90	0.494	0.181	120	0.414	0.235	150	0.653	0.086

Table 10A: Multivariate cross-sectional regressions for 15-minute returns. Volume coefficients

We divide a trading day into thirty 15-minute time intervals starting 08:00 and finishing 15:15. For each time interval t and lag k , we run a multiple cross-sectional regression of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + \beta_{k,t}v_{i,t-k} + u_{i,t}$, where $r_{i,t}$ is the logreturn on stock i at time t , and $v_{i,t-k}$ is the natural logarithm of the percentage change in trading volume of stock i from $t-k-1$ to $t-k$. Regressions are estimated for all combinations of 15-minute interval t , from Jul 1, 2010 to Dec 30, 2010 (3 885 intervals), and lag k , with values 1 through 150 (past 5 trading days). The table presents time-series averages of $\beta_{k,t}$ in %, and the associated p-values. The analysis is done for OMXS 30 stocks.

Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value
1	-0.154	0.177	31	-0.142	0.202	61	-0.170	0.137	91	-0.177	0.106	121	-0.046	0.372
2	-0.058	0.354	32	0.247	0.050	62	-0.002	0.399	92	0.311	0.019	122	0.153	0.175
3	0.090	0.305	33	0.109	0.256	63	0.088	0.295	93	-0.264	0.038	123	-0.094	0.283
4	0.134	0.186	34	-0.105	0.272	64	-0.101	0.269	94	0.019	0.394	124	-0.005	0.399
5	-0.114	0.249	35	0.081	0.317	65	0.011	0.397	95	0.102	0.269	125	0.003	0.399
6	0.034	0.384	36	-0.174	0.154	66	0.008	0.398	96	-0.200	0.084	126	0.083	0.314
7	0.005	0.399	37	-0.137	0.201	67	-0.010	0.397	97	-0.081	0.314	127	-0.091	0.298
8	-0.010	0.397	38	-0.031	0.386	68	0.010	0.397	98	0.056	0.345	128	-0.266	0.024
9	-0.035	0.376	39	-0.079	0.295	69	-0.030	0.384	99	0.114	0.237	129	0.292	0.009
10	0.144	0.159	40	0.013	0.396	70	0.146	0.171	100	-0.143	0.140	130	-0.133	0.201
11	-0.026	0.389	41	0.077	0.305	71	-0.051	0.357	101	0.008	0.398	131	0.024	0.390
12	0.002	0.399	42	0.095	0.272	72	-0.034	0.380	102	0.081	0.284	132	-0.044	0.366
13	0.152	0.130	43	-0.075	0.314	73	0.121	0.191	103	-0.131	0.173	133	-0.092	0.270
14	-0.073	0.296	44	-0.064	0.319	74	-0.092	0.262	104	0.055	0.342	134	0.010	0.397
15	-0.024	0.388	45	0.043	0.361	75	0.102	0.236	105	0.116	0.184	135	-0.042	0.364
16	-0.099	0.245	46	0.048	0.355	76	-0.014	0.395	106	-0.131	0.183	136	0.073	0.301
17	0.055	0.339	47	-0.121	0.206	77	0.112	0.198	107	-0.027	0.384	137	-0.023	0.388
18	-0.107	0.207	48	-0.167	0.087	78	-0.072	0.294	108	-0.052	0.343	138	0.037	0.371
19	0.131	0.162	49	0.069	0.312	79	0.094	0.270	109	0.035	0.376	139	0.041	0.364
20	-0.083	0.288	50	0.091	0.274	80	-0.056	0.343	110	-0.001	0.399	140	-0.229	0.033
21	-0.002	0.399	51	0.012	0.396	81	-0.021	0.390	111	0.047	0.355	141	0.163	0.113
22	-0.045	0.365	52	-0.207	0.050	82	0.009	0.397	112	-0.107	0.210	142	0.053	0.352
23	-0.063	0.335	53	-0.005	0.398	83	0.005	0.398	113	0.131	0.176	143	-0.052	0.345
24	0.000	0.399	54	0.080	0.300	84	-0.043	0.369	114	0.092	0.261	144	0.031	0.383
25	-0.011	0.397	55	0.035	0.376	85	-0.004	0.399	115	-0.017	0.393	145	0.058	0.337
26	-0.012	0.396	56	-0.159	0.124	86	-0.114	0.214	116	0.147	0.145	146	-0.164	0.133
27	0.082	0.301	57	0.056	0.345	87	0.092	0.262	117	-0.249	0.024	147	0.128	0.205
28	0.161	0.140	58	-0.082	0.300	88	-0.203	0.071	118	0.041	0.375	148	0.134	0.170
29	-0.080	0.293	59	0.056	0.350	89	0.028	0.384	119	-0.101	0.257	149	0.065	0.337
30	0.054	0.347	60	0.249	0.021	90	0.040	0.369	120	0.045	0.368	150	-0.028	0.386

Table 11A: Multivariate cross-sectional regressions for 30-minute returns. Return coefficients

We divide a trading day into 15 half-hour time intervals starting 08:00 and finishing 15:00. For each time interval t and lag k , we run a multiple cross-sectional regression of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + \beta_{k,t}v_{i,t-k} + u_{i,t}$, where $r_{i,t}$ is the logreturn on stock i at time t , and $v_{i,t-k}$ is the natural logarithm of the percentage change in trading volume of stock i from $t-k-1$ to $t-k$. Regressions are estimated for all combinations of 30-minute interval t , from Jul 1, 2010 to Dec 30, 2010 (1 942 intervals), and lag k , with values 1 through 75 (past 5 trading days). The table presents time-series averages of $\gamma_{k,t}$ in %, and the associated p-values. The analysis is done for OMXS 30 stocks.

Lag	Estimate	P- value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value
1	-3.767	0.000	16	0.226	0.380	31	0.933	0.165	46	0.495	0.300	61	-0.221	0.381
2	-1.128	0.123	17	-0.840	0.190	32	0.615	0.276	47	-1.249	0.078	62	-1.108	0.102
3	-1.887	0.020	18	-1.321	0.056	33	-0.894	0.196	48	0.756	0.215	63	0.881	0.186
4	-0.663	0.280	19	0.064	0.397	34	-0.496	0.318	49	-0.137	0.393	64	-0.233	0.375
5	1.718	0.039	20	-0.419	0.339	35	0.668	0.261	50	0.936	0.183	65	0.307	0.361
6	0.203	0.386	21	-0.058	0.398	36	0.793	0.236	51	-0.190	0.388	66	0.522	0.308
7	-1.748	0.038	22	0.325	0.367	37	0.974	0.197	52	0.713	0.270	67	0.181	0.389
8	-1.271	0.114	23	0.966	0.201	38	-0.617	0.297	53	-0.150	0.391	68	2.262	0.005
9	0.277	0.374	24	0.039	0.398	39	1.340	0.081	54	0.676	0.261	69	-0.683	0.270
10	1.318	0.079	25	-1.123	0.099	40	-0.344	0.364	55	0.762	0.256	70	-0.270	0.376
11	-0.206	0.384	26	-0.608	0.283	41	1.319	0.079	56	-0.859	0.197	71	-0.117	0.393
12	1.206	0.103	27	0.053	0.398	42	0.689	0.231	57	-0.455	0.330	72	-0.128	0.392
13	0.492	0.309	28	-0.536	0.296	43	1.016	0.152	58	-0.773	0.194	73	-0.315	0.359
14	0.677	0.240	29	-0.174	0.384	44	0.676	0.253	59	-0.811	0.183	74	-0.470	0.307
15	1.304	0.032	30	0.926	0.092	45	0.801	0.147	60	0.351	0.326	75	-0.209	0.369

Table 12A: Multivariate cross-sectional regressions for 30-minute returns. Volume coefficients

We divide a trading day into 15 half-hour time intervals starting 08:00 and finishing 15:00. For each time interval t and lag k , we run a multiple cross-sectional regression of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + \beta_{k,t}v_{i,t-k} + u_{i,t}$, where $r_{i,t}$ is the logreturn on stock i at time t , and $v_{i,t-k}$ is the natural logarithm of the percentage change in trading volume of stock i from $t-k-1$ to $t-k$. Regressions are estimated for all combinations of 30-minute interval t , from Jul 1, 2010 to Dec 30, 2010 (1 942 intervals), and lag k , with values 1 through 75 (past 5 trading days). The table presents time-series averages of $\beta_{k,t}$ in %, and the associated p-values. The analysis is done for OMXS 30 stocks.

Lag	Estimate	P- value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value	Lag	Estimate	P-value
1	0.340	0.119	16	0.155	0.320	31	0.018	0.398	46	0.065	0.380	61	-0.010	0.398
2	0.027	0.395	17	0.001	0.399	32	-0.110	0.353	47	-0.090	0.368	62	-0.018	0.397
3	-0.021	0.397	18	-0.453	0.054	33	0.094	0.365	48	-0.316	0.136	63	-0.244	0.200
4	0.018	0.397	19	0.051	0.385	34	-0.023	0.396	49	0.330	0.110	64	0.172	0.276
5	0.048	0.388	20	0.055	0.382	35	-0.032	0.394	50	-0.052	0.386	65	-0.070	0.376
6	0.175	0.271	21	-0.123	0.327	36	0.023	0.396	51	-0.204	0.223	66	0.104	0.341
7	-0.023	0.396	22	0.105	0.341	37	-0.037	0.391	52	0.303	0.090	67	-0.041	0.389
8	-0.180	0.257	23	-0.076	0.368	38	0.046	0.385	53	-0.236	0.155	68	0.054	0.384
9	0.039	0.390	24	-0.053	0.381	39	0.118	0.321	54	0.037	0.389	69	0.112	0.319
10	-0.132	0.327	25	0.117	0.322	40	-0.166	0.277	55	0.145	0.293	70	-0.353	0.083
11	-0.012	0.398	26	-0.234	0.179	41	0.050	0.386	56	-0.056	0.382	71	-0.023	0.396
12	-0.258	0.148	27	0.122	0.325	42	0.052	0.383	57	0.295	0.121	72	0.237	0.196
13	0.162	0.271	28	0.000	0.399	43	-0.185	0.252	58	0.008	0.399	73	-0.518	0.008
14	0.363	0.085	29	-0.261	0.171	44	-0.263	0.163	59	-0.157	0.292	74	0.500	0.015
15	-0.253	0.152	30	0.173	0.288	45	-0.115	0.332	60	-0.089	0.356	75	-0.368	0.078