School of Finance

University of St.Gallen

THE ROLE OF DAYTIME STOCK AUCTIONS IN INTRADAY RETURN SEASONALITY

EKATERINA SERIKOVA

WORKING PAPERS ON FINANCE NO. 2019/14

SWISS INSTITUTE OF BANKING AND FINANCE (S/BF – HSG)

JULY, 2019

The Role of Daytime Stock Auctions in Intraday Return Seasonality*

Ekaterina Serikova†

July 2019

The paper provides a fresh look at the role of daytime auctions in intraday periodicity of stock returns. First, I show that daytime auctions, together with market opening and market closing intervals, drive the periodicity of stock returns. Second, by applying the model of infrequent rebalancing, I find that price impact is the highest during the fifteen-minute interval after daytime auctions. Combining this evidence with high realized returns, high volume changes and high return volatility, I conclude that after-auction periods take over a large share of infrequent rebalancing, being attractive for a concentration of liquidity traders. Small, low-fragmented stocks heavily traded on the home market show the strongest evidence for infrequent rebalancing after the daytime auctions. Finally, I show that post-auction returns predict returns before the US market opening and before the domestic market closing, which might be further evidence on clustered liquidity trading.

KEY WORDS: Market microstructure, market design, auctions, intraday periodicity

*I thank Paul Söderlind, Albert J. Menkveld, Vincent Bogousslavsky, Farshid Abdi, Angelo Ranaldo, and Andrei Kirilenko for helpful suggestions and remarks that improved the paper. The paper also benefited from the comments at the 2017 Market Microstructure Summer School in Lugano, the Fall 2017 Finance seminar at the University of St. Gallen, and the 2019 International Risk Management Conference.

†University of St. Gallen. *Address:* s/bf-HSG, University of St. Gallen, Unterer Graben 21, CH-9000 St. Gallen, Switzerland. *E-mail:* ekaterina.serikova@unisg.ch.

1 Introduction

Stock auctions are a pre-scheduled session, during which traders' supply and demand determine the price of an asset. The auctions on stock exchanges usually take place twice a day: at the market open (opening auction) and the market close (closing auction). This paper focuses on daytime auctions: they occur at daytime, in addition to the closing and opening auctions.

The goal of this paper is to analyze the volume dynamics of daytime auctions and to shed light on the impact of auctions on market behavior. Do the same market factors influence trading during the continuous market and the auctions? Do daytime auctions create any patterns in stock returns? How do auctions influence stock price dynamics? Are there any models that can explain trading around the auctions? The paper demonstrates an essential role of the daytime auctions in forming predictable patterns in cross-section of stock returns. Understanding daytime auctions thoroughly is important because of current changes in market regulations and because auctions serve as one of the widely discussed options for the optimal stock market design.

A market regulatory framework is currently under the change, which calls for more analysis of daytime auctions. This is especially important in Europe, where the new Markets in Financial Instruments Directive II Regulation (MiFID II) came into force in 2018. The main goal of this new EU-wide law is to increase the transparency of European stock markets and to bring back the trading from dark pools to public exchanges. In particular, during the last six years, the share of European stocks traded on dark pools rose up to 10% from less than 2% in 2010.[1] The regulation, among other standardization procedures, imposed a cap on dark pool trading to reverse this trend. Dark pools are generally attractive because they allow investors to buy and sell stocks without revealing in advance the size and the price they are willing to accept. These features are especially advantageous for investors who wish to trade in blocks, but reduce the flow of public information and avoid fast traders, who can detect these trades and trade against them.

With the new regulation, a natural alternative to dark pools is the auctions. The auctions technically take place "in the light" on lit markets, but orders are still hidden until they can be matched. This mechanism provides similar advantages to dark pools, allowing investors (1) to place a large block of trades in a way that reduces market impact, (2) to avoid fast traders, who can spot block trades and exploit them. Consequently, the MiFID II Regulation motivated European stock markets to initiate daytime auctions: in 2013, the NASDAQ Nordic announced introduction of daytime auctions for some market segments; in 2017, the German market Xetra closed its dark pool for stocks, claiming that it will mostly rely on auctions[2]; in 2016, the London Stock Exchange established its first midday auction. Even American stock markets seem to follow the pattern, although having a different motivation: the NYSE recently considered implementing daytime auctions" to boost liquidity in thinly traded stocks".[3]

[1] *"Dark pools in European equity markets: emergence, competition, and implications"*, European Central Bank, No.193 / July 2017

[2] *Deutsche Boerse confirms dark pool closure*, The Trade, February 2017

[3] *NYSE liquidity drive pushes midday auctions*, Financial Times, May 2016

Even though the role of daytime auctions grows, empirical literature seems not to cover the research questions related to the potential impact of the auctions on price dynamics and traders' behavior. Existing auction research is largely concentrated on the opening and/or closing auctions (Pagano and Schwartz 2005, Kandel et al. 2012, Pagano et al. 2013, Comerton–Forde et al 2007, etc.). The other large research segment is focused on advocating auctions as an optimal market model (Budish et al. 2015 and Farmer and Skouras 2012). I contribute to this literature by showing that daytime auctions generate periodicity in cross-section of stock returns, which can be partially explained by traders' rebalancing after the auctions.

For the analysis, I use data from the only large stock market that has a long history of daytime auctions - the German electronic platform Xetra. It is a perfect representative market that one can use as a proxy for major stock exchanges. First, it is one of the largest European and world markets: the third-largest in Europe and the tenth-largest in the world based on market capitalization.[4] Second, apart from the daytime auctions, the Xetra handles trading through "continuous trading in connection with auctions" model - a standard setting of most other stock exchanges (besides additional third daytime auction in a day). Eventually, the German market itself fell within the purview of the MiFID II Regulation. Being conducted on the dataset of a representative market, the results of this analysis are transferable and can be thus generalized for other stock markets.

The main findings are the following. First, I identify that different market factors influence auction volumes compared to the continuous-trading volumes. Second, I find that fifteen minutes after daytime auctions contribute to the daily periodicity of a cross-section of stock returns. In particular, the return spread on the daily momentum strategy around the auctions earns on average 1.89 basis points per day.[5] This effect is more pronounced for large, small, and domestic[6] stocks. Second, in order to understand whether theoretical findings can explain this empirical, I apply the model of infrequent rebalancing (Bogousslavsky 2016) to the data. This model belongs to the group of theoretical models on non-synchronous trading. Bogousslavsky 2016 explains the mechanism of his theoretical model and show that it might explain the periodicity in the cross-section of stock returns around the close on the NYSE. He studies stock portfolios built on different market anomalies and observes how their returns vary during a day.

My approach is different - I study mechanics of the model and define four features that should hold on the market if the model is valid (e.g., if infrequent rebalancing is present): high price impact, high realized returns, high volatility of returns, and high trading volume. Also, applying this model to the market with *three* intraday auctions might reveal interesting conclusions. Infrequent investors can behave differently than on the market without the daytime auctions. For example, they can rebalance more often than once a day or adjust their rebalancing time to the daytime auctions. Alternatively, they can ignore these auctions and still rebalance at the close. I show that infrequent rebalancing is present during the fifteen minutes after daytime auctions and is more pronounced for small low-fragmented stocks. Also, post-auction returns for these stocks predict the returns before the US market opening and at the Xetra close. This evidence on

[4] *World Federation of Exchanges*, as of April 2016, excluding open market

[5] The value is not adjusted for trading costs.

[6] In the paper, domestic stocks are German stocks.

intraday momentum is consistent with the model and is driven by the concentration of liquidity traders at these intervals of a trading day.

The paper is structured as follows. First, I provide institutional insights about the daytime auctions, together with an aggregate analysis of factors that affect auction trading volumes. Then in Section 4, I provide empirical evidence on stock return periodicity and report its main drivers. In section 5, I analyze and compare theoretical models that can help to explain the pattern. After selecting the model of infrequent rebalancing as the main candidate for the explanation of my findings, I apply the model to the data. Section 6.1 contains an additional empirical finding of intraday momentum, consistent with the model. Discussion and conclusions in Section 7 complete. The next section provides a literature overview and helps position this paper within the existing research.

2 Related literature

This paper is mainly related to two strands of literature. The first line of research studies predictive patterns in stock returns at different frequencies and tackles to explain them; the other direction of relevant research investigates auctions directly. I contribute by merging these two areas and report evidence on the role of daytime auctions in generating return seasonality.

2.1 Evidence on intraday return patterns

A critical paper that provides the basis for seasonality part of the analysis is Heston et al. 2010. The authors examine intraday dynamics in the cross-section of NYSE stock returns and show that those are positively related to the one-day subsequent returns. This relationship is found to be especially pronounced at the market open and market close. Investors flows are suggested as a potential explanation for the pattern because the revealed periodicity is of the same magnitude as institutional commission rates and a quoted half-spread. The authors thus claim that institutional traders can reduce trading costs by timing their trades in the same manner as the daily recurrence of intraday prices.

The role of investor flows in generating return seasonality was also reported to cause return periodicity at lower frequencies. In particular, Lou 2012 demonstrates that when retail investors transfer their flows to mutual funds, it creates predictable price pressure to individual stocks. This trading of mutual funds positively forecasts future stock and fund returns in the short run, and negatively - in the long run. In a similar vein, Coval and Stafford 2007 study fire sales and show that when mutual fund managers wish to increase their cash holdings by liquidating assets via fire sales, they drive stock prices away from their fundamental values. Alternatively, Sun et al. 2016 find strong evidence that high-frequency changes in investor sentiment have predictive power for the S&P 500. Another driver of stock return predictability is offered by Cont et al. 2013. They suggest that order flow imbalance determines stock price changes and is robust to intraday seasonality effects. The relation between price changes and the trading volume is, however, found to be noisier and less robust.

Seasonality in stock trading is not only a US phenomenon. Ohta 2006 studies the Tokyo market and connects price clustering to the dynamics of a bid-ask spread. In particular, as the market opening is characterized by greater uncertainty, price clustering is usually high in this period. This uncertainty at the open also relates to more substantial information asymmetry and, together with a higher degree of price clustering, generates wider spreads. Similarly, Abhyankar et al. 1997 investigate the London Stock Exchange and show that intraday bid-ask spreads are the highest at the market open, stay relatively constant during a day and become larger again at the close. Trading volume peaks around the opening then falls to the lowest level and increases before the closing. The authors associate such a pattern with the dynamics of price discovery, which depends on how efficiently the market absorbs new information through trade flows at the close/open.

Opening and closing auctions can also generate return seasonality. Pagano et al. 2013 find that the introduction of opening and closing auctions on the NASDAQ created a positive spillover effect of auctions at the open on the price formation during continuous trading. Brooks and Moulton 2004 discover that bid-ask spread in the continuous market can be attributed to the price change during the opening auction. They also observe that there are no price reversals right after the opening auction, suggesting that market opening may be more efficient at handling information than the continuous market.

Despite the extensive literature on intraday return patterns, related empirical evidence for the German market is limited. Hussain 2011 finds a J-shaped intraday volatility and L-shaped patterns of intraday volumes for DAX stocks. Gomber et al. 2004 find a pronounced U-shaped liquidity intraday pattern for the largest stocks, showing that transaction costs on the Xetra increase around the start of trading on the NYSE. This finding is at odds with Goodfellow at al 2010, who report the decreased costs and improved liquidity corresponding to the NYSE opening. The time of four years between these two studies could change the market characteristics and explain the different findings. For example, the dynamics of trading cost can change due to technological innovations.

The existing studies explain the evidence on intraday seasonality mainly through the channel of trading flows and supply-demand imbalances. In terms of auctions, existing research mainly focuses either on opening or closing auctions. To the best of my knowledge, this is the first paper that investigates the cross-section of the whole German stock market by using intraday data for more than four years. Also, a thorough search of the relevant literature yielded no studies that combine the analysis of daytime stocks auctions and their impact on asset price dynamics.

2.2 Auctions as a trading model

The other area of related research analyzes stock auctions from the point of view of an optimal stock market design. In particular, it was shown that auctions have essential benefits that make them more advantageous to the most conventional setting, continuous markets with limit order books. Earlier literature advocates auctions in favor of limit order book markets primarily because auctions contribute to better price discovery. Cohen and Schwartz 1989, Madhavan 1992, and Economides and Schwartz 1995 claim that auctions enhance price efficiency. In particular, Madhavan 1992 finds that during the auctions, the aggregation of the otherwise dispersed information is achieved by waiting for investors with both private- and common-value information to arrive at the market. Thus, periodic auctions efficiently aggregate information and are more robust to the problems of informational asymmetry - it can operate when continuous markets fail. Related to that, Economides and Schwartz 1995 propose a similar aggregation of information through conducting periodic auctions three times a day: at the open, midday, and the close. Having several call auctions during a trading day would allow investors to have a choice between waiting for the next call or using a continuous trading mechanism for immediate execution. In a similar vein, Grauer and Odean 1995 advise to minimize execution costs by using systems like the Arizona Stock Exchange that offers call sessions several times per day.

With time, markets have become much faster and a new type of investors, high-frequency traders, appeared. Given evidence on the negative impact of these traders on market quality (Foucault, Kozhan and Tham 2015, Baldauf and Mollner 2015), the more recent literature has favored auctions precisely because they prevent a high-frequency speed race. In particular, Budish et al. 2015 and Farmer and Skouras 2012 argue that continuous trading leads to the competition for speed and that batch auctions are fairer because they stop this race. Budish et al. 2015 demonstrates that the presence of such race does not affect the size of arbitrage present in continuous trading. He shows that instead of eliminating arbitrage opportunities, high-frequency traders continually raise the bar for how fast one has to be in order to capture a ”prize”. Switching from continuous trading to the auction market design would eliminate the speed race and change the nature of competition into the price competition, rather than the competition on quickness. In particular, the authors propose a market design when a trading day is divided into highly frequent but discrete time intervals so that all requests are treated as having arrived simultaneously. At the end of each interval, orders are proceeded in batch through an auction, as opposed to the serial processing in continuous markets.

Few studies analyze auctions on the German market. Clapham and Zimmermann 2016 investigate price convergence around the auctions. In particular, they study the price discovery of the cross-listed DAX stocks on a home German and on other EU markets. The authors show that the domestic price informativeness of indicative prices during the auctions is higher and more relevant for price discovery than on the other markets. This finding suggests that market participants assess the Xetra auction price as more relevant for future stock prices. However, this conclusion depends on the level of stock fragmentation: for the less fragmented trading, the contribution of the home market to price discovery is more substantial. The other study investigates the role of designated market makers (DMM) during the Xetra daytime auctions (Theissen and Westheide 2017). DMMs are particular market participants (market makers) who supply additional liquidity for small and mid-cap stocks during the auctions. The study shows that intraday auctions have the highest share of DMM participation among other intraday auctions. Overall, it was found that DMMs contribute substantially to price continuity, providing thus a valuable service to the market.

This section represented an overview of the literature with extensive evidence on return predictability, its potential drivers, and the advantages of auction market design. However, there seems to be a gap in investigating the role of daytime auctions in connection to the return periodicity. The next section will provide the institutional details of the market and trading in the daytime auctions. I will also describe the dataset and represent factors that influence trading volumes during the auctions.

3 Daytime auctions through the lens: market setting and volume dynamics

3.1 Mechanics of daytime auctions

An electronic trading system Xetra was first introduced in 1997 and has been operated by the Deutsche Boerse. This market is one of the few[7], who had a standard procedure of daytime auctions for many years – since 1998. Xetra accounts for more than 90% of the total German stock market.[8] It is a fully electronic platform, organized as an anonymous open limit order book with a central counterparty clearing that offsets orders. The market carries a trading model that combines continuous trading with three pre-scheduled intraday auctions: an opening auction at 8:50, a daytime auction at 13:00[9], and a closing auction at 17:30. The market is open daily from 9:00 (after the opening auction) until 17:30 (followed by the closing auction).

Each day at 13:00, continuous trading is interrupted by a regular daytime auction. A primary purpose of these auctions is to determine a ”fixing” price for stocks at the time of the day when liquidity is low.[10] The determination of such price is possible because auctions concentrate the buying and selling interest at the same time. This is especially important for less liquid stocks: if a trading interest in a stock is low, traders might not have enough incentive to participate in a continuous market (Hasbrouck 2017), and trade these stocks during the intervals of pooled liquidity, e.g., during auctions. Two arrangements on the Xetra support such a concentration of liquidity during auctions. First, there is no distinction between the transaction fees for continuous trading and auctions. Thus, auction trading costs are far less than half a basis point.[11] Second, increased liquidity during auctions is enhanced by the presence of designated market makers

[7]Vienna stock exchange and Zagreb stock exchange also had daytime stock auctions before the introduction of the MiFID II.

[8]*Xetra Cash market statistics*, Monthly report April 2016

[9]The intraday call auction is held between 13:00 and 13:02 for DAX and TecDAX stocks, between 13:05 and 13:07 – for MDAX and SDAX stocks, and between 13:15 and 13:17 for other stocks. The MDAX, SDAX, and TecDAX consist of the stocks that are traded in the prime standard segment and whose are free float trading volume is smaller than the DAX stocks. The TecDAX comprises the 30 largest technology stocks outside of the DAX. The MDAX and SDAX contain 50 stocks from non-technology sectors. The 50 stocks of the MDAX are the next 50 stocks after the DAX stocks, the 50 stocks of the SDAX are those that follow after.

[10]This is similar to commodity fixing - the process of setting the price of a commodity based on supply and demand needs.

[11] Budimir M. 2015 *The Xetra intraday auction. Growing potential for strong price discovery*

(DMMs).[12] This special type of traders is required to submit buy and sell limit orders to the auctions and to quote bid and ask prices during the continuous trading session. They have to meet a minimum participation rate in the call auctions and a minimum quotation time during the continuous trading. Designated market makers do not have any informational advantage (e.g., exclusive access to the limit order book, as the NYSE specialists had), and their quotes are subject to the same rules of price and time priority as orders submitted by the agency and principal traders.

Similar to opening and closing auctions, daytime auctions consist of two phases: a call phase and a price determination phase (Figure 1). During the call phase, all received orders are automatically collected in one order book. The order book is partially closed: only information on the indicative price (if available) or the bid/ask limit is displayed to the market participants. If a current order book is not yet crossed, the accumulated volumes are displayed in addition to the best bid/ask limits. In case of the crossed order book, the volume for a corresponding indicative price is shown. In order to discourage any probable tactics of price manipulation, the end of the call phase is randomized. This approach is consistent with Hasbrouck 2017, who demonstrates that even a small amount of uncertainty may be enough in order to discourage manipulations based on last instant moves.

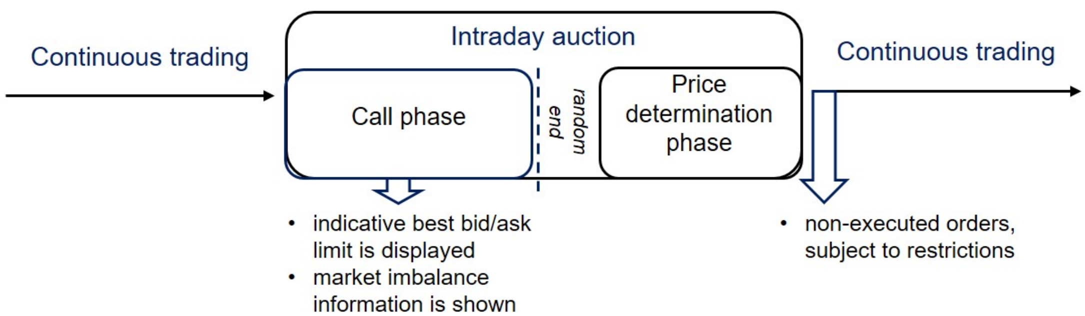

Figure 1: The process of daytime auctions on the Xetra

The settlement (fixing) price is determined according to the principle of the maximum executable trading volume with the lowest surplus. As soon as this price is defined, the matching orders are immediately executable without a possibility to retrieve the submitted orders. At the end of the auction, those orders that were not or were only partially executed are redirected to the next possible trading form, according to their respective order sizes and trading restrictions. Continuous trading restarts at the end of the auction; executed auction price, time of price determination, and executable volumes are displayed for each stock.

The described auction mechanism is different from the continuous trading in several aspects. The first distinction is the market information available to traders – the order book is fully open during continuous trading: the first ten bid/ask limits, the number of orders per limit and the

[12]Designated market makers on the Xetra are officially called ”designated sponsors”. I use a modified term of designated market maker, which is more common in research.

order volumes accumulated for each limit are displayed. During the auctions, only indicative price, imbalance and the side on which the imbalance exists are shown. Second, the execution of quotes in continuous trading follows the price-time priority, thus rewarding higher speed. In particular, each incoming order is immediately checked whether it can be executed against orders on the other side of the order book. Consequently, in continuous trading, traders are encouraged to be the first to act on new information. Priority principles of auctions rather focus on matching the interests of supply and demand at a single point in time and minimize the rewards for being the fastest. This leads to another difference – trading speed. Trading in auctions is naturally slower than in continuous trading. As mentioned, the liquidity during auctions is not provided by speedy players, who prefer the low-latency environment of continuous trading. Thus, the latency of the market dealer does not matter for auctions.

3.2 Data description

The trading data during auctions is not a part of Level I and Level II market data. For the analysis, I combine two different datasets. The first dataset includes the following fields at a one-minute frequency: date/time stamp, stock ticker, low price, high price, trade price, number of stocks traded. The second part of the dataset contains all trades on a tick basis with information on stock ISIN, trade price, price flag[13], the number of assets traded. Both datasets cover a period between August 2010 – May 2015. The initial datasets contain all instruments traded on the German stock exchanges. Based on *Bloomberg Database* with an additional verification from *Thomson Reuters Datastream*, I select only common stocks traded on the Xetra and adjust the sample for delisted stocks and stocks that changed their tickers during the sample period. Following market microstructure literature (e.g., Heston et al. 2010), I further exclude stocks with prices lower than €5 and stocks that had less than thirty trading days during the sample period. The final sample includes 875 common stocks, from which 539 are domestic German stocks and 336 are foreign (defined as stocks with an ISIN country code different from ”DE”). Most foreign stocks are European (190 stocks) or North-American (144 stocks). To enable the analysis on a stock level, I retrieve stock information on firms’ size, country, aggregate trading volume (including markets besides Xetra) from the *Thomson Reuters Datastream*.

The limitation of the combined dataset is that it does not allow to observe the trading flows *inside* auctions. Consequently, I cannot observe the dynamics of supply and demand sides, the number of participants, and unexecuted volumes during the auction process. Instead, only a stock settlement price and settled volume are reported in the second part of my dataset.

Nearly all stocks of the sample are traded during both continuous trading and via daytime auctions: only 0.12% of trading volume is traded only in the continuous market, but not during daytime auctions on a given day. In 2014-2015, an average trade size during daytime auctions was eight times higher than in continuous trading – €91,580 and €11,270 respectively.

[13]The following price flags are available: end-of-day auction, opening auction, opening price, intraday auction, mid-day auction price, liquidity circuit breaker, mini auction, closing auction, closing price, single auction, special auction, volatility auction, closing price from the day before, issuing period.

Once a month, a settlement day for the options traded on the Eurex takes place. On these days, the duration of Xetra daytime auctions extends from two up to five minutes. My sample confirms a special role of these days: the share of volume traded via daytime auctions reaches 20% on average (six times higher than on the rest of the days), with the maximum value of 43% on October 18, 2013. For further analysis, I exclude these option settlement days from the sample.[14]

Table 1 provides summary statistics in terms of traded volumes. On aggregate, opening, daytime, and closing auctions account for 16.1% of the total daily volume, 80.9% of which belong to closing auctions, 16.2% – to opening auctions, and 2.9% – to daytime auctions. In terms of time, it is worth mentioning that all three auctions amount to just seventeen minutes of a trading day, with the shortest daytime auctions lasting for only two minutes. A high volume share of the closing auction is supported by the stylized fact that institutional traders mainly trade at or near the close (Cushing and Madhavan 2000). The trading volume of domestic stocks is more disseminated: 77.4% is traded during the continuous period with the rest 22.6% – via auctions, while the corresponding values for foreign stocks are 90.4% and 9.6%. Trading volumes of foreign stocks via daytime auctions are twice lower than those of domestic stocks.

There is a positive relationship between stocks' size and trading volume during daytime auctions: the more actively a given stock is traded during a continuous trading phase, the larger trading volume during the daytime auction it has (see Figure A1 in Appendix). In terms of stock size, closing auctions take over the trading volumes of large stocks, while middle-size and small stocks are mostly traded in opening auctions (Figure 2). The volume share of the daytime auction for small stocks is almost twice higher than that of large stocks (7% as opposed to 3.7%).

Even with the excluded settlement days, the volume traded via daytime auctions is rather heterogeneous, with a standard deviation of 177.5% based on daily observations, compared to the less volatile opening (40%) and closing (33%) auctions.

[14] Settlement days take place on the third Friday of each month. The exact dates were retrieved from the Eurex website. Totally, 62 settlement days are excluded from the analysis.

	Opening auction	Daytime auction	Closing auction	Continuous trading	Auction trading
(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
German domestic stocks	6.4%	3.7%	89.8%	77.4%	22.6%
Foreign stocks	26.0%	2.0%	72.0%	90.4%	9.6%
Total	16.2%	2.9%	80.9%	83.9%	16.1%
Large stocks	6.6%	3.7%	89.6%	77.8%	22.2%
Middle-size stocks	58.5%	5.0%	36.5%	91.0%	9.0%
Small stocks	61.7%	7.0%	31.3%	88.6%	11.4%
Standard deviation (daily)	40.4%	177.5%	33.0%	25.7%	33.7%
Standard deviation (monthly)	22.7%	49.4%	12.5%	18.1%	12.9%

Table 1: Summary statistics of auction trading on the Xetra. The table demonstrates the breakdown of the daily Euro trading volume. Domestic stocks are those whose ISIN starts with "DE", foreign stocks are those with any other country code. Large, middle-size, and small stocks are defined based on the free-float market capitalization on 31/01/2013 from *Thomson Reuters Datastream.* Opening auctions take place every day at 8:50, daytime auctions start at 13:00, closing auctions – at 17:30. Column *(6)* denotes the total Euro volume traded during the opening, daytime, and closing auctions.

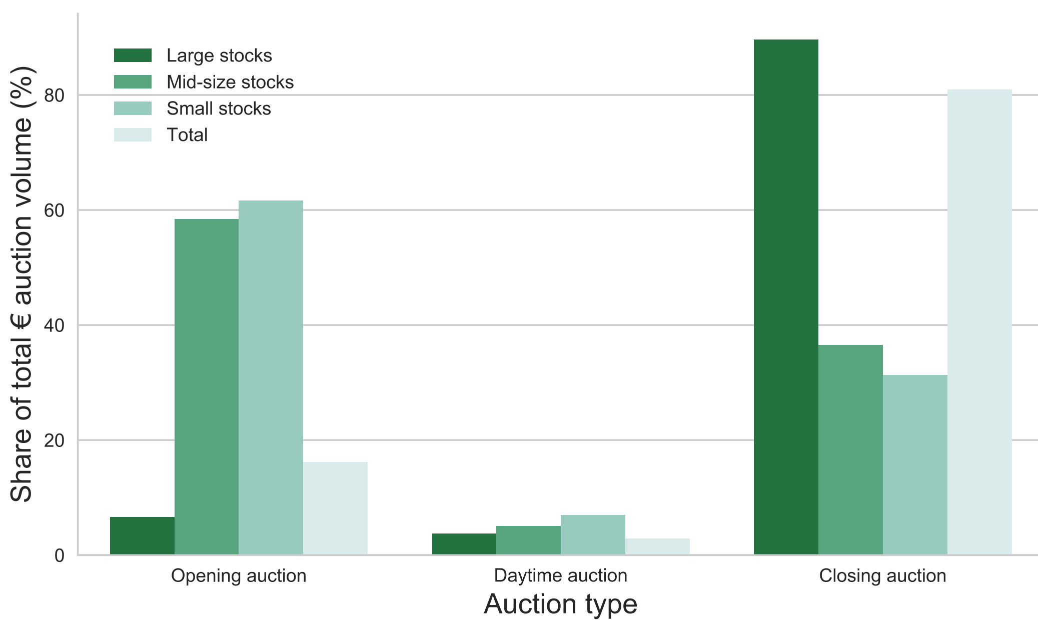

Figure 2: Split of auction trading volume on the Xetra. The figure demonstrates the breakdown of the auction volume. Small stocks are those whose free-float market capitalization on 31/01/2013 from *Thomson Reuters Datastream.* is at the lowest 33% of the sample. Large stocks are 33% with the highest free-float market capitalization.

3.3 Market liquidity and daytime auction volumes

Before going deeper into auctions, it is worth to understand which market factors influence the aggregate volume traded via the daytime auctions. How much does auction trading activity vary on a day-to-day basis? Are there any systematical regularities during the exact days of the week? What generates the movements in daytime auction volumes? Understanding the drivers of auction volumes is necessary from the perspectives of policy regulation, exchange organization, and market design.

Chordia, Roll, and Subrahmanyam 2002 study factors that influence the dynamics of the US market activity proxied, among others, by trading volume (in continuous trading sessions). They find that market index return, changes in the Federal Funds Rate, the difference between the yield on 10-year Treasury bonds and the Federal Funds rate, and the dummy corresponding to the two trading days before GDP announcements, as well as some days of the week are significant determinants of the stock traded volume. I take these measures as a set of candidates for explanatory factors of auction volume. In order to determine whether the same or different drivers move the volume dynamics of daytime auctions and continuous trading, I reproduce the time-series regression of two types. In the first set of regressions, a dependent variable of interest is the changes in daytime auctions, in the other setting – continuous trading volume.

There is a negative dependence of -0.36 in the first lag in a daily change of auction volumes; a corresponding value for the continuous volume is -0.30. I thus apply the Cochrane/Orcutt iterative correction procedure (first-order only) in the regression.[15] Explanatory variables have a moderate correlation, so a potential issue of multicollinearity is avoided. The following regression is estimated on a daily frequency:

$$\begin{aligned} \Delta vol_t = \alpha + \beta_1 \Delta MKT(+) + \beta_2 \Delta MKT(-) + \beta_3 \Delta short\_rate + \\ + \beta_4 \Delta term\_spread + \beta_5 GDP + \beta_{6-9} Wday + \epsilon_t, \end{aligned} \tag{1}$$

where Δvol_t is the daily changes in Euro volume during daytime auctions or during continuous trading, $\Delta MKT+$ ($\Delta MKT-$) is the daily HDAX[16] return if it is positive (negative) and zero otherwise, $\Delta Short_rate$ is the daily first difference in the Euribor, $\Delta Term\_spread$ is the daily change in the difference between the yield curve rates based on ten-year government bonds and the short rate, GDP equals 1 on the two trading days prior to the GDP announcement and 0 otherwise,[17] $Wday$ are dummies corresponding to the four days of week: Monday, Tuesday, Thursday or Friday.

Judging by the results of the estimation (Table 2), different factors influence auction trading volumes compared to those of continuous sessions. When the market index goes up, there is a significant decrease in daytime auction trading, while this relationship is reverse for the continuous trading period. This result supports the findings for the US continuous market,

[15]The results using a simple OLS regression is not qualitatively different from the one received by applying the Cochrane/Orcutt method.

[16]The HDAX is a German stock market index that contains all composites of the DAX, MDAX, and TecDAX.

[17]GDP is announced every month, announcement dates are retrieved from the *Eurostat* website.

where this relationship between volumes and the index is positive/negative when the index goes up/down. Combining these conclusions, traders seem to prefer auctions when the market is on the decline and continuous sessions – when the market rises.

Auction trading activity increases before the GDP announcements, while this effect does not occur for continuous trading volumes. This finding might indicate the differences in anticipation of to-be-announced GDP measure causing the disturbance of earlier uninformed trading. As an announcement day approaches, the number of informed traders might increase, and their competition could bring additional liquidity to the auctions (Admati and Pfleiderer 1988).

There is a strongly pronounced day-of-week effect for both trading periods. Auction trading volume remarkably increases on Fridays, although all Eurex settlement Fridays were removed.[18] This might indicate that investors use auctions more actively before a rather long time without trading (weekends). The dummies for Tuesday and Thursday are also positive and significant, while auction volume slows down on Mondays and Wednesdays. Conversely, continuous trading is lower on Friday and higher on Tuesdays and Thursdays.

Alternative regressions exclude day-of-week dummies and include two additional measures of market uncertainty: a European proxy for the VIX, VSTOXX and an interaction term of the falling market index returns when volatility is high (*MKT(-)*VSTOXX* in Table 2). By adding them, I aim to address the proposition that auctions are a fairer trading design for investors. In other words, if there is uncertainty on the market, more traders would opt for auctions, if they do not require immediacy. The results show that uncertainty measured by the interaction term increases trading for both auctions and continuous trading. Changes in $VSTOXX$ do not affect continuous trading but negatively impact auction volumes. So, they rise only when the market is much in stress and uncertainty, i.e., when returns drop *and* uncertainty increases.

Dependent variable:	ΔAuc_vol		$\Delta Cont\_vol$	
(1)	*(2)*	*(3)*	*(4)*	*(5)*
$\Delta MKT(+)$	-14.09* (-1.81)	-36.40*** (-2.85)	8.02*** (6.42)	7.44*** (4.61)
$\Delta MKT(-)$	7.46 (0.91)	-0.41 (-0.11)	-11.64*** (-9.49)	-9.97*** (-5.66)
$\Delta Short\_rate$	3.25 (0.80)	-3.37 (-0.67)	0.30 (0.47)	-0.13 (-0.19)
$\Delta Term\_spread$	0.21 (0.41)	-0.44 (-0.69)	-0.15** (1.97)	-0.21*** (-2.45)
GDP	0.24* (1.87)	0.21 (1.17)	-0.005 (-0.27)	-0.008 (-0.39)

[18] A joint test that coefficient on Friday is the same as on each of the other days of the week is rejected with a p-value less than 0.0001.

(1)	(2)	(3)	(4)	(5)
Monday	-1.07***		-0.05***	
	(-14.10)		(-4.99)	
Tuesday	0.36***		0.07***	
	(4.82)		(6.73)	
Thursday	0.37***		0.04***	
	(4.94)		(4.06)	
Friday	0.42***		-0.02**	
	(4.79)		(-2.25)	
$\Delta VSTOXX$		-7.64***		-0.37
		(-3.18)		(-1.55)
$MKT(-) * \Delta VSTOXX$		75.49*		12.25***
		(1.84)		(2.76)
Intercept	0.02	0.02	-0.04***	-0.04***
	(0.39)	(0.61)	(-5.44)	(-6.22)
Adjusted R^2	0.016	0.016	0.23	0.09

Table 2: Time-series regressions. This table demonstrates the result from time-series regressions on a daily frequency. The dependent variable is the daily logarithmic changes in Euro volumes of daytime auction (columns 2-3) or continuous trading (columns 4-5). $\Delta MKT+$ ($\Delta MKT-$) is the daily HDAX return if it is positive (negative) and zero otherwise, $\Delta short\_rate$ is the daily first difference in the Euribor, $\Delta term\_spread$ is the daily change in the difference between the yield curve rates based on ten-year government bonds and the short rate, GDP equals 1 on the two trading days prior to the GDP announcement and 0 otherwise. $Wday$ are dummies corresponding to the four days of week: Monday, Tuesday, Thursday or Friday. *t*-statistics are in the brackets under corresponding values. Cochrane/Orcutt iterative correction procedure (first-order lag) was applied.

4 The role of daytime auctions in return periodicity

This section demonstrates that daytime auctions, along with opening and closing intervals and *alone*, contribute to the seasonality of the cross-section of stock returns. I show that market factors such as volume, bid-ask spread, and volatility do not explain the revealed pattern. By analyzing different cross-sectional subsamples, I find that predictability is more pronounced for small, large, and for domestic stocks.

4.1 Aggregate evidence on return periodicity

To study intraday patterns of returns, I start with breaking down a trading day into smaller intervals. Existing studies (Heston et al. 2010, Bogousslavsky 2016) suggest taking half-hour intervals in order to limit the influence of microstructure effects but to still capture a rich set of dynamics. However, given that auction duration is only two minutes, taking half-hour intervals might be misleading. In particular, if the effect is short-lived, it might be underrated for the thirty-minute intervals. Thus, I decide upon a more frequent sampling frequency of fifteen minutes.[19] With regular trading hours between 9:00 and 17:30, I end up with 34 intervals per day. This excludes after-trading and overnight open-close price movements. I then compute logarithmic returns based on the first and the last trading prices available inside each interval.

I follow the methodology of Jegadeesh 1990 used in Heston et al. 2010 for analyzing cross-section of return periodicity. For each lag *k*, I run regression of stock returns at interval *t* on the returns lagged by *k* intervals:

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

where $r_{i,t}$ is return on stock *i* in the fifteen-minute interval *t*, based on trade prices. The slope coefficients $\gamma_{k,t}$ indicate the return responses at time *t* to their returns at time *t-k*. Using Fama-MacBeth 1973 methodology, return responses are defined as time-series averages of estimates $\gamma_{k,t}$.

Figure 3 demonstrates the average return responses across stocks at different lags up to one week (170 fifteen-minute lags) and the corresponding *t*-statistics. Consistent with the previous literature, the first several return responses are negative. Bid-ask bounce, time variation in the frequency of trades occurring at bid versus ask prices, or temporary liquidity imbalance can be the potential drivers of such a reversal (as in Keim 1989). Compared to evidence reported for the US market, the first order return response on the Xetra is more negative: -7% compared to -2% for the NYSE market.[20] This difference indicates that the German market takes a longer time for reversal, implying lower liquidity than in the US.

After the reversal period, return responses peak on exact multiples of one trading day, as well as corresponding *t*-statistics (the highest bars in Figure 3). The discovered return pattern provides a clear piece of evidence on return continuation at the daily frequency. This finding can also be interpreted as return momentum: if a stock has higher returns at a particular time today, it will also have high returns at the same time tomorrow. This pattern is long-lived – it lasts up to two weeks, after which the *t*-statistics become insignificant.

It is important to note that the estimates from cross-sectional regressions (2) are different from being simple autocorrelation of stock returns. In particular, the cross-sectional regressions remove an overall market effect, which lowers variance and focuses on returns *relative* to other stocks. The return responses $\gamma_{k,t}$ can thus be interpreted as *excess* returns. According to Lo and MacKinlay 1990, the average $\gamma_{k,t}$ coefficient in equation 2 reflects three components: (1) return autocorrelation, (2) return cross-autocorrelation, and (3) cross-sectional variation in average returns. The average cross-section regression coefficient $\gamma_{k,t}$ can be decomposed as follows. If

[19] The results stay the same upon using half-hour sampling frequency, please see *Robustness* section.
[20] A number for the US market is taken from Heston et al. 2010.

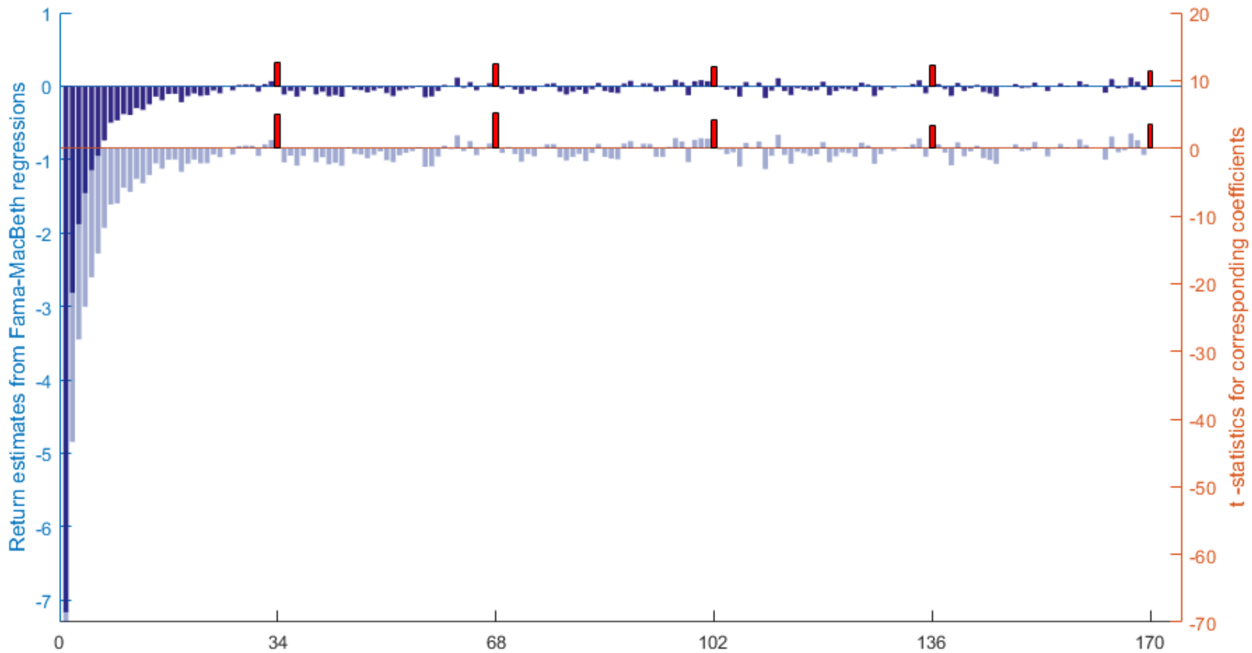

Figure 3: Time-series averages of return responses. The figure demonstrates results from (2): average return responses and corresponding *t*-statistics. A trading day is divided into 34 disjoint intervals, each containing fifteen minutes. For interval *t* and lag *k*, I run a simple univariate cross-sectional 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 return of stock *i* during interval *t* and $r_{i,t-k}$ is the return of stock *i* during interval *t-k*. The cross-sectional regressions are estimated for all combinations of interval *t* (49,130 intervals) and lag *t*, with values 1 through 170 (corresponding to the previous five days). The left *y*-axis shows the time-series averages $\gamma_{k,t}$ (in percents), the right *y*-axis corresponds to the respective Fama-MacBeth 1973 *t*-statistics. An upper *x*-axis corresponds to the left *y*-axis, a lower – to the right *y*-axis. Tick 34 relates to one trading day, tick 68 – to two trading days, etc. The analysis uses Xetra-listed stocks for a period of August 2010-May 2015.

$\bar{r}_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t}$, the estimate of slope is:

$$\hat{\gamma}_{k,t} = \frac{1}{\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-k} - \bar{r}_{t-k})^2} \underbrace{\sum_{i=1}^{N} r_{i,t} \frac{1}{N} (r_{i,t-k} - \bar{r}_{t-k})}_{\equiv \pi_t(l)}.$$

In this equation, $\pi_t(l)$ is related to a trading strategy of going long past winners and going short past losers, based on their return in period *t-k*. Defining the calendar function *c(t)*, which provides the calendar period for each date *t*, the expected return on the strategy in *c(t)* is:

$$\mathbb{E}[\pi_t(k)|c(t)] = \frac{1}{N}\sum_{i=1}^{N} Cov[r_{i,t}, r_{i,t-k}|c(t)] - Cov[\bar{r}_t, \bar{r}_{t-k}|c(t)] + \\ + \frac{1}{N}\sum_{i=1}^{N}(\mu_{i,c(t)} - \mu_{c(t)})(\mu_{i,c(t-k)} - \mu_{c(t-k)}), \tag{3}$$

where $\mu_{i,c(t)} \equiv \mathbb{E}[r_{i,t}|c(t)]$ and $\mu_{c(t)} \equiv \mathbb{E}[\bar{r}_t|c(t)]$. Consequently, the average coefficient $\gamma_{k,t}$ reflects three components: return autocorrelation, return cross-autocorrelation, and cross-sectional variation in average returns.

Robustness. Two tests help to check whether the results are (1) robust to a different intraday sampling frequency, (2) economically sizable.

First, I change a sampling frequency from fifteen-minute intervals to thirty/minute periods. The daily return periodicity holds, demonstrating higher average return responses than in the benchmark case of fifteen minutes (Figure A2 in the Appendix).

Second, the magnitude of the average return responses does not express much in terms of economic size. In order to measure the effect, I pursue a trading strategy that aims to exploit periodicity. In particular, I estimate the returns of an equally-weighted long-short portfolio constructed according to stocks' historical returns. Two different rebalancing frequencies are applied. In the first setting, one goes long those stocks whose return was among 10% highest *k* intervals ago and goes short the 10% worst-performing stocks *k* intervals ago. Figure A5 in the Appendix shows that return spread of such strategy peaks precisely at the multiples of a trading day earning 1.58 basis points on the first daily lag.[21] The profitability stays significant until the sixth day. Given that an investor needs to simply shift his trade instead of taking a one-day risk to earn equity premium, the effect in terms of the incremental Sharpe ratio might be even higher. Thus, when a stock goes up one day, buyers earn a return premium by buying the stock prior to the same time interval on coming days. This means that the trading strategy that ranks stocks according to their returns during the historical lags of multiples of seventeen earns the highest returns among other *k* intervals.

An alternative strategy is to sort stocks according to their historical returns *during* several past intervals, i.e., during the previous day. Table A5 in the Appendix reports the return spreads of both strategies for lags up to a week. The strategy marked "daily" is based on the stock performance a day ago, while a "nondaily" strategy uses average performance of stocks during the previous day. An average return spread of the daily strategy is positive and significant, unlike the nondaily strategy that loses.

[21] The value does not account for trading costs.

4.2 Daytime auctions and return periodicity

The reported daily seasonality does not indicate which intraday clock intervals drive the revealed periodicity pattern. I thus re-estimate (2) for each fifteen-minute interval separately, using a lag of one day: returns are regressed on the returns at the same interval exactly one day ago, two days ago, etc. (k=34, 68, and so forth). Average *daily* return responses up to the tenth trading day are reported in Table 3. Return periodicity is the most pronounced at market close (column 17:15), market open (column 9:00), and after a daytime auction (columns 13:03 and 13:17).[22] Comparing the intervals between 13:03–13:17 (after-auction interval for most of large stocks) and 13:17–13:30 (after-auction interval for most of the small, less liquid stocks), the latter demonstrates a three times higher economic magnitude (0.88 basis points compared to 2.78 basis points). In particular, the estimate of after-auction interval for smaller stocks is comparable with that of the market close and open.

I further use daily lags for measuring a trading strategy based on precisely past-*day* lags. Stocks are sorted based on their historical return at each fifteen-minute interval on the previous days, with a rebalancing frequency from one up to five days. For example, I buy those stocks today at 12:00 that performed best yesterday at the same time and short the worst-performing ones. I decrease a rebalancing frequency up to five days: I trade the portfolio based on stock returns at the same time five days ago. For an aggregate picture, I average the returns for a period of five days. Results are displayed in Figure 4 and show that the largest weekly average return spread of 7.53 basis points happens at the market open, with the highest value corresponding to the first-day lag (12 basis points). The second-largest interval is the last trading interval before the market close, earning 2.89 basis points on average during a week. The interval corresponding to the post-auction brings a positive return of 1.89 basis points.[23]

The returns from the momentum strategy support evidence on the role of the return continuation for three intraday intervals. The dynamics of stock returns on the Xetra is W-shaped (Figure 4). This finding contributes to the existing literature on intraday return pattern that mostly concentrates on the markets with two, opening and closing, auctions. In particular, Wood, McInish and Ord 1985, McInish and Wood 1990, and Lockwood and Linn 1990 find a U-shaped pattern of intraday returns and trading volumes on the New York and Toronto stock exchanges. For later periods, however, intraday volume profiles have become more back-loaded, resembling more a J-shaped pattern (Kissel 2014). My results innovatively show that the market with a daytime auction has an additional spike that arises right after the daytime auctions.

[22] The time of daytime auctions is different depending on the stock. Most stocks in the large size portfolio start auction trading at 13:00, while small-size stocks – at 13:17. The analysis takes care for this different timing.

[23] This value does not account for trading costs.

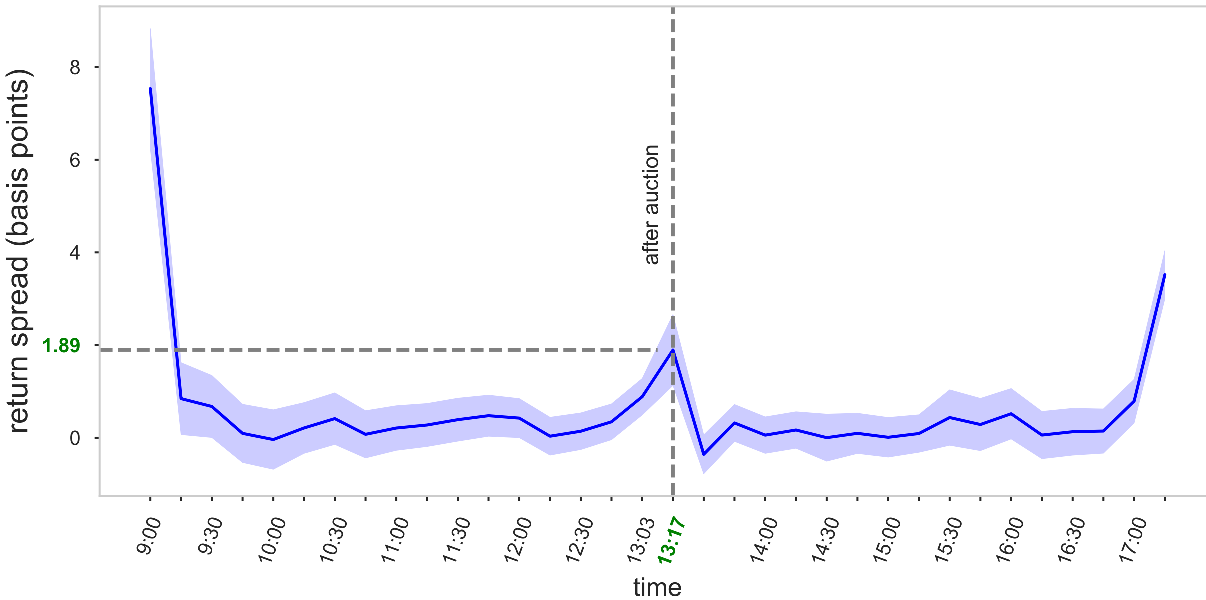

Figure 4: Average return spread of the daily momentum strategy. This figure shows the average return spread of the daily momentum strategy for each fifteen-minute interval during a day. The stocks are sorted based on their historical returns at the same interval one, two, three, four, and five days ago. The strategy goes long 10% top-performing stocks and goes short 10% least-performing stocks, with a rebalancing frequency depending on the chosen lag. Values on the y-axis are the weekly average returns of the long-short portfolio, in basis points. The strategy is applied for the whole sample period and does not account for trading costs. The shaded area shows 5% confidence level, based on weekly deviations in the strategy spread. The analysis uses Xetra-listed stocks for a period of August 2010-May 2015.

Robustness. If after-auction periods add substantially to the return periodicity, this periodicity would also be generated by daytime auctions *alone*, e.g., excluding market opening and closing intervals. I thus re-estimate (2) with 32 fifteen-minute intervals left in a trading day, after eliminating opening and closing intervals. Results support a benchmark case: the coefficients of return responses still peak on a daily frequency, as well as their corresponding t-statistics (Table A2 in the Appendix). It means that midday auctions *alone* contribute to the intraday predictability of stock returns.

Motivated by the literature that finds a day-of-week effect for the US market (e.g., Cross 1973, Jaffe and Westerfield 1985)[24], I analyze whether the periodicity is driven by individual day of the week. I run daily momentum strategies for each day of the week separately. On Mondays, the return spread at the open is the highest among other days of the week. Unlike, there is no weekday effect after the daytime auctions (Figure A7 in Appendix).

[24]There is also literature on a special role of Januaries (a ”January effect”). However, the length of my sample is only five years, which is not enough to properly check whether this effect is present.

4.3 Return periodicity and market factors

To understand the origin of return periodicity further, I analyze whether there is an identical pattern in trading volumes. As shown in Section 2, institutional volumes can naturally influence stock prices and generate patterns in returns. As the volume is known to be a persistent process, it makes sense to use changes in volumes in estimating (2). Figure A6 in the Appendix displays a volume pattern that largely resembles the pattern seen for stock returns, with a stronger magnitude of time-series averaged coefficients. Similar to return periodicity, volume responses decay with longer lags. However, the pattern remains positive and statistically significant up to three months, thus being more persistent than price changes. This finding signals that investor flows can generate the shown periodicity.

To analyze whether other market factors can help to explain the pattern, I apply multivariate regressions of returns on volume, volatility, and liquidity proxied as the bid-ask spread. As my dataset does not contain bid and ask prices, I estimate the bid-ask spread using the methodology of Corwin and Schultz 2012. If these market-wide factors explain the return periodicity, the inclusion of these factors in (2) will decrease the magnitude of return responses $\gamma_{k,t}$. The resulting regression is:

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

where vector $V_{i,t-k}$ includes three variables: percentage changes in volume (measured as the total number of shares traded during the interval k lags ago), in volatility (measured as the absolute value of returns), and in liquidity (measured as the Corwin and Schultz 2012 measure).

Adding these variables does not decrease the magnitude of return response estimates on the daily multiples. They all, including those related to the multiples of one-day lags, become bigger (Table A2 in the Appendix). Moreover, none of these market variables is significant, except for past returns. The results also hold for the subsample of liquid stocks, defined as stocks whose high price equal low price on more than 120 days during the sample period.

Finally, I run (4), but instead of taking all market factors as explanatory variables, each of them is separately included in a univariate setting:

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + \beta_{k,t} v_{i,t-k} + e_{i,t}, \tag{5}$$

where $v_{i,t-k}$ includes percentage changes in *one* of the variables (volume, volatility, or bid-ask spread). Including the variables separately cannot as well explain the pattern: none of the coefficients are significant on the daily multiples (Table A3 in the Appendix). The largest R^2 of 3.8% belongs to the estimation of returns on their lagged returns and the bid-ask spread.

Thus far, the results reveal a predictable pattern in the cross-section of stock returns on a daily basis. Daytime auctions play a significant role in creating these dynamics. The trading volume demonstrates similar patterns to returns, but cannot, together with market factors, explain the daily return responses. After identifying timing drivers of periodicity, I analyze whether the pattern is more pronounced for a specific group of stocks. The next section focuses on this.

	9:00	9:15	9:30	9:45	10:00	10:15	10:30	10:45	11:00	11:15	11:30	11:45	12:00	12:15	12:30	12:45	13:03
day 1	**3.11**	0.27	0.18	-0.21	-0.07	-0.13	0.01	-0.04	0.33	0.05	0.03	0.09	0.28	0.13	0.31	0.63	**0.88**
day 2	**1.66**	0.96	0.30	0.27	0.04	0.08	-0.46	**0.70**	-0.08	0.38	0.15	-0.06	**0.47**	0.12	-0.17	0.25	**0.65**
day 3	**1.72**	**0.56**	0.12	-0.46	-0.06	0.64	0.38	0.12	0.11	0.16	-0.13	-0.12	0.18	-0.26	-0.39	0.20	**0.91**
day 4	**1.10**	0.56	-0.26	0.33	0.00	-0.12	1.98	0.24	-0.33	0.10	**0.49**	0.22	0.34	-0.25	0.22	0.13	**0.30**
day 5	**1.44**	1.05	0.39	0.10	0.53	0.41	-0.06	0.13	-0.11	-0.41	0.30	0.11	-0.14	-0.14	0.12	-0.21	0.29
day 6	**1.41**	0.39	**0.63**	0.21	0.11	0.24	-0.40	0.26	0.40	-0.31	0.54	0.12	-0.31	-0.02	-0.21	0.09	**0.49**
day 7	**1.93**	0.31	0.42	0.38	0.28	0.05	-0.12	0.26	0.07	0.04	0.05	-0.12	0.16	0.27	0.19	-0.01	**0.21**
day 8	**0.95**	0.02	0.14	0.22	0.09	0.14	0.33	0.05	-0.16	-0.24	-0.07	0.01	-0.18	0.21	0.09	-0.21	0.04
day 9	0.83	0.13	0.07	0.41	-0.11	-0.26	-0.12	0.28	-0.29	-0.25	-0.02	-0.23	0.19	-0.49	0.36	0.42	**0.59**
day 10	1.44	**0.51**	0.05	0.43	-0.01	-0.45	0.17	0.10	0.02	-0.14	0.17	-0.26	-0.20	0.11	-0.01	-0.36	0.25

...	13:17	13:30	13:45	14:00	14:15	14:30	14:45	15:00	15:15	15:30	15:45	16:00	16:15	16:30	16:45	17:00	17:15
day 1	**2.78**	**-1.05**	0.18	-0.30	0.96	-0.20	0.26	-0.42	0.24	0.23	-0.22	0.05	-0.03	0.21	-0.06	0.47	**2.64**
day 2	**1.93**	**-0.89**	0.20	0.73	0.22	0.47	0.24	0.20	0.01	0.56	-0.07	0.09	0.11	0.52	-0.06	0.26	**2.01**
day 3	**0.93**	0.39	-0.14	-0.38	-0.08	-0.26	0.24	0.19	-0.12	**0.75**	0.05	0.06	**0.62**	0.17	0.26	0.14	**1.32**
day 4	**1.08**	0.28	0.31	0.18	-0.06	0.11	-0.17	-0.10	0.17	**0.84**	-0.32	-0.33	-0.24	0.12	-0.52	0.39	**1.49**
day 5	**0.72**	-0.04	0.01	-0.49	0.15	-0.44	**0.51**	-0.05	0.01	0.64	-0.41	0.11	-0.12	0.42	0.39	0.21	**1.56**
day 6	**0.66**	0.15	0.08	0.35	0.21	**0.59**	0.03	0.28	-0.09	0.47	-0.24	-0.28	0.01	**-0.67**	0.15	0.02	**1.33**
day 7	**0.67**	-0.23	-0.07	-0.01	0.19	-0.44	-0.38	0.24	-0.17	0.05	-0.07	-0.18	-0.36	0.14	0.35	0.15	**1.01**
day 8	**0.76**	**-0.56**	-0.16	0.07	-0.08	0.26	-0.20	0.11	-0.13	0.54	0.14	0.01	-0.09	0.64	0.30	0.33	**0.72**
day 9	**0.46**	0.33	0.29	0.01	-0.24	-0.11	-0.55	-0.19	-0.06	0.07	**0.51**	-0.02	0.30	0.04	-0.30	0.19	0.65
day 10	**0.67**	0.01	0.04	-0.21	-0.10	-0.02	0.04	-0.21	0.42	**0.75**	-0.03	0.11	-0.15	0.24	0.34	-0.13	**0.96**

Table 3: Average return responses for each intraday interval. I regress a cross-section of stock returns at time t on their daily lagged returns at time t-k, where k = 34, 68, etc. I then average the resulting coefficients for each lag k. The table shows time-series averages of return responses coefficients $\gamma_{k,t}$ for the sample of 875 stocks for the period August 2010 – May 2015. Each interval indicates a starting time for the upcoming fifteen-minute interval (e.g., 9:00 implies an interval between 9:00-9:15). Coefficient estimates are scaled so that values are reported as percentages. Values in bold are statistically significant at the 5% level.

4.4 Cross-sectional drivers of return periodicity

As the sample size of 875 stocks allows me to break stocks into different portfolios, I study whether the predictability is more pronounced for some stocks than for the others.

Keeping the most straightforward sample split based on firm size and country, I divide my universe into three respective portfolios. First, the sample is split into three parts according to the stock size, proxied by stock's free-float market capitalization. The portfolio of large firms contains the top 33% stocks sorted by market capitalization in each quarter. Similarly, I define middle- and small-cap stock portfolios. Re-estimating the average return responses in (2) for three size portfolios reveals that the return periodicity is stronger for the smallest stocks – these portfolios have the highest average return responses of 0.37% on a daily periodicity and are the most persistent up to the lag of five days in terms of significance (Table A4 in Appendix). This might indicate a regularly high concentration of trading volumes in small stocks.

Also, the pattern is distinct for a portfolio of large stocks, with a comparable magnitude of coefficients. The timed rebalancing of institutional trades st the market close might potentially create seasonality for these stocks. The periodicity does not hold for middle stocks: daily return responses are the lowest and significance is lost already on the first daily lags.

Second, I repeat a similar split for domestic versus foreign stocks. Intraday return seasonality is mostly present for domestic stocks (Table A5 in Appendix). The return responses are close to that of small stocks (0.33%) and stay significant up to a trading week.

This section provided evidence on intraday return predictability in cross-section of Xetra stock returns at a daily frequency. Daytime auctions substantially contribute to this pattern: (1) they alone generate such a periodicity, (2) the magnitude of average return responses drops by 18% if after-auction intervals are removed. The pattern is mostly driven by small, large, and domestic stocks. Volume, volatility, and the estimated bid-ask spread cannot explain the revealed return dynamics. As volume demonstrates similar return periodicity, investor flows and timed trades are the primary candidates causing it.

5 Understanding periodicity after daytime auctions

5.1 Models of slow-moving capital

As shown in Section 4, intraday periodicity of a cross-section of stock returns is also reflected in the dynamics of volumes (Figure A6 in Appendix). Thus, the models that build on investor flows in relation to return dynamics are the natural candidates for the interpretation of the revealed return periodicity. In this section, I analyze several theoretical models that link trading flows and stock return periodicity. The model of infrequent rebalancing illustrates the mechanism of how clustering of trading flows generate return periodicity. Bringing the model to the data, I show that it works decently for a part of the sample (small stocks), suggesting evidence on rebalancing for after-auction periods.

A voluminous literature centers on the models of non-synchronous trading coming from inattentive investors. Limited market participation of some investors is critical to these models. The idea of this research area is opposite to neoclassical models of dynamic asset pricing with the fundamental assumption that investors monitor the market regularly and adjust their trading decisions at each point in time. According to Duffie 2010, in reality, most investors do not focus on trading plenty of time and *infrequently* come to the market to adjust their portfolios. He shows that, at each point in time, asset prices mostly reflect the marginal trade-offs of a rather small investor group. His model shows that only when these traders return to the market, the price movement is reversed.

This literature is further expanded by the model of Hendershott et al. 2018. The authors build on the above-mentioned model and suggest the mechanism of how the limited market participation generates price deviations from the semi-strong market efficiency. This model has three types of agents: market makers, attentive investors, and multiple groups of inattentive investors who arrive at the market stochastically. A gap process, which is the difference between the target and actual portfolios of inattentive investors, generates the dynamics in the model. The authors use impulse response functions to measure the deviation between the prices present on the market and efficient prices. Calibrating the model using several data sets for the NYSE stocks, the authors show that return autocorrelations are significantly negative during the first twenty days, which indicates that at least a part of the original pricing error is still persistent. Fitting the GMM estimation to the data and testing for various inattention frequency, it is shown that the persistence of a pricing error reaches twenty days, being mostly dominated by monthly inattentive investors. The model has several important advantages, such as being invariant to the sampling frequency and having analytic estimations for any state-space dimensionality. However, although the model provides both evidence and mechanism on how returns are ”polluted” by pricing errors, there is no direct link between investor inattention and cross-sectional stock return seasonality.

Return periodicity may also be created by liquidity traders who enter the market at specific points of time and thus generates seasonality. For example, institutional investors can trade exceptionally at the market open or the market close and thus create seasonality in mean liquidity trading. This would create periodic cross-sectional fluctuations in asset returns. Bogousslavsky 2016 simulates the economy with persistent liquidity shocks and two types of assets. For the first group of assets, the mean supply of traders is constant, while for the second group, there is one period with a different mean supply of liquidity traders. The results of simulations show that such periodicity in mean supply truly generates periodicity in average return responses, like from (2). The reason is that the price of risk in such a setting is not the same across time. However, in simulation results, the average return responses (bars corresponding to the daily multiples in Figure 3) do not decay with time.

5.2 A model of infrequent rebalancing

A dynamic model of infrequent rebalancing is another candidate to explain why cross-sectional variation in returns is more substantial in some periods than in others. The model is built on investor flows that generate the asset return periodicity. Building on the model of Duffie

2010, Bogousslavsky 2016 theoretically shows that cross-sectional variation in average returns increases in periods when more traders rebalance. According to the model, infrequent rebalancing has a large impact on return and volume periodicity patterns at different frequencies.

The model assumes two types of investors: frequent and infrequent. Frequent traders are always on the market. The second group of agents, infrequent traders, trade to maximize the value of their terminal wealth and then they leave the market for some time. According to the model, infrequent rebalancing is analogous to serially correlated liquidity shocks. For example, a large negative liquidity shock happens at t: stock price drops. The agents, who are present on the market at the moment, absorb this shock. They do so by buying more assets than suggested otherwise by a steady-state level. Later, at time $t+k+1$, these infrequent traders arrive at the market in order to rebalance their holdings again. Since liquidity trading is transient, these infrequent traders now hold an abnormal position in the asset relative to the current asset supply and therefore liquidate part of their excess holdings. The resulting order flow is thus another liquidity shock per se. This process increases the return covariance between the two periods because a liquidity shock today transmits to the future when agents rebalance their holdings again. Consequently, although such systematic trading is entirely expected, it causes predictable return patterns.

As shown in Section 4, average $\gamma_{k,t}$ in (2) reflects three components: return autocorrelation, return cross-autocorrelation, and cross-sectional variation in average returns (Lo and MacKinlay 1990). The model of infrequent rebalancing relies only on the autocorrelation component of this decomposition, so the estimates from (2) are almost identical to autocorrelations in the model. The model suggests that infrequent rebalancing creates periodicity in the factor risk premium, rather than creates an additional risk factor.

Calibration of the model shows that infrequent trading switches the sign of return autocorrelations precisely around the rebalancing horizon, making it positive. As infrequent traders trade in the same direction as the liquidity shock that they absorbed during their previous rebalancing interval, this effect does not depend on the persistence of liquidity trading on the market. According to the model, without infrequent rebalancing, all return autocorrelations have the same sign and decay exponentially. The evidence demonstrated in Figure 3 is supported by the model, assuming that a rebalancing horizon is one day.

In order to bring the model to the market with three intraday auctions, I first define four features that (1) according to the model, should be present on the market at the intervals of rebalancing, (2) can be empirically tested using my dataset.

The model states that when a large proportion of trading by investors with heterogeneous rebalancing occurs, the market can be characterized by several features.

- When traders hit by endowment shocks rebalance their portfolios, the price impact of these transitory shocks is high;
- Traders who are always present on the market (frequent traders in the model) require a larger return to hold an asset when they expect liquidity to decline in the next period. As a result, market makers require a high return for trading the assets during the rebalancing

interval;

- Trading volume is high when more traders rebalance;
- Volatility is particularly high.

Next, I bring the model to the data and show that the model can explain the return dynamics after daytime auctions, especially for small stocks.

5.3 Bringing the model of infrequent rebalancing to the data

5.3.1 Empirical proxies

The goal of this section is to define whether the model characteristics emerge around daytime auction on the Xetra. Empirical estimation of the model features is the first step.

Price impact. A standard high-frequency proxy of price impact used in the literature is the measure suggested by Hasbrouk 2009. He defines it as a slope coefficient from regressing five-minute stock return on the signed square-root of trading volume. Due to the limitations of my dataset (direction of trade is not available), the estimation of this measure is not possible. I use an alternative benchmark, the Amihud (Amihud 2002) illiquidity measure (hereafter *Amihud*). It captures a price response associated with the given trading volume. There are two reasons why I consider this measure to be a relevant proxy for price impact. First, following the definition of price impact used in the model of infrequent rebalancing, there is a one–to–one relationship between the Amihud measure and the price impact defined in the model, after controlling for the price level.[25] Second, existing research provides evidence on the ability of the Amihud measure to capture price impact. In particular, Lou and Shu 2014 show that the Amihud measure highly correlates with five-minute price impact, with a correlation coefficient of 0.803. Some previous studies (Hasbrouk 2009, Goyenko, Holden, and Trzinka 2009) also document that the Amihud measure does well capturing the price impact. This measure is thus used as a proxy for the price impact.

I calculate the Amihud measure for each fifteen-minute interval per stock:

$$A_{i,t} = \sum_{j=1}^{t} \frac{|r_{i,j}|}{dvol_{i,j}}, \tag{6}$$

where $|r_{i,j}|$ is the absolute value of one-minute returns inside the corresponding fifteen-minute interval for stock i, $dvol_{i,j}$ is Euro trading volume for a corresponding stock. The thinner the market is, the stronger the trading volume changes prices available on the market. After estimating the price impact for each stock, it is aggregated across the market as the value-weighted average of all stocks with the available measure.

[25]Please refer to the Appendix A.2 for the derivation of this proposition.

Returns. The average realized returns during each interval are calculated as follows. As return volatility is not constant during a day, it is critical to control for heteroskedasticity by dividing the returns of each interval to the corresponding standard deviation of the same interval. By doing so, I compute average *excess* returns on top of the standard deviation, which does not change the coefficients themselves, but instead adjusts standard errors. Following Smirlock and Starks 1986, μ_k is estimated via the following regressions:

$$\frac{r_t}{\hat{\sigma}_t} = \sum_{k=1}^{K} \frac{1_{t,k}}{\hat{\sigma}_k} \mu_k + \epsilon_t, \tag{7}$$

where $\hat{\sigma}_k$ denotes the standard deviation of returns in period *k*, $1_{t,k}$ equals one if interval *t* belongs to period *k* and zero otherwise, $\hat{\sigma}_t = \sum_{k=1}^{K} 1_{t,k}\hat{\sigma}_k$. Estimating (7) is identical to computing average returns in excess of return volatility separately for each interval.

Volatility. Volatility is measured as the standard deviation of one-minute returns during each 15-minute interval.

Volumes. The average volume for each fifteen-minute interval is estimated by applying the same regression as (7) for volume changes.

As the model of infrequent rebalancing belongs to the theoretical research, it does not state any numerical criteria for how high should be the parameters. I define each estimate of the model features as high when the value is (1) among top 10% compared to all other intraday intervals, (2) statistically significant, and (3) its mean is statistically different from the mean at the market open and close intervals. Given 34 intervals in a day, a corresponding value should be among three highest values to satisfy the criteria (1).[26]

5.3.2 Model fit for size portfolios

The periodicity pattern is more pronounced for small, large, and domestic stocks (shown in Section 4). I thus estimate the features of the model of infrequent rebalancing for three size portfolios: small, middle, and large.[27] Table 4 clearly shows that most estimates peak at the market open for all portfolios. At this time, the market might react to overnight news, because the US market opens when the Xetra is closed.

All features of the model, except for return volatility, hold for the portfolio of small stocks. Price impact and average return peak right after daytime auctions (13:17–13:30). The tests for differences in means between post-auction and closing/opening intervals for both measures reject the null hypothesis of equal means at 1% level. The volume of the portfolio of small stocks is the highest after the daytime auctions. The volatility of returns is the same as at the open, around the US market open, and around the close.

[26] If the highest value includes the market open and another value is the fourth-largest, I still consider it as ”high”.

[27] Each group contains 33% of the total sample and is formed based on the quarterly free-float market capitalization (retrieved from *Thomson Reuters Datastream*).

Portfolio of large stocks does not show a full fit for the model like small stocks, supporting only some model features. For large stocks, after-auction price impact is almost as high as at the market open and as at 16:45-17:00. Average return peaks at the highest level after daytime auctions. Return volatility and average volumes are high at both after the daytime auction and at the market close. There is no particular pattern for middle-size stocks. According to these results, the model better fits for the portfolio of small stocks, providing the mixed evidence for the large stocks.

5.3.3 A role of trading fragmentation

The existing research provides a significant number of studies that analyze the asset price dynamics when a stock is traded across multiple markets. In these studies, the role of the home market or the market on which stocks are traded most is found to play a leading role in price formation (Froot and Dabora 1999, Pascual et al. 2006, Frijns et al. 2010 and others). Regarding the German market, Clapham and Zimmermann 2015 discover a leading price formation role of Xetra during the daytime auction for the DAX stocks. They show that the trading on the largest multilateral trading facility Chi–X Europe evaporates at the time when Xetra switches to the daytime auction. As soon as the auction prices are defined, the Chi–X market accepts the prices from the Xetra.

Combining these research conclusions with evidence on stronger return periodicity pattern reported for domestic stocks, I further divide the size portfolios in smaller portfolios based on stocks' trade fragmentation. In particular, evidence on rebalancing should be stronger for the stocks with a higher trading share on Xetra. I define such stocks as low-fragmented stocks and create a proxy of stocks' fragmentation – market share, on a stock level. This is the proportion of the daily trading volume of each stock on the Xetra relative to the stocks' total trading value, including all foreign markets:

$$MS_{i,t} = \frac{TrVol_{Xetra\ i,t}}{TrVol_{total\ i,t}}, \tag{8}$$

where $TrVol_{Xetra\ i,t}$ is a Euro trading volume on the Xetra of stock *i* on day *t*. $TrVol_{total\ i,t}$ is a Euro trading volume of stock *i* on day *t* on all markets. The trading volumes on other markets are retrieved from *Bloomberg*.[28]

The average MS for a portfolio of large stocks with the biggest market share is 52.4%, with the medium market share – 22.5%, with small market share –7.17%. Correspondingly, for the small stocks the average MS values are 61.08% – 33.6% – 7.20% respectively. Small stocks have higher average market share because the sample also contains foreign stocks that are cross-listed in Germany: most of them are large companies based on their free-float market capitalization.

For each of the resulting six portfolios, I re-estimate four indicators of the model of infrequent rebalancing: realized returns, volatility, volume, and price impact.

[28] For each stock, I retrieve the trading value from all existing markets on each day, adjusting currency to Euro.

The results for small low-fragmented stocks are tabulated in Figure 5. This portfolio supports the rebalancing argument from the model of infrequent rebalancing. In particular, the returns and volume are the highest right after daytime auctions compared to all other fifteen-minute intervals. Similarly, price impact and volatility also satisfy the criteria of being high according to the model. Moreover, this result is driven by the domestic stocks.[29]

According to the results, the rebalancing of small domestic stocks occur after the daytime auctions. This conclusion is in line with the purpose of daytime auctions – they provide a fixing price for relatively small and less liquid stocks. Unlike the evidence on the return spike at the market close reported for the US market (Bogousslavsky 2017), small stocks on Xetra have low returns before the market close and negative returns at the market close (both adjusted for the standard deviation). Combining the findings, small stocks are mostly rebalanced after the daytime stock auctions on the market with auctions, and at the market close – if the market does not have intraday auctions.

Switching from the low–fragmented stocks to the stocks with a higher trading share *outside* the Xetra weakens the evidence on after–auction rebalancing. In particular, return volatility is not high and not statistically significant anymore; the volume is low, although after–auction realized returns are still the highest (Table 5).

Degree of fragmentation	Returns	Price impact	Volume	Volatility
low	✔	✖	✔	✔
mid	✖	✔	✖	✖
high	✖	✖	✖	✖

Table 6: Features of the model of infrequent rebalancing for large stocks This table demonstrates whether the estimated indicators for three different portfolios of large stocks are in line with the model of infrequent rebalancing for after-daytime-auction period. The first line shows returns, volatility, price impact, and average volume respectively for large stocks with the highest share of trading value happening on the Xetra. Orange tick for volume means that its value is high but insignificant. The line in the middle related to the model indicators for a portfolio of large, but with a lower trading share on the Xetra, higher trading on other markets(s). Similarly, the lower line shows measures for large stocks with the highest trading activity outside the Xetra market. Green ticks mean that the corresponding after-auction estimates (1) are significant at the confidence interval at least 10%, (2) are among the 10% highest intervals during a day, and (3) have the mean that is statistically different from the value that corresponds to the market close interval. The red cross means that at least one of these criteria is not satisfied for a corresponding portfolio.

[29] 80% stocks in this portfolio are domestic German stocks. If I exclude foreign stocks the results stay robust.

	9:00	9:15	9:30	...	12:30	12:45	13:03	13:17	13:30	13:45	...	15:00	15:15	...	16:45	17:00	17:15
Panel A. Price impact																	
small	0.018	0.01	0.02		0.009	0.009	0.07	0.02	0.009	0.01		0.01	0.01		0.02	0.008	0.01
	(23.4)	(5.2)	(6.0)		(5.6)	(5.4)	(5.5)	(9.1)	(6.0)	(5.7)		(5.9)	(5.4)		(5.9)	(6.7)	(6.4)
middle	0.33	0.30	0.28		0.22	0.23	0.21	0.24	0.22	0.21		0.22	0.24		0.19	0.21	0.24
	(8.2)	(10.0)	(9.6)		(9.5)	(9.4)	(9.0)	(9.6)	(9.5)	(8.9)		(8.9)	(8.5)		(10.6)	(10.8)	(11.3)
large	0.13	0.11	0.11		0.09	0.08	0.09	0.07	0.09	0.08		0.08	0.07		0.09	0.08	0.06
	(7.2)	(8.5)	(8.5)		(8.0)	(8.1)	(7.5)	(8.1)	(7.6)	(7.5)		(8.2)	(8.1)		(7.8)	(8.3)	(8.4)
Panel B. Average return																	
small	3.74	-1.55	0.47		-0.04	-0.29	-0.02	0.28	-0.10	-0.02		0.01	0.22		0.001	-0.003	-0.07
	(31.5)	(-20.1)	(16.6)		(-0.6)	(-2.1)	(-0.2)	(2.1)	(-3.0)	(-0.6)		(0.4)	(8.4)		(1.1)	(-0.05)	(-12.3)
middle	2.53	-1.69	1.71		0.01	-0.30	1.15	0.74	0.38	-1.93		-1.80	-0.34		0.82	1.59	-0.49
	(3.9)	(-4.9)	(5.4)		(0.07)	(-1.7)	(6.2)	(5.3)	(2.1)	(-18.4)		(7.1)	(5.3)		(2.1)	(4.1)	(-1.0)
large	0.33	0.00	0.12		0.11	0.25	0.71	0.05	-0.16	-0.01		-0.21	0.20		0.19	0.53	0.44
	(2.4)	(0.2)	(0.6)		(1.0)	(2.7)	(5.7)	(0.5)	(-0.7)	(-0.5)		(-0.7)	(0.9)		(1.4)	(2.3)	(1.6)
Panel C. Average volume																	
small	-4.81	0.21	-0.44		0.24	0.16	0.25	1.59	-1.03	-3.03		-0.46	-2.01		-0.08	-1.36	-0.55
	(-0.34)	(2.15)	(-1.0)		(0.07)	(0.8)	(1.6)	(1.96)	(-1.8)	(-0.9)		(-2.2)	(0.9)		(0.92)	(-1.8)	(-1.9)
middle	11.4	5.11	4.73		3.45	5.77	4.78	3.96	4.78	4.45		7.31	6.24		8.76	9.72	8.38
	(39.0)	(26.0)	(27.4)		(6.5)	(7.0)	(7.4)	(6.7)	(6.8)	(6.7)		(6.3)	(33.1)		(27.3)	(28.1)	(23.3)
large	-0.56	-0.00	0.12		0.04	0.09	0.08	-0.09	0.09	-0.04		0.05	0.03		0.24	0.05	0.42
	(-4.76)	(-1.03)	(1.72)		(0.47)	(1.23)	(1.33)	(-0.96)	(1.08)	(-0.14)		(0.81)	(0.36)		(2.43)	(0.46)	(4.13)
Panel D. Volatility of returns																	
small	0.11	0.02	0.009		0.005	0.005	0.001	0.003	0.002	0.001		0.001	-0.002		0.008	0.04	0.01
	(4.4)	(3.4)	(2.3)		(1.6)	(1.4)	(2.3)	(3.7)	(1.8)	(2.7)		(2.4)	(2.9)		(1.9)	(1.6)	(3.2)
middle	0.39	-0.01	-0.03		0.04	0.03	0.04	0.02	0.008	-0.01		0.06	0.02		-0.01	0.07	0.05
	(6.7)	(-0.2)	(-0.8)		(1.5)	(1.4)	(7.4)	(6.7)	(6.8)	(6.7)		(1.9)	(0.99)		(-0.5)	(2.7)	(2.2)
large	0.05	0.05	0.04		0.04	0.04	0.05	0.003	0.004	0.04		0.03	0.04		0.03	0.04	0.05
	(8.6)	(4.5)	(4.3)		(5.4)	(5.5)	(5.2)	(4.0)	(4.7)	(5.0)		(4.9)	(4.3)		(5.0)	(5.4)	(7.1)

Table 4: Intraday market features for stocks of different size. Stocks are allocated into three size portfolios: small, middle, and large portfolios, based on the 20th and 50th percentiles of Xetra free-flow market capitalization as of 31/01/2013 according to *Thomson Reuters Datastream*. Price impact is measured by the *Amihud* measure and is scaled by 10^6 for representative purposes, returns are in percents, volatility is scaled by 10^3. Each interval indicates a starting time for the fifteen-minute interval (e.g., 9:00 implies an interval between 9:00-9:15). Values marked green correspond to the after-daytime-auction period. The sample is composed of Xetra common stocks from August 2010 to May 2015. Standard t-statistics are shown in parentheses.

Degree of fragmentation	Returns	Price impact	Volume	Volatility
Low	✔	✔	✔	✔
Middle	✔	✔	✖	✖
High	✖	✖	✖	✖

Table 5: Features of the model of infrequent rebalancing for small stocks. This table demonstrates whether the estimated features for three different portfolios of small stocks are consistent with the model of infrequent rebalancing during the fifteen–minute after the daytime auctions. The first line shows returns, volatility, price impact, and average volume respectively for small stocks with the highest share of trading on the Xetra. The line in the middle relates to the model indicators for a portfolio of small stocks that have higher trading on other markets(s) than the Xetra. The lower line shows measures for small stocks with the highest trading activity outside the Xetra. Green ticks mean that the corresponding after-auction estimates (1) are significant at the confidence interval at least 10%, (2) are among the 10% highest intervals during a day, and (3) have the mean that is statistically different from the value that corresponds to the market close interval. The red cross means that at least one of these criteria is not satisfied for a corresponding portfolio.

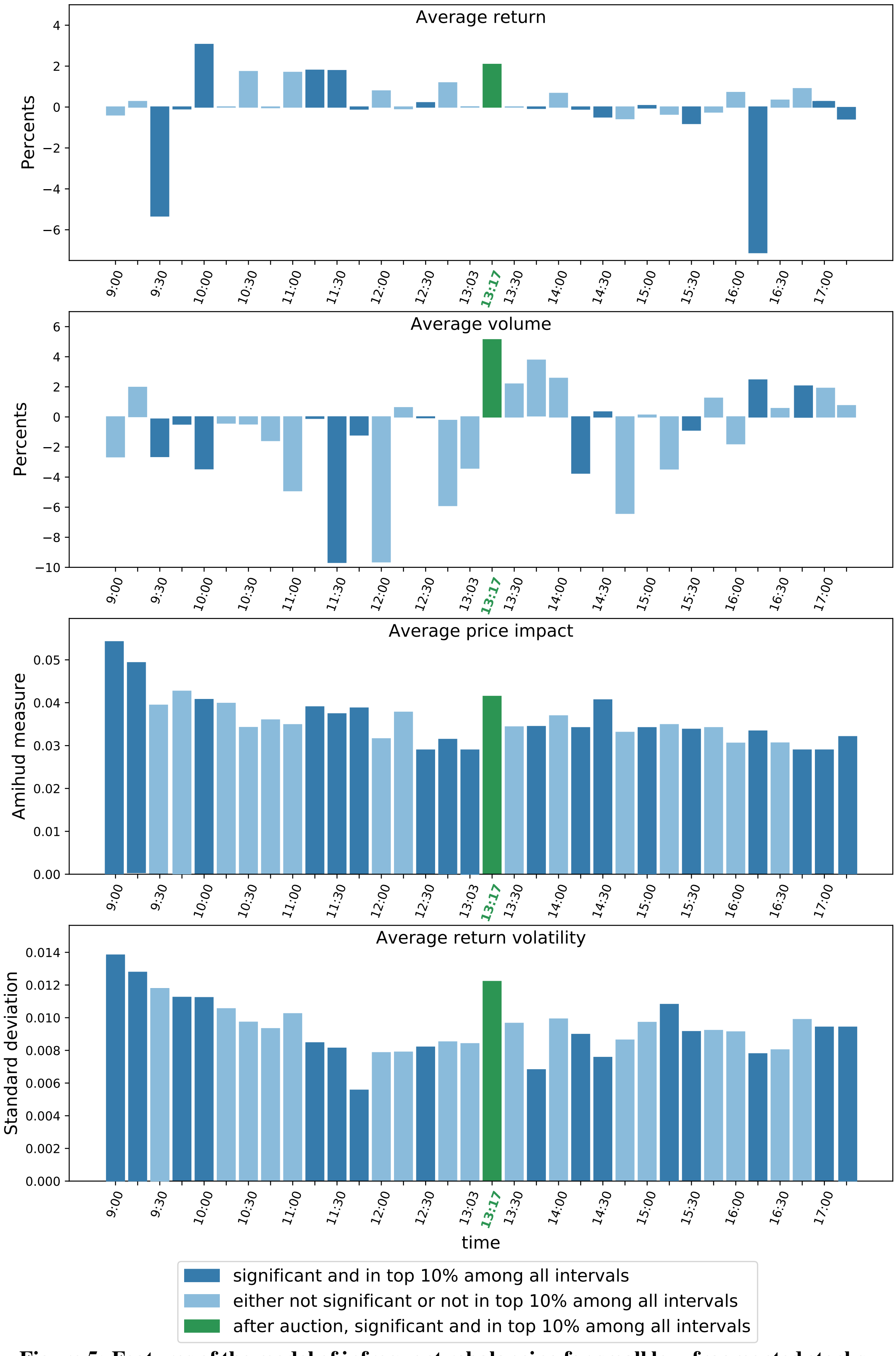

Figure 5: Features of the model of infrequent rebalancing for small low-fragmented stocks. Average returns and average volumes are defined as μ_k from (7). Coefficients are average returns adjusted for the standard deviation; the price impact is based on the Amihud measure from (6); return volatility is the standard deviation of returns during corresponding period. Average number of stocks in this subsample is 83 firms. Each interval indicates a starting time for the fifteen-minute interval (e.g., 9:00 implies an interval between 9:00-9:15).

The estimation of the model for a portfolio of large firms with the lowest trade fragmentation provides mixed evidence. In particular, average returns are high after the auction, but the time intervals preceding the US market opening demonstrate higher returns. Price impact has almost the same magnitude as the market closing and pre–US market opening intervals. Trading volume performs similarly – it is high after the daytime auctions, but not statistically significant. At the same time, post-auction volatility is still high (Figure 6).

Consequently, the results for large stocks with high market share weakly support the model. Given that these stocks are liquid (e.g., constitutes of the DAX-indices) and can be easily traded during the continuous trading, these results are not surprising. In a setting when price impact is low after daytime auctions, frequent traders are aware that the price is likely to be reversed in the following period. This might suggest that frequent traders are subject to some endowment shocks that are more volatile after at the periods after the daytime auctions. Moreover, results show that the US market opening might cause the variation pattern for large stocks. A potential reason is that large German stocks might be more exposed to foreign investor influence. Traders on the German market require thus higher return right before the US market opening. Not surprisingly, large stocks with higher trading fragmentation provide even weaker support for the model of infrequent rebalancing (Table 5), because factors present on foreign markets might be crucial for these stocks.

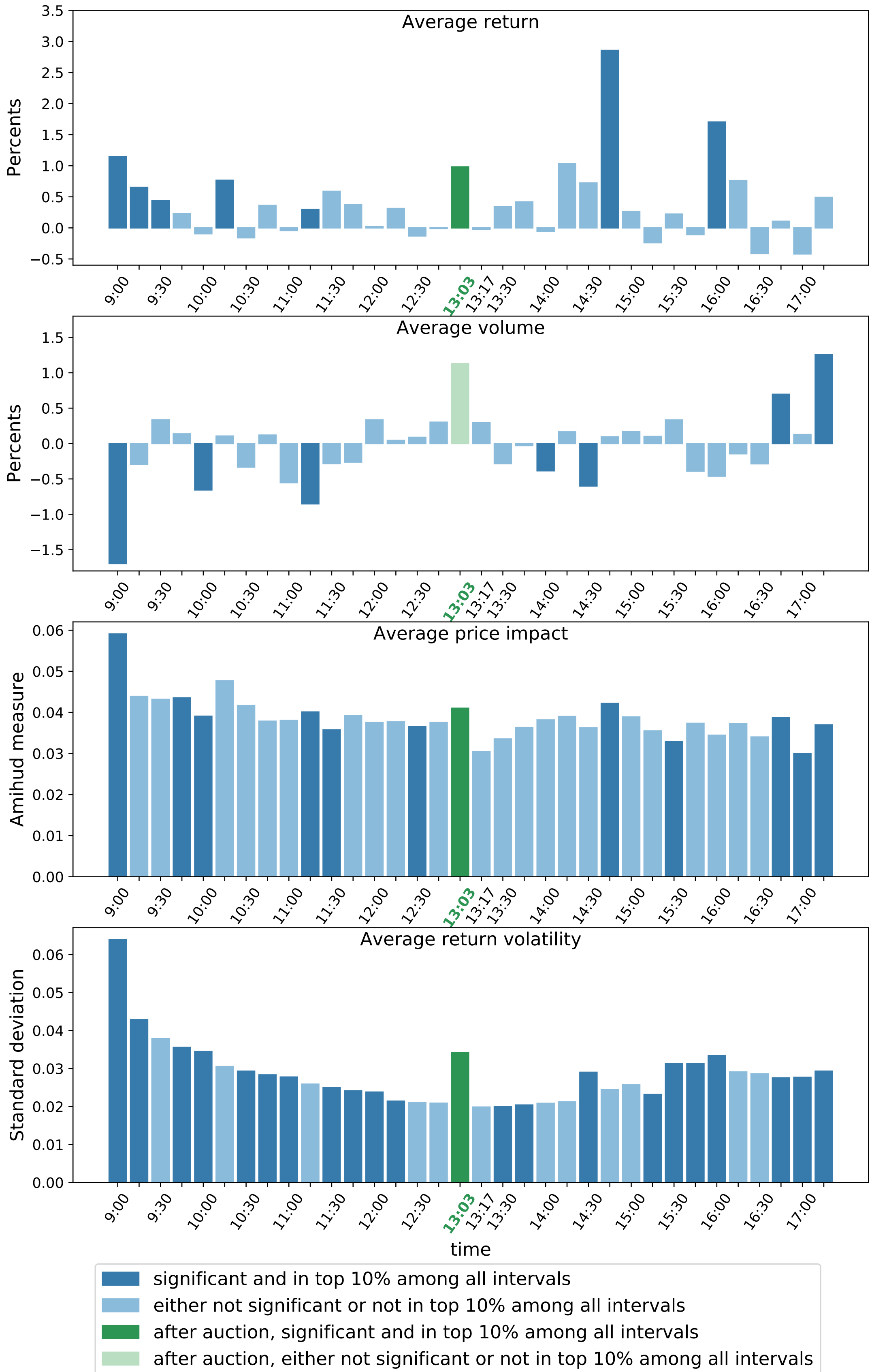

Figure 6: Features of the model of infrequent rebalancing for large low-fragmented stocks. Average returns and average volumes are defined as μ_k from (7). Coefficients are average returns adjusted for the standard deviation; the price impact is based on the Amihud measure from (6); return volatility is the standard deviation of returns during corresponding period. Average number of stocks in this subsample is 97 firms. Each interval indicates a starting time for the fifteen-minute interval (e.g., 9:00 implies an interval between 9:00-9:15).

Robustness. According to the Xetra trading model, the orders that are not executed or partially executed in the daytime auctions are either taken into continuous trading or the next auction, depending on the instructions. Therefore, the estimations of the model might be mechanically driven by the execution of remaining orders after auctions. Addressing this issue directly is not possible with the available, because it does not contain information on non-executable auction orders. However, when contacting Xetra, I was informed that most of the orders received in daytime auctions are restricted to "only-auctions" type, meaning that they are either carried to the next auction or removed if not being executed during the daytime auctions. Also, reestimating the model features skipping first one minute after the end of auctions does not change the results for the six portfolios (not reported).

This section applied the model of infrequent rebalancing to the Xetra market. In order to analyze the potential of infrequent rebalancing to explain return periodicity, I estimated four model characteristics for each fifteen–minute interval: high average return, high average volume, high return volatility, and high price impact. Aggregate portfolios of small and large stocks provide partial evidence on infrequent rebalancing at the period after daytime auctions. Small stocks traded mostly on the Xetra support the model entirely. Increasing the degree of fragmentation weakens the rebalancing argument for both size portfolios. Based on results, investors with different rebalancing horizons drive periodicity in returns, especially for small stocks.

6 Rationales behind after-auction rebalancing

6.1 Evidence on intraday predictability

Motivated by the results for after–auction period for a portfolio of small stocks, I look later in a trading day and analyze whether these returns predict other returns, for example, at market close. There are several reasons behind a potential intraday momentum. If liquidity traders drive return and volume periodicity, they can arrive at the market several times a day. If daytime auctions truly play an important role in price discovery, there might be late–informed investors, who may learn about prices after auctions and thus react slower. Also, some investors might wait for the US market opening before making decisions about adjusting their portfolios.

Following the methodology of Goh et al. 2013, I create a time series of value–weighted average returns and run the following predictive regressions:

$$r_{\tau,t} = \alpha_\tau + \beta r_{19,t} + u_t \qquad t = 1, ..., T, \tag{9}$$

where $r_{\tau,t}$ are the returns during each interval following daytime auction, $r_{19,t}$ is the after–auction fifteen-minute returns on day t, T is the total number of trading days.

I find that post–auction returns positively predict the closing returns (17:15-17:30), with a coefficient of 4.25% and returns before the US market opening (15:15-15:30) (Table 7). Combining these results with evidence on infrequent rebalancing, it might be the case that some investors adjust their portfolios later, but still considering the fixing after–auction price. This conclusion is consistent with the informational channel: the price discovery after the auction motivates traders to rebalance. Alternatively, liquidity traders can cluster around auction time and later in a day. Their choice of trading time is defined endogenously and is not driven by price discovery.

	13:30	13:45	14:00	14:15	14:30	14:45	15:00	15:15	15:30	15:45	16:00	16:15	16:30	16:45	17:00	17:15
α_τ	-0.001	0.000	-0.000	-0.000	-0.000	-0.001	-0.000	-0.000	-0.001	-0.001	-0.001	-0.000	-0.000	-0.001	0.000	0.000
β_{r19}	1.30	0.29	1.35	6.77	-0.32	2.58	-2.80	**6.32**	-1.45	0.32	5.81	**5.36**	0.45	2.57	-2.84	**4.25**
	(0.42)	(0.12)	(0.54)	(1.57)	(-0.14)	(1.04)	(-0.85)	(2.08)	(0.63)	(0.15)	(1.29)	(2.32)	(0.24)	(0.97)	(-1.18)	(2.01)

Table 7: Predictability of the subsequent intraday returns by after-auction returns. The table reports the results from (9). The after-auction return r_{18} is calculated from the trade price after the auction between 13:18-13:30 CET. The estimations show in-sample results. Newey and West (1987) robust t-statistics are in parentheses. The sample is composed of 289 small Xetra stocks. Each interval indicates a starting time for the fifteen-minute interval (e.g., 9:00 implies interval 9:00-9:15).

Next, I will go deeper into these two alternative stories that can help to understand the rationale behind after-auction trade dynamics.

6.2 Liquidity trading versus trading on new information

Various potential rationales can be implied by the revealed time–series predictability. For example, it might suggest that these are different types of investors, who rebalance after the daytime auctions and later during a trading day, based on the new information that became public after the auction. Late-reacting investors can be out of the market and adjust their portfolio later. Such behavior could be driven by the new information that became public right after the intraday auction. Alternatively, traders can choose the timing of their trading endogenously as a result of their strategic behavior. Below I provide a short description of both concepts from the market microstructure literature and show that concentration of liquidity traders is supported with the data.

The main motivation behind auction trading is that institutional investors can avoid speed race of the continuous trading and execute large blocks of trades without large price impact because of the concentration of liquidity that makes the market thicker. Thus, trading in auctions may be dominated by flows of institutional traders. When the auction ends, auction information (fixing price and traded volume per stock) becomes public. This is comparable to public announcements when information becomes public at a single moment. Several studies of such events show that after the news that contain new information prices shift and stay on the new level after revealing the information. This is consistent with the efficient market hypothesis that postulates that if the new information is incorporated into the stock in one single price jump upon public release, the market is efficient. Among empirical studies in support of this evidence are Ball and Brown 1968, MacKinlay 1997, Fama et al. 1969, and others.

The other group of models shows mechanisms of how investors choose to concentrate their trading at a single point in time in order to benefit from the liquidity externalities generated by other traders. For example, Admati and Pfleiderer 1988 develop a rational expectation model with common private signal.[30] In this model, traders choose when to trade and whether to get privately informed regarding future returns of assets or not. Two types of traders make strategic decisions in the model: informed traders and liquidity traders, while market makers are assumed to be passive.[31] Informed traders define the volume of their orders in every single period. Liquidity traders instead choose the time, when they trade so that to minimize the cost of transactions and satisfy their demands. The strategies of other traders and trading terms are considered to be given to both types of traders. The authors show that the only robust equilibria in the model are when all liquidity trading is concentrated in the same period. Such increased trading induces more active informed trading. As a result, such concentration of trading results in a higher volume because of (1) an increase in volumes by liquidity traders and (2) pronounced volume by informed trading. This result is even more pronounced when the model is extended to the setting when a number of informed traders fluctuates (i.e., when traders can buy private information at a cost). This happens because a larger number of informed traders lowers cost of trading for liquidity traders, thus inducing the aggregation of trading at a specific point in time.

In regards to the concentration around the after-auction trading, liquidity trading is concentrated, because it is harder to trade small stocks in continuous trading either before or after the daytime auctions. Analyzing the application of the model with the relaxed assumption that liquidity traders trade only once, intraday momentum could be explained as follows. According to the model setting, when traders can allocate their trades between several periods, they would choose to trade in an earlier period. For example, consistent with the model, some liquidity traders can realize their demands after the daytime auction and then closer to the end of a trading day.

In order to determine whether the data provide evidence on either information or liquidity argumentation for small stocks, I run Fama-MacBeth 1973 regressions of the form:

$$
\begin{aligned}
r18_{i,t} &= \alpha_t + \beta_t r19_{i,t} + u_{i,t} \\
\hat{\beta} &= \frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_t,
\end{aligned}
\tag{10}
$$

where $r18$ corresponds to the returns of the interval lasting from right before the start of the auction until the end of the auction, and $r19$ are the returns during the first after-auction period. The main difference of this method compared to a time-series approach in (9) is that in (10) I focus on the average cross-sectional effect rather than time-series dependency. In particular,

[30] Among other models are Pagano 1989, Foster and Viswanathan 1990

[31] Market makers set prices in a way that satisfies their expected profit of zero. They only observe the total order flow. Informed traders become informed as a cost.

I check whether the stocks with high over-auction price change ($t = 18$) have high after-auction ($t = 19$) price change. This approach helps to define how an auction price "surprise" behaves after the auction, as soon as the auction price becomes public. The estimation produces $\hat{\beta} = -0.061$ with corresponding t-statistics of -31.12. Such after-auction price bounce advocates for a liquidity channel as a driver for the infrequent rebalancing after the daytime auctions (the bottom part of Figure 7).

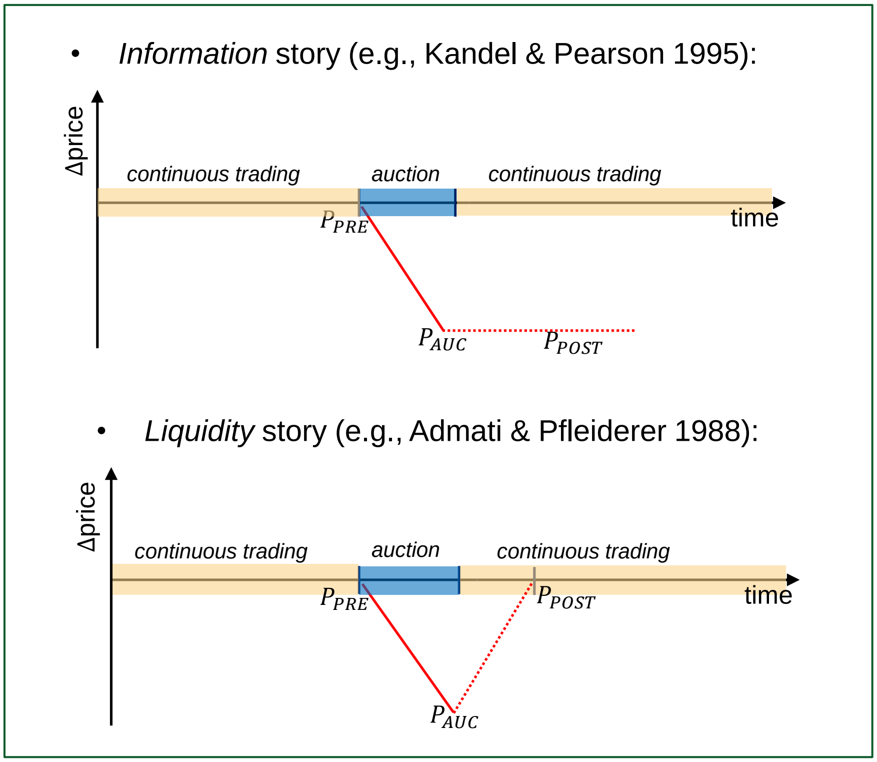

Figure 7: Price behaviour consistent with informational and liquidity models. The figure represents the dynamics of stock prices after intraday auctions implied by two different market microstructure models. The upper graph corresponds to the price dynamics according to Kander and Pearson 1995. The bottom graph corresponds to the price dynamics according to Admati and Pfleiderer 1988.

7 Conclusion

The paper sheds light on daytime auction trading and provides fresh evidence on its role in the periodicity of cross-section of stock returns.

First, market liquidity factors influence trading volumes in daytime auctions differently than volumes in continuous trading. The returns of the market index and changes in volatility have a negative relationship with the auction volumes and positive – with continuous volumes. Term spread has a negative impact on continuous trading and has no effect on auction volume. Both trading sessions demonstrate a strong day-of-week effect.

Second, I show that after-auction, market open, and market close intervals drive the return periodicity on a daily frequency. Moreover, after-auction periods alone are able to generate such a seasonality. A long-short portfolio based on after-auction returns from the previous day earns 1.89 basis points. The revealed return pattern is most pronounced for portfolios of small, large, and domestic (German) stocks. Return volatility, and the estimated bid-ask spread cannot explain the revealed return dynamics. In addition, volume changes do not provide statistical coefficients, although demonstrate a similar periodicity as returns.

Third, as volumes also represent seasonality, investor flows is a main candidate to explain return periodicity. The model of infrequent rebalancing suggests that when a large share of infrequent traders is present on the market to rebalance their portfolios, liquidity deteriorates and the realized returns, return volatility, volume, and price impact are high. I apply these features to the dataset and show that the portfolio of small low-fragmented stocks possesses these features during fifteen–minute after the daytime auctions. This evidence means that infrequent traders are likely to rebalance these stocks during this interval. Large stocks with low fragmentation provides mixed evidence on relation to the model. A different type of investors and different market factors are likely to drive the variation of returns for small and large stocks. Alternatively, the model of infrequent rebalancing might be extended to account for the market fragmentation of stocks, given different empirical results depending on the degree of fragmentation.

Eventually, I find an after-auction return bounce for those stocks, whose price changed much during the auction. Supposedly, this finding means that the infrequent rebalancing is mainly driven by the concentrated liquidity traders rather than by informational channel.

The conclusions of the paper can be of use for policy regulators. Currently, the trading volume during daytime auctions is truly increasing at the sake of dark pool outflows.[32] Given a tendency for European markets on initiation of daytime auctions to their markets, one should consider consequences of changing the price dynamics and trading concentration as found in the paper.

The study has several limitations. First, with the available dataset, there is no opportunity for more flexibility in applying other empirical proxies of the model indicators. Second, it is hard to make conclusions regarding the profitability of trading strategies based on the revealed results because the dataset cannot account for trading costs. Further, it would be potentially interesting to focus future research on analyzing (1) possible informed trading before the start of the daytime auctions, (2) whether and how stocks price surprise, a difference between the before–auction price and the price determined in the auction, matters for the degree of its after-auction features, e.g., infrequent rebalancing.

[32] Hadfield W. and V. Vaghela. "Goldman leads banks with stock auctions as a MiFID II workaround", *Bloomberg*, April 9, 2018

A Appendix

A.1 Appendix A

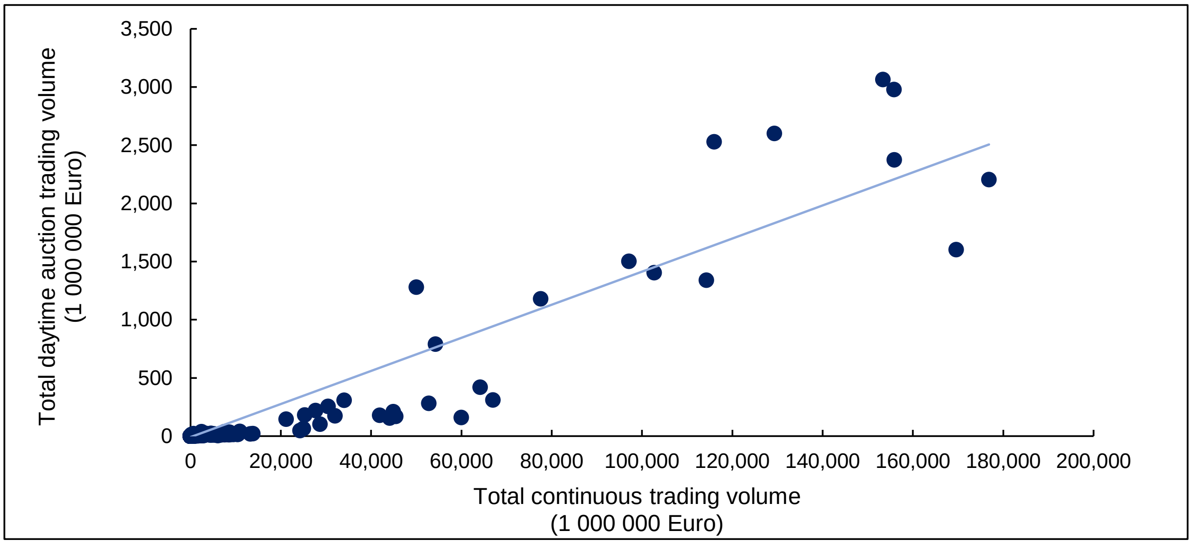

Figure A1: Relationship between volume in daytime stock auctions and in continuous trading
The figure plots the stock size, measured as the total daily total volume versus its daytime auction volume, both in Euro. Volume is defined as price of a given stock multiplied by the number of stocks traded. The sample consists of 875 stocks traded on the Xetra. Volume is aggregated throughout the whole sample period of August 2010 - May 2015. The line represents a linear fit.

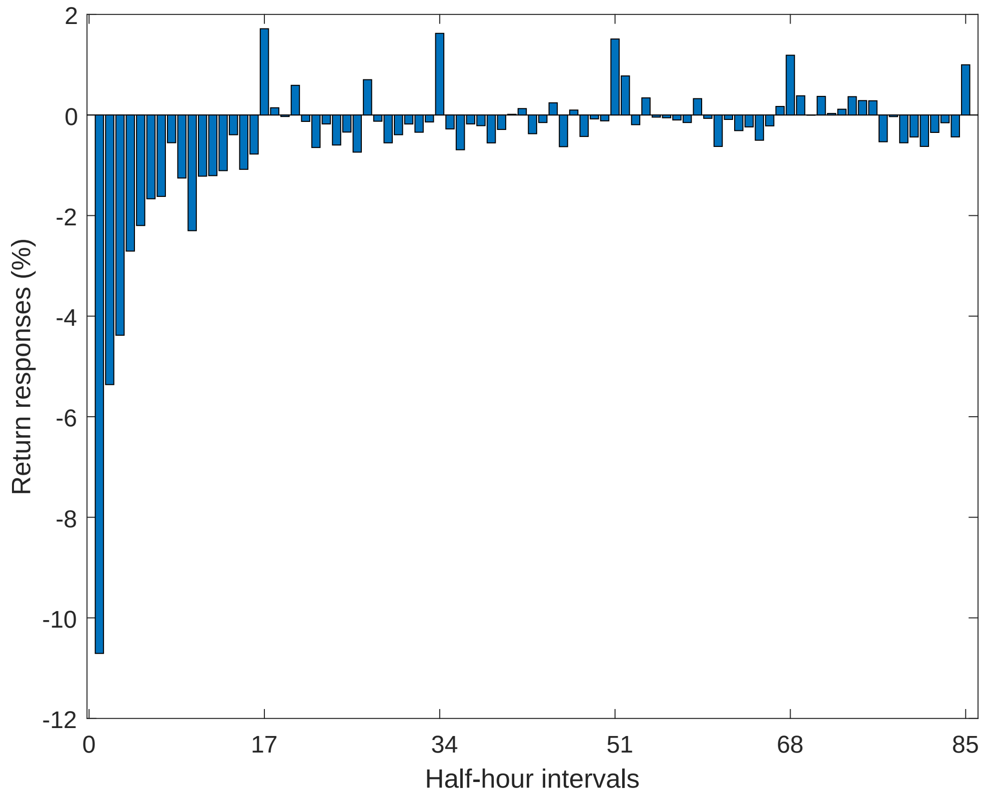

Figure A2: Time-series averages of return responses. Half-hour sampling frequency

The figure demonstrates results from (2): average return responses and corresponding *t*-statistics. A trading day is divided into 17 disjoint intervals, each containing thirty minutes. For interval *t* and lag *k*, I run univariate cross-sectional regressions $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ is the return of stock *i* during interval *t* and $r_{i,t-k}$ is the return of stock *i* during interval *t*-*k*. The cross-sectional regressions are estimated for all combinations of interval *t* and lag *t*, with values 1 through 85 (corresponding to the previous five trading days). The resulting coefficients are averaged across time. The *y*-axis shows the time-series average return responses $\gamma_{k,t}$, in percents. The analysis uses 875 Xetra-listed stocks for a period of August 2010-May 2015.

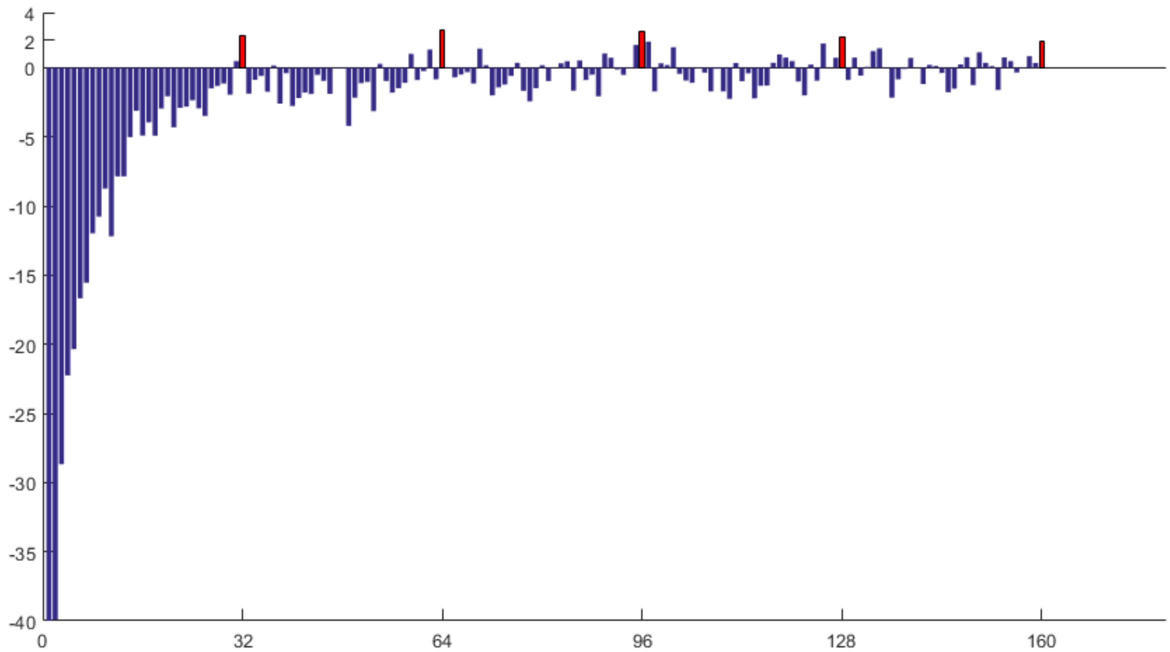

Figure A3: *t*-statistics of averages return responses without market open and close intervals
The figure demonstrates results from (2): average return responses and corresponding *t*-statistics. A trading day is divided into 32 disjoint intervals, each containing fifteen minutes. For interval *t* and lag *k*, I run a simple univariate 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 return of stock *i* during interval *t* and $r_{i,t-k}$ is the return of stock *i* during interval *t-k*. The cross-sectional regressions are estimated for all combinations of interval *t* and lag *t*, with values 1 through 160 (corresponding to the previous five days). The red bars represent average return responses from the regressions that contain 32 intervals, excluding intervals of the market open and market close. The analysis uses Xetra-listed stocks for a period of August 2010-May 2015.

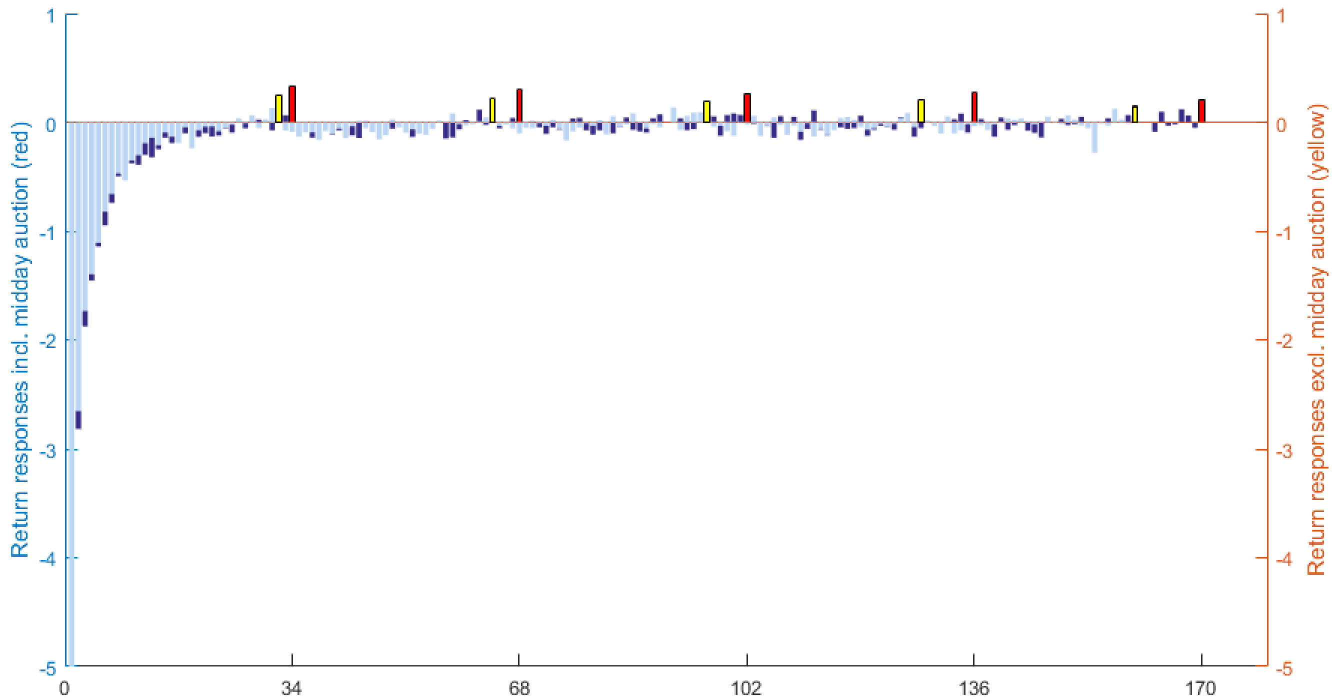

Figure A4: Time-series averages of return responses with and without daytime auctions
The figure demonstrates results from (2): average return responses and corresponding *t*-statistics. A trading day is divided into 34 disjoint intervals, each containing fifteen minutes. For interval *t* and lag *k*, I run a simple univariate 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 return of stock *i* during interval *t* and $r_{i,t-k}$ is the return of stock *i* during interval *t*-*k*. The cross-sectional regressions are estimated for all combinations of interval *t* (49,130 intervals) and lag *t*, with values 1 through 170 (corresponding to the previous five days). The red bars represent average return responses from the regressions that contain 33 intervals, excluding intervals post-daytime auctions. The analysis uses Xetra-listed stocks for a period of August 2010-May 2015.

Strategy	Long-short return
Day 1	
Daily (lag 17)	1.58 (7.32)
Non-daily (lags1-16)	-2.30 (-15.51)
Day 2	
Daily (lag 17)	1.04 (4.69)
Non-daily (lags 1-16)	-1.09 (-7.69)
Day 3	
Daily (lag 17)	1.32 (6.01)
Non-daily (lags 1-16)	-0.89 (-6.28)
Day 4	
Daily (lag 17)	0.76 (3.64)
Non-daily (lags 1-16)	-0.89 (-6.28)
Day 5	
Daily (lag 17)	0.66 (3.16)
Non-daily (lags 1-16)	-0.49 (-3.49)

Table A1: Return spread of two momentum strategies

This table shows the return difference between the top and bottom portfolio of two momentum strategies. The strategy denoted as ”daily” goes long top 10% performing stocks and shorts 10% worst performing stocks 17-multiple periods ago. ”Non-daily” strategy sorts stocks according to their average return during the previous 16 lags. The first column indicates the strategy. The portfolios are equally-weighted. The values of return spread do not account for trading costs. The analysis is done for the whole sample period between August 2010-May 2015. Values in brackets are t-statistics.

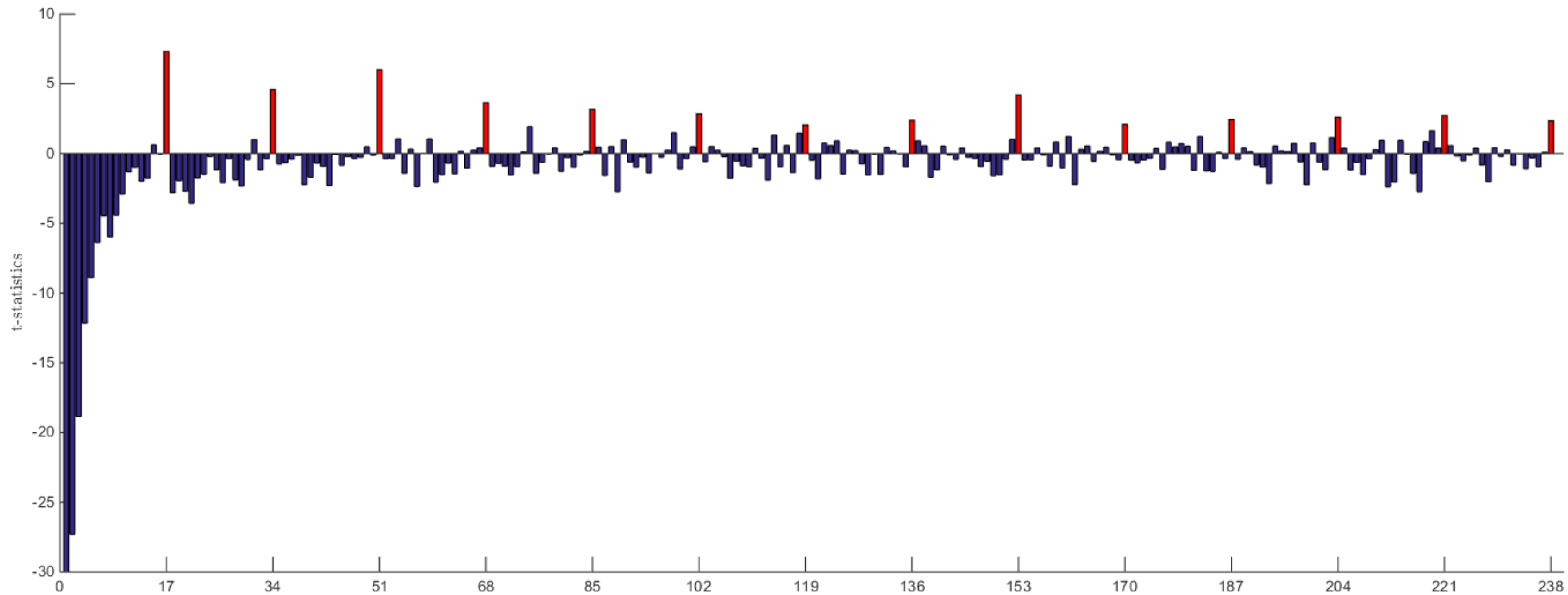

Figure A5: t-statistics of the return spread of long-short portfolio based on momentum strategy k days ago

The figure represents t-statistics of the return spread of momentum strategy that is built on the revealed daily return periodicity. Stocks are sorted based on their returns k intervals ago ($k \in [1, ..., 238]$), 10% of best performing stocks are bought and 10% of worst performing are sold. Labels on the x-axis represent one, two, ans so-forth full days (there are 17 half-hour intervals during each day).

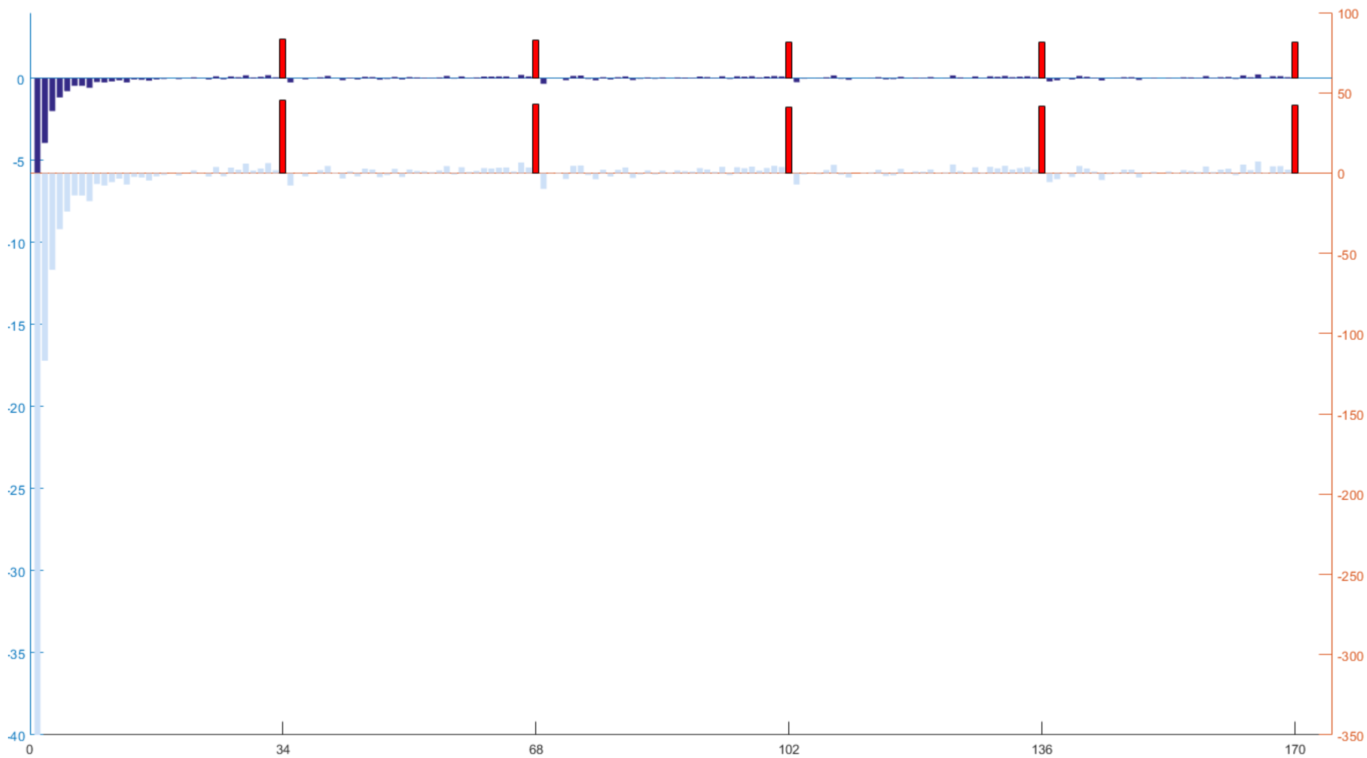

Figure A6: Average time–series volume change responses coefficients from cross–sectional regressions

The figure demonstrates results from (2): average volume changes and corresponding *t*-statistics. A trading day is divided into 34 disjoint intervals, each containing fifteen minutes. For interval *t* and lag *k*, I run univariate cross-sectional regressions 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 volume change of stock *i* during interval *t* and $r_{i,t-k}$ is the volume change of stock *i* during interval *t-k*. The cross-sectional regressions are estimated for all combinations of interval *t* and lag *t*, with values 1 through 170 (corresponding to the previous five days). The red bars represent average return responses from the regressions that contain 33 intervals, excluding intervals post-daytime auctions. The analysis uses Xetra-listed stocks for a period of August 2010-May 2015.

	Lag 34	Lag 68	Lag 102	Lag 136	Lag 170
Lagged returns	**1.27**	**0.57**	**0.63**	**0.19**	**0.64**
	[6.87]	[3.21]	[3.48]	[1.11]	[3.66]
Lagged returns*	**1.61**	**0.79**	**0.48**	**0.35**	**0.58**
	[3.76]	[3.34]	[2.29]	[1.99]	[2.68]
Lagged volatility	0.0001	0.0001	-0.0005	0.004	-0.0004
	[0.22]	[0.23]	[1.36]	[0.95]	[-0.49]
Lagged volatility*	0.005	-0.004	0.002	0.004	-0.0001
	[0.19]	[-1.61]	[1.62]	[0.15]	[-0.94]
Lagged volume	0.0008	0.0007	0.0002	0.0003	0.00006
	[1.82]	[0.18]	[0.62]	[0.54]	[0.01]
Lagged volume*	-0.0005	0.001	-0.001	-0.003	-0.0004
	[-0.04]	[0.97]	[-1.20]	[-1.69]	[0.39]
Lagged spread	-0.0001	0.0006	-0.0001	0.0009	0.0004
	[-0.18]	[1.36]	[-0.02]	[1.83]	[0.70]
Lagged spread*	**-0.02**	0.005	0.01	0.06	0.03
	[-2.02]	[0.24]	[0.58]	[1.12]	[0.49]

Table A2: Estimations from regressing returns on market factors

This table shows results of the following regression: $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + \delta'_{k,t} V_{i,t-k} + \epsilon_{i,t}$, where vector $V_{i,t-k}$ includes the percentage changes in volume, volatility, and bid-ask spread. Regressions are based on fifteen-minute intervals of the trading day. The variables marked * relates to the subsample of the most liquid stocks – I exclude stocks whose high price equals low price on more than 120 days during the sample period. The numbers in brackets are t-statistics. Corresponding R^2 are presented for each estimation and for each lag.

	Lag 34	Lag 68	Lag 102	Lag 136	Lag 170
Lagged returns	**0.26**	**0.27**	**0.41**	**0.16**	**0.26**
	[3.44]	[3.84]	[6.06]	[2.39]	[4.01]
Lagged volatility	0.0001	0.0001	0.0008	0.004	0.0001
	[0.65]	[0.98]	[0.12]	[0.49]	[0.61]
R^2	0.022	0.021	0.020	0.020	0.019
Lagged returns	**0.34**	**0.32**	**0.42**	**0.19**	**0.34**
	[3.52]	[3.34]	[6.19]	[2.29]	[3.89]
Lagged volume	0.005	-0.004	0.002	0.004	-0.002
	[0.19]	[-1.61]	[1.62]	[0.15]	[-0.94]
R^2	0.011	0.011	0.010	0.010	0.009
Lagged returns	**0.51**	**0.41**	**0.40**	0.22	**0.34**
	[4.45]	[3.72]	[3.65]	[1.92]	[3.27]
Lagged spread	0.007	0.0004	0.014	-0.004	0.003
	[0.96]	[0.31]	[1.01]	[-0.83]	[1.11]
R^2	0.038	0.036	0.033	0.033	0.032

Table A3: Estimations from regressing returns on lagged returns and each market factor

This table shows results of the following regression: $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + \beta_{k,t} v_{i,t-k} + e_{i,t}$, where $v_{i,t-k}$ includes percentage changes in one of the variables (volume or volatility or bid-ask spread) regressing returns on lagged returns and volatility (upper block), lagged returns and volume (middle block), lagged returns and spread (lower block). Regressions are based on fifteen-minute intervals of the trading day. Corresponding R^2 are presented for each estimation and for each lag.

	Large stocks	Medium stocks	Small stocks
Lag 34			
Estimate	**0.32**	0.23	**0.37**
t–statistics	[3.29]	[0.49]	[2.85]
Lag 68			
Estimate	**0.16**	0.45	**0.17**
t–statistics	[3.02]	[1.57]	[1.91]
Lag 102			
Estimate	**0.37**	0.15	**0.43**
t–statistics	[4.05]	[0.58]	[4.27]
Lag 136			
Estimate	0.23	**0.32**	**0.33**
t–statistics	[1.34]	[2.03]	[2.57]
Lag 170			
Estimate	**0.13**	**0.32**	**0.58**
t–statistics	[1.67]	[1.32]	[3.14]

Table A4: Average daily return responses of size portfolios

This table shows time-series of average $\gamma_{k,t}$ and their corresponding *t*-statistics in brackets. Large, medium, and small stocks represent 33% of the sample ranked according to the free-float market capitalization retrieved from *Thomson Reuters Datastream* as of 31/03/2013. Values at each lag are reported as percentages.

	German stocks	Foreign stocks
Lag 34		
Estimate	**0.33**	0.22
t–statistics	[3.42]	[1.86]
Lag 68		
Estimate	**0.32**	0.21
t–statistics	[3.62]	[1.83]
Lag 102		
Estimate	**0.47**	**0.48**
t–statistics	[4.82]	[4.53]
Lag 136		
Estimate	**0.23**	-0.03
t–statistics	[2.59]	[-0.30]
Lag 170		
Estimate	**0.37**	0.03
t–statistics	[4.74]	[0.27]

Table A5: Average return responses of domestic and foreign stocks
This table shows time–series of average $\gamma_{k,t}$ and their corresponding *t*-statistics in brackets below the values. Domestic or foreign stocks are defined based on the stock ISIN. Domestic stocks are German, foreign stocks are all other than German, based on the ISIN information retrieved from *Thomson Reuters Datastream*. Values at each lag are reported as percentages.

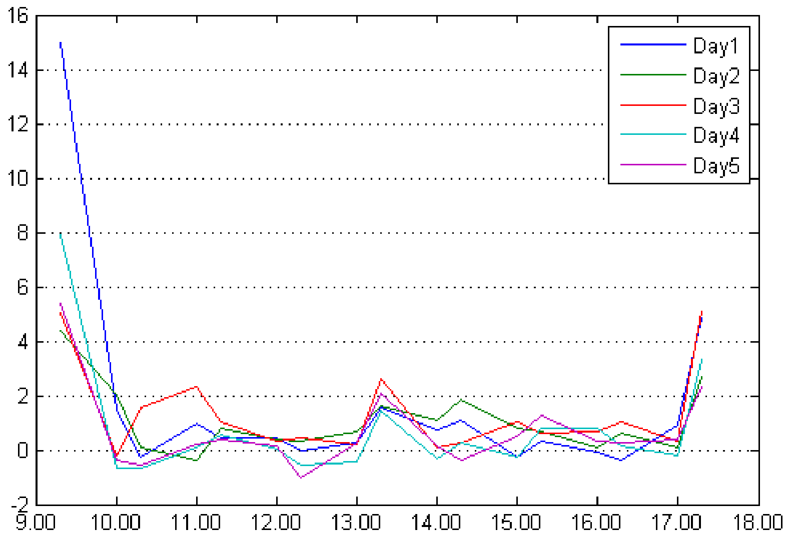

Figure A7: The intraday distribution of return spreads of the daily strategy for each day of the week

Strategy (lag)	Return	*t*-statistic	Strategy (lag)	Return	*t*-statistic
17	1.58	7.32	170	0.44	2.09
34	1.04	4.59	187	0.53	2.43
51	1.31	6.01	204	0.55	2.60
68	0.76	3.64	221	0.59	2.73
85	0.66	3.16	238	0.52	2.34
102	0.61	2.84	255	0.27	1.23
119	0.45	2.05	272	0.49	2.24
136	0.54	2.39	289	0.39	1.77
153	0.90	4.20	306	0.24	1.21

Table A6: Two-week performance of a daily momentum strategy based on historical *thirty*-minute returns on daily lags

This table shows the return spread of the long-short portfolios that are formed according to the stock returns one, two, etc. days ago (34, 68, etc, *lags* ago) I sort stocks every day based on their returns one, two, etc. days ago. Returns are scaled so that each return value is reported as percentage. Each lag value corresponds to the multiples of one day. The reported values do not account for trading costs.

	9:00	9:15	9:30	...	12:30	12:45	13:03	13:17	13:30	13:45	...	15:00	15:15	...	16:45	17:00	17:15
Panel A. Average return																	
big MS	-0.38	0.26	-5.32		0.21	1.18	0.005	2.023	-0.06	0.000		0.11	-0.34		0.89	0.26	-0.43
	(-1.4)	(2.2)	(-12.0)		(26.6)	(1.4)	(0.11)	(15.1)	(-2.8)	(0.33)		(1.9)	(-1.9)		(5.9)	(1.7)	(-6.4)
middle MS	-10.85	-3.04	-0.24		0.09	-0.02	-0.13	18.38	3.73	-0.05		2.27	0.01		12.68	2.34	1.84
	(-4.2)	(-1.0)	(-2.6)		(0.9)	(-1.7)	(-0.7)	(4.7)	(1.5)	(-0.7)		(8.9)	(8.5)		(0.35)	(4.8)	(11.3)
small MS	-1.26	5.58	-8.70		-0.09	-2.02	-7.11	4.11	1.74	-0.12		-0.08	23.07		0.08	0.08	1.73
	(-2.7)	(1.4)	(-8.5)		(-1.7)	(-1.0)	(7.5)	(0.9)	(1.9)	(-0.7)		(8.2)	(8.1)		(7.8)	(8.3)	(8.4)
Panel B. Return volatility																	
big MS	0.14	0.13	0.12		0.008	0.009	0.008	0.12	0.009	0.007		0.009	0.11		0.1	0.09	0.09
	(11.5)	(14.1)	(1.0)		(2.6)	(1.1)	(2.7)	(4.1)	(1.6)	(3.0)		(5.4)	(5.2)		(1.1)	(6.05)	(15.3)
middle MS	0.23	0.13	0.10		0.23	0.008	0.008	0.10	0.006	0.002		0.13	0.14		0.04	0.11	0.15
	(3.9)	(4.9)	(5.4)		(15.0)	(1.7)	(6.2)	(5.3)	(2.1)	(8.4)		(7.1)	(5.3)		(2.1)	(4.1)	(7.9)
small MS	0.25	0.2	0.23		0.11	0.13	0.009	0.14	0.12	0.14		0.11	0.1		0.09	0.15	0.17
	(4.3)	(9.8)	(11.2)		(5.5)	(3.7)	(1.9)	(2.6)	(2.7)	(3.5)		(6.7)	(2.7)		(1.4)	(3.9)	(5.7)
Panel C. Average volume change																	
big MS	-2.65	1.94	-3.54		0.07	-6.41	-3.40	5.13	0.34	3.28		-0.56	-3.85		2.45	1.90	0.74
	(-0.3)	(1.8)	(-1.0)		(0.0)	(-0.7)	(-1.7)	(2.1)	(1.3)	(1.4)		(-1.9)	(-0.4)		(2.3)	(0.7)	(1.6)
middle MS	3.12	-5.61	4.28		0.48	0.32	0.17	0.52	-2.06	-6.13		-5.31	0.03		-1.76	2.71	-1.12
	(2.0)	(-1.4)	(0.63)		(1.8)	(0.7)	(7.4)	(6.7)	(6.8)	(6.7)		(0.01)	(1.2)		(-21.3)	(2.1)	(-1.7)
small MS	-0.78	24.06	48.74		21.72	0.55	1.65	-10.61	-7.63	45.77		4.45	-8.66		11.60	-13.57	2.76
	(-8.6)	(4.5)	(4.3)		(5.4)	(5.5)	(5.2)	(4.0)	(4.7)	(5.0)		(4.9)	(4.3)		(5.0)	(5.4)	(7.1)
Panel D. Price impact																	
big MS	0.56	0.48	0.40		0.29	0.32	0.29	0.41	0.34	0.33		0.35	0.36		0.28	0.28	0.38
	(17.4)	(7.4)	(20.3)		(4.6)	(14.4)	(2.3)	(3.7)	(1.8)	(2.7)		(2.4)	(2.9)		(3.9)	(4.6)	(3.2)
middle MS	0.48	0.46	0.37		0.32	0.37	0.29	0.41	0.35	0.33		0.31	0.32		0.25	0.30	0.26
	(14.7)	(15.2)	(10.8)		(7.5)	(10.4)	(27.4)	(16.7)	(16.8)	(6.7)		(3.9)	(7.9)		(17.5)	(12.7)	(12.2)
small MS	0.65	0.49	0.45		0.31	0.39	0.20	0.25	0.28	0.31		0.31	0.19		0.46	0.34	0.51
	(7.6)	(6.2)	(4.3)		(5.4)	(5.5)	(5.2)	(4.0)	(4.7)	(5.0)		(7.1)	(8.3)		(4.1)	(6.5)	(5.1)

Table A7: Intraday market features for small stocks with different market share. Stocks are allocated into small, middle, and large portfolios based on the 20th and 50th percentiles of Xetra free-flow market capitalization each quarter. Stock and volume returns are computed using the first trade of the day and the last trade in each interval. Price impact is measured by the *Amihud* measure and is scaled by 10^6 for representative purposes, returns are scaled by 10^4 , volatility is scaled by 10^5. 9:00 indicates the half-hour interval that starts at 9:00 and ends before 9:15. The sample is composed of Xetra common stocks from August 2010 to May 2015. Standard t-statistics are shown in parentheses.

A.2 Appendix B

Price impact in the model of infrequent rebalancing is based on Campbell at al. 1993. This part shows that the price impact in the model of infrequent rebalancing has a one-to-one relationship with the *Amihud* measure after controlling for a price level.

The following economy is considered:

- risk-free asset in elastic supply with a guaranteed rate of return $R = 1 + r$
- fixed supply of stock shares per capita
- each share pays a dividend $D_t = \bar{D}_t + \tilde{D}_t$ (stochastic component of the dividend)
- two types of investors (investor A and investor B) with constant absolute risk aversion parameters α and b_t respectively. ω is the fraction of type A investors.

Each period investors solve the following problem:

$$\max E_t[-exp(-\Psi W_{t+1})], \qquad \Psi = \alpha, b_t \tag{11}$$

subject to

$$W_{t+1} = W_t R + X_t(P_{t+1} + D_{t+1} - RP_t), \tag{12}$$

where W_t is wealth, X_t is the holding of the risky asset, and P_t is the ex dividend share price of the stock, all measured at time *t*.

For such an economy, there exists an equilibrium price of the stock that has the following form:

$$P_t = F_t - D_t + (p_0 + p_z Z_t), \tag{13}$$

where F_t is defined as cum–dividend fundamental value of the stock, Z_t is the risk aversion of the marginal investor in the market and $p_z = -((R - \alpha_z)/2\sigma_z^2)[1 - \sqrt{1 - (\sigma_z^2/\sigma_z^{*2})}]$ and $p_0 = (1 - \alpha_z)p_z\bar{Z}/r < 0$.

Defining the excess return per share on the stock realized at time *t+1* is $Q_{t+1} \equiv P_{t+1} + D_{t+1} - EP_t$ and expressing it via expected excess return with the serial correlation of returns, the solution of the optimization problem (11) is:

$$\begin{aligned} X_t^a &= \frac{E[Q_{t+1}|P_t, D_t, S_t]}{a \,\text{var}[Q_{t+1}|P_t, D_t, S_t]} = \frac{1}{a} Z_t, \\ X_t^b &= \frac{E[Q_{t+1}|P_t, D_t, S_t]}{b_t \,\text{var}[Q_{t+1}|P_t, D_t, S_t]} = \frac{1}{b_t} Z_t, \end{aligned} \tag{14}$$

where X_t^a and X_b^a are, respectively, the optimal stock holdings of type A and type B investors.

Changes in investors' preferences relative to one another generate trading. X_t^a and X_b^a thus change as Z_t changes: $X_t^a - X_{t-1}^a = (1/\alpha)(Z_t - Z_{t-1})$. Trading volume is then $V_t = \omega|X_t^a - X_{t-1}^a| = (\omega/\alpha)|Z_t - Z_{t-1}|$.

Define $\Delta_t = \frac{\omega}{\alpha}(Z_t - Z_{t-1})$, thus $V_t = |\Delta_t|$. Also, define $\epsilon_{F,t} = F_t - E_{t-1}[F_t]$, which gives the innovation process to F_t. Then,

$$Q_{t+1} = p_z(Z_{t+1} - Z_t) + \epsilon_{F,t+1} \tag{15}$$

From the definition of Q_{t+1} from above, we have: $Q_{t+1} = P_{t+1} + D_{t+1} - RP_t$. Assuming that $D_{t+1} = 0$ and that R=1, we have $Q_{t+1} \approx P_{t+1} - P_t$.

Given that $\Delta_t = \frac{\omega}{\alpha}(Z_t + Z_{t+1})$, we can rewrite: $P_{t+1} - P_t = p_z * \frac{\omega}{\alpha} * \Delta_{t+1}$

Dividing both sides by P_t, we have $\frac{P_{t+1}-P_t}{P_t} = p_z * \frac{\alpha}{\omega} * \frac{1}{P_t} * \Delta_{t+1}$

$\frac{Ret_{t+1}}{\Delta t+1} = p_z * \frac{1}{P_t} * \frac{\alpha}{\omega} \Rightarrow |\frac{Ret_{t+1}}{V_{t+1}}| = |\frac{p_z}{P_t} * \frac{\alpha}{\omega}|$, because positive volume means positive shock, which generates the volume to trade. Right side is also positive, because α is a parameter of the exponential utility (positive) and ω is the fraction of type A traders defined above (positive). P_t is a positive price of a stock. Appendix of the paper shows that the solution for p_z is with positive sign as well. The left side is Amihud illiquidity measure.

References

Abhyankar, A., D. Ghosh, E. Levin, and R.J. Limmack. 1997. *Bid-ask spreads, trading activity, and trading hours: intraday evidence from the London Stock Exchange*. Working paper.

Admati, A. R. and P. Pfleiderer. 1988. A theory of intraday patterns: volume and price variability. *Review of Financial Studies* 1, pages 3-40.

Amihud Y. 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5, pages 31-56.

Baldauf, M. and J. Mollner. 2015. High-frequency trading and market performance. Manuscript, Stanford University

Ball, B. and P.Brown. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6: pages 159-178

Barber, B.M. and T. Odean. 2000. Trading is hazardous to your wealth: the common stock investment performance of individual investors. *Journal of Finance* 2: pages 773-806.

Bogousslavsky, V. 2016. Infrequent rebalancing, return autocorrelation, and seasonality. *Journal of Finance* 71: pages 2967-3006.

Bogousslavsky, V. 2017. *The cross-section of intraday and overnight returns*. Working paper.

Bollerslev, T., D. Osterrieder, N. Sizova, and G. Tauchen. 2013. Risk and return: Long-run relations, fractional co-integration, and return predictability. *Journal of Financial Economics* 108: pages 409-424.

Brooks, M.R. and J. Moulton. 2004. The interaction between opening call auctions and ongoing trade: Evidence from the NYSE. *Review of Financial Economics* 13(4): pages 341–356.

Budish, E., P. Cramton, and J. Shim. 2015. The high-frequency trading arms race: frequent batch auctions as a market design response. *Quarterly Journal of Economics* 130, pages 1547-1621.

Campbell, J.Y., S.J. Grossman, and J. Wang. 1993. Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics* 108, pages 905-939.

Cao, C., E. Ghysels, and F. Hatheway. 2000. Price discovery without trading: evidence from the Nasdaq preopening. *Journal of Finance* 55, pages 1339-1365.

Chordia, T., R. Roll, and A. Subrahmanyam. 2002. Market liquidity and trading activity. *Journal of Finance* 56, pages 501-530.

Clapham, B. and K. Zimmermann. 2015. Price discovery and convergence in fragmented securities markets. *International Journal of Managerial Finance* 12(04): pages 381-407.

Comerton-Forde, C., S. Lau, and T.H. McInish. 2007. Opening and closing behavior following the introduction of call auctions in Singapore. *Pacific-Basin Finance Journal* 15, pages 18-35.

Cont R., A. Kukanov, and S. Stoikov. 2014. The price impact of order book events. *Journal of Financial Econometrics* 12: pages 47-88.

Corwin S.A. and P. Schultz. 2012. A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance* 67: pages 719-760.

Coval J. and E. Stafford. 2005. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86: pages 479-512.

Cohen, K.J., and R.A. Schwartz. 1989. An electronic call market: its design and desirability. *The Challenge of Information Technology for the Securities Markets: Liquidity, Volatility, and Global Trading*, pages 55-85.

Cross, F. 1973. The behavior of stock prices on fridays and mondays. *Financial Analysts Journal* 29/6, pages 67–69.

Cushing, D. and A. Madhavan. 2000. Stock returns and trading at the close. *Journal of Financial Markets* 3, pages 45–67.

Demsetz H. 1968. The cost of transacting. *Quarterly Journal of Economics* 82, pages 33-53.

Duffe, D. 2010, Presidential address: Asset price dynamics with slow-moving capital. *Journal of Finance* 65: pages 1237-1267.

Economides, N. and R. Schwartz. 1995. Electronic call market trading. *Journal of Portfolio Management*, 21(3), pages 10-18.

Farmer, J.D. and S. Skouras. 2012. Review of the Benefits of a Continuous Market vs. Randomized Stop Auctions and of Alternative Priority Rules (Policy Options 7 and 12). *UK Governments Foresight Project, The Future of Computer Trading in Financial Markets*, Economic Impact Assessment EIA11.

Fama, E.F., Fisher, L., Jensen, M.C., and R. Roll. 1969. The adjustment of stock prices to new information. *International Economic Review* 10, pages 1-21.

Fama, E.F. and J.D. MacBeth. 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* 81, pages 607-636.

Fleming, M.G. and W. Liu. 2014. *Intraday Pricing and Liquidity Effects of U.S. Treasury Auctions*. Working Paper, Federal Reserve Bank of New York.

Foucault, T., O. Kadan, and E. Kandel. 2005. Limit order book as a market for liquidity. *Review of Financial Studies* 18, pages 1171-1217.

Foucault T., R. Kozhan, and W.W. Tham. 2015. Toxic arbitrage. Manuscript, HEC Paris

Frijns, B., A. Gilbert, and A. Tourani-Rad. 2010. The dynamics of price discovery for cross-listed shares: Evidence from Australia and New Zealand. *Journal of Banking and Finance* 34, pages 498-508.

Froot, K.A. and E. Debora. 1999. How are stock prices affected by the location of trade? *Journal of Financial Economics* 2, pages 189-216.

Gao, L., Han, Y., Li, S.Z., and G. Zhou. 2018. Market intraday momentum. *Journal of Financial Economics* 129, pages 394-414.

Gerety, M.S. and J.H. Mulherin. 1992. Trading halts and market activity: an analysis of volume at the open and the close. *Journal of Finance* 47, pages 1765-1784.

Gomber, P., Schweickert U., and Theissen E. 2013. Liquidity dynamics in an electronic open limit order book: an event study approach. *European Financial Management* 21, pages 52-78.

Goodfellow C., Schweickert U., and Theissen E. 2010. How do trading costs vary across the day? A note on the innovative XLM measure for small caps at the Frankfurt Stock Exchange. *The Journal of Trading* 4, pages 78-87.

Goyenko, R.Y., C.W. Holden, and C.A. Trzinka. 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics* 92, pages 153-181.

Grauer, F. and T. Odean. 1995. The internal call market: a clean, well-lighted place to trade, in Risk Management: problems and solutions by W. Beaver and G.P. Parker. McGraw-Hill.

Grossman S.J. and M.H. Muller. 1988. Liquidity and market structure *Journal of Finance* 43, pages 617-633.

Jaffe, J. and R. Westerfeld. 1985. The week-end effect in common stock returns: the international evidence. *Journal of Finance* 40: pages 433-454.

Hartmann P. 1998. Trading volumes and transaction costs in the foreign exchange market. Evidence from daily dollar-yen spot data. *Journal of Banking and Finance* 23, pages 801-824.

Hasbrouk, J. 2009. Trading costs and returns for U.S. equities: estimating effective costs from daily data. *Journal of Finance* 64, pages 1445-1477.

Hasbrouk, J. 2017. *Securities Trading: Principles and Procedures*. Manuscript, version 12.

Hendershott, T., A.J.Menkveld, R. Praz, and M.S. Seasholes. 2018. *Asset price dynamics with limited attention*. Working paper.

Heston, S.L., R.A. Korajczyk, and R. Sadka. 2010. Intraday patterns in the cross-section of stock returns. *Journal of Finance* 65: pages 1369-1407.

Hussain, S.M. 2011. The intraday behavior of bid–ask spreads, trading volume and return volatility: evidence from DAX30. *International Journal of Economics and Finance* 3, pages 23-34.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *Journal of Finance* 45, pages 881-898.

Keim, D.B. 1989. Trading patterns, bid-ask spreads, and estimated security returns: The case of common stocks at calendar turning points. *Journal of Financial Economics* 25, pages 75-97.

Kalay, A., L. Wei, and A. Wohl. 2002. Continuous trading or call auctions: revealed preferences of investors at the Tel Aviv Stock Exchange. *Journal of Finance* 1, pages 523-543.

Kandel, E., B. Rindi, and L. Bosetti. 2012. The effect of a call auction on market quality and trading strategies. *Journal of Financial Intermediation* 21, pages 23-49.

Kissel R. 2014. The science of algorithmic and trading and portfolio management. Academic Press.

Lo, A.W. and A.C. MacKinlay. 1990. When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3: pages 17-205.

Lou, D. 2012. A flow-based explanation for return predictability. *The Review of Financial Studies* 25: pages 3457-3489.

Lou, D., H. Yan, and J. Zhang. 2013. Anticipated and repeated shocks in liquid markets. *Review of Financial Studies* 26: pages 1891-1912.

Lockwood, L.J. and S.C. Linn. 1990. An examination of stock market return volatility during overnight and intraday periods 1964-1989. *Journal of Finance* 45, pages 591-601.

Lou, X. and T. Shu. 2017. *Price impact or trading volume: why is the Amihud (2002) measure priced?* Working paper.

MacKinlay A.C. 1997. Event studies in economics and finance. *Journal of Economic Literature* 35, pages 13-39.

Mclean R.D. and J. Pontiff. 2016. Does academic research destroy stock return predictability? *Journal of Finance* 71, pages 5-32.

Madhavan, A. 1992. Trading mechanisms in securities markets. *Journal of Finance* 47, pages 607-642.

Malinova, K. and A. Park. 2013. Liquidity, volume and price efficiency: the impact of order vs. quote driven trading. *Journal of Financial Markets* 16(1), pages 104-126.

McInish, T. and R.A. Wood. 1992. A flow-based explanation for return predictability. *The Review of Financial Studies* 25, pages 3457–3489.

Ohta, W. 2006. An analysis of intraday patterns in price clustering on the Tokyo Stock Exchange. *Journal of Banking and Finance* 30, pages 1023-1039.

Pagano, M.S., L. Peng, and R. Sadka. 2010. A call auction's impact on price formation and order routing: Evidence from the NASDAQ stock market. *Journal of Financial Markets* 16: pages 331-361.

Pagano, M.S. and R.A. Schwartz. 2005. NASDAQ's closing cross: Has its new call auction given NASDAQ better closing prices? Early findings. *Journal of Portfolio Management* 31, pages 100-111.

Pascual, R., Pascual-Fuster, B., and F. Climent. 2006. Cross-listing, price discovery and the informativeness of the trading process. *Journal of Financial Markets* 9, pages 144-161.

Sigaux, J. 2017. *Trading Ahead of Treasury Auctions*. Working Paper.

Smirlock, M. and L. Starks. 2009. Day-of-the-week and intraday effects in stock returns. *Journal of Financial Economics* 17, pages 197-210.

Sun, L., M. Najand, and J. Shen. 2016. Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking and Finance* 73: pages 147-164.

Theissen E. and Westheide C. 2017. *Call of duty: designated market maker participation in call auctions*. Center for Financial Research Working paper, No. 16-05.

Wood, R.A., McInish T.H., and J.K. Ord. 1985. An investigation of transactions data for NYSE stocks. *Journal of Finance* 40, pages 723-739.

Zhu H. 2013. Do dark pools harm price discovery? *Review of Financial Studies* 27, pages 747-789.