Essays on market microstructure and return predictability of mutual funds

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Ekaterina Serikova

from

Russia

Approved on the application of

Prof. Paul Söderlind, PhD

and

Prof. Dr. Albert Menkveld

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Summary

This thesis contains three papers. Each paper addresses a distinct research question and is implemented on a separate dataset.

The first paper concludes that daytime auctions, together with market opening and closing intervals, contribute to the periodicity of the cross-section of stock returns. By applying the model of infrequent rebalancing, I show that model parameters fit the data for the after-auction intervals. I thus conclude that after-auction periods take over a large share of infrequent rebalancing and show that this effect is driven by the 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.

The second paper sheds light on how traders allocate risk of stock portfolios in a trading day. Traders decrease risk before the market close. They do so by selling stocks with the highest marginal risk and buying stocks that decrease the risk of their portfolio the most. As our measure of portfolio risk relates to the one that clearing houses use for the margin requirements, we conclude that the risk-reduction behavior is driven by traders' reluctance to provide end-of-day margin contributions to the CCP. These trading flows in the direction of risk contraction distort closing stock prices.

The third paper replicates and combines eight prominent predictors of mutual fund returns to obtain a composite, aggregate fund predictor. While only three of the eight individual variables are significant predictors of future fund performance in a multivariate setting, the composite predictor has strong forecasting power. A hypothetical quintile-based long-short strategy based on the composite predictor realizes a four-factor alpha of 6% per year. The performance spread is robust to different regression specifications, is similar for different size classes and investment styles, and persists over time. Our results point towards inefficiency in the market for actively managed equity funds.

Zusammenfassung

Vorliegende Doktorarbeit umfasst drei wissenschaftliche Studien. Jede Studie befasst sich mit einer spezifischen Forschungsfrage und wird auf separaten Datensatz angewendet.

Die erste Studie zeigt, dass Tagesauktionen zusammen mit Marktöffnungs- und -schließungs-intervallen zur Regelmässigkeit des Aktienrenditeprofils beitraten. Durch die Anwendung des Modells des infrequent Rebalancing zeige ich, dass die Modellparameter mit den Nachauktionsintervallen übereinstimmen. Ich schließe daher, dass die Nachauktionsphasen einen großen Teil des infrequent Rebalancing ausmachen. Dieser Effekt wird durch die Konzentration von Liquiditätshändlern verursacht. Kleine, niedrig fragmentierte Aktien zeigen die stärksten Anzeichen für Rebalancing nach Tagesauktionen.

Die zweite Studie zeigt, wie Händler das Risiko von Aktienportfolios während eines Handelstages verteilen. Händler verringern das Risiko vor Marktschluss. Sie tun dies, indem sie die Aktien mit dem höchsten Grenzrisiko verkaufen während sie die Aktien kaufen, die das Risiko ihrer Portfolios am stärksten verringern. Da unsere Methode für das Portfoliorisiko derjenigen entspricht, welche Clearing-Häuser zur Margenanforderungen verwenden, kommen wir zum Schluss, dass das Verhalten der Risikominimierung von der Zurückhaltung der Trader bei der Bereitstellung von End-of-Day-Margenbeiträgen bestimmt ist. Diese Handelsströme in Richtung Risikokontraktion verzerren die Schlusskurse.

Die dritte Studie repliziert und kombiniert acht bekannte Prädiktoren für die Erträge von Investmentfonds, um einen zusammengesetzten Fondsprädiktor zu erhalten. Während nur drei der acht Einzelvariablen signifikante Prädiktoren für die zukünftige Fondsperformance in einem multivariaten Umfeld sind, hat der Composite Prädiktor eine starke Prognosefähigkeit. Eine hypothetische, quintilbasierte Long-Short-Strategie, die auf dem Composite Prädiktor basiert, realisiert einen Vier-Faktor Alpha von 6% pro Jahr. Der Performance-Spread ist robust gegenüber verschiedenen Regressionsspezifikationen, ist für verschiedene Größenklassen und Anlagestile ähnlich und hält sich über die Zeit. Unsere Ergebnisse deuten auf eine Ineffizienz im Markt für aktiv verwaltete Aktienfonds hin.

The Role of Daytime Stock Auctions in Intraday Return Seasonality

Ekaterina Serikova *

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ABSTRACT

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.

JEL-Code: G12, G14

Keywords: Market microstructure, market design, auctions, intraday periodicity

*Ekaterina Serikova is with the School of Finance at the University of St.Gallen (HSG), s/bf-HSG, Unterer Graben 21, CH-9000, St.Gallen, Switzerland, ekaterina.serikova@unisg.ch. I thank Paul Sderlind, 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.

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

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

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]

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

[2] *Deutsche Boerse confirms dark pool closure*, The Trade, February 2017
[3] *NYSE liquidity drive pushes midday auctions*, Financial Times, May 2016

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

[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.

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 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

[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.

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 (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.

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

[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.

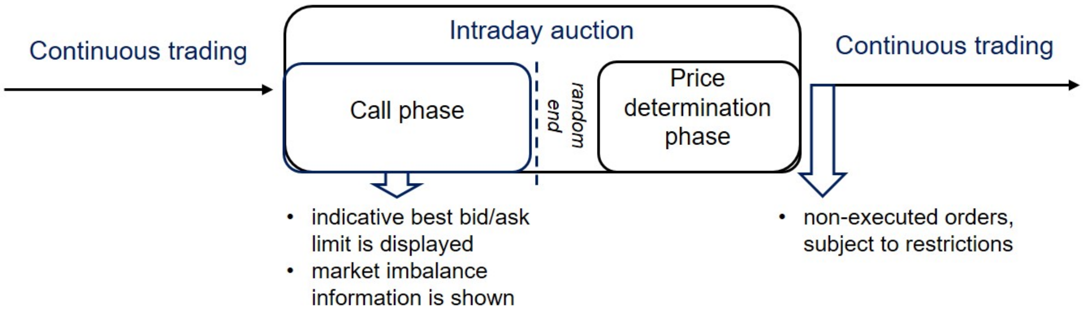

Figure 1: The process of daytime auctions on the Xetra

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 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

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.

[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.

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.

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 8 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

[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.

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.

	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.

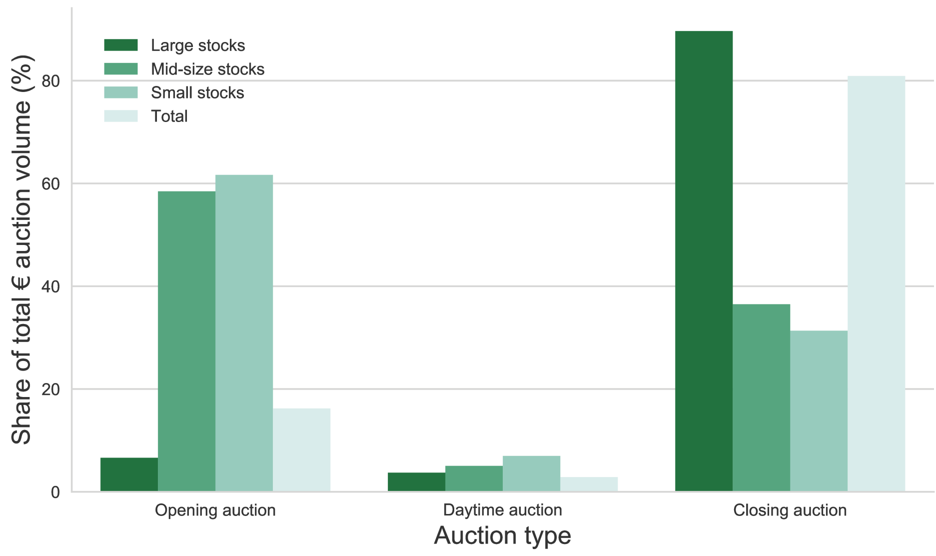

Figure 2: Split of auction trading volume on the Xetra. The figure demonstrates the breakdown of the auction volume. Small stocks are those whose free-float market capitalization on 31/01/2013 from *Thomson Reuters Datastream.* is at the lowest 33% of the sample. Large stocks are 33% with the highest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

[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.

continuous trading period. This result supports the findings for the US continuous market, 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.

[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.

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

[19]The results stay the same upon using half-hour sampling frequency, please see *Robustness* section.

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

[20] A number for the US market is taken from Heston et al. 2010.

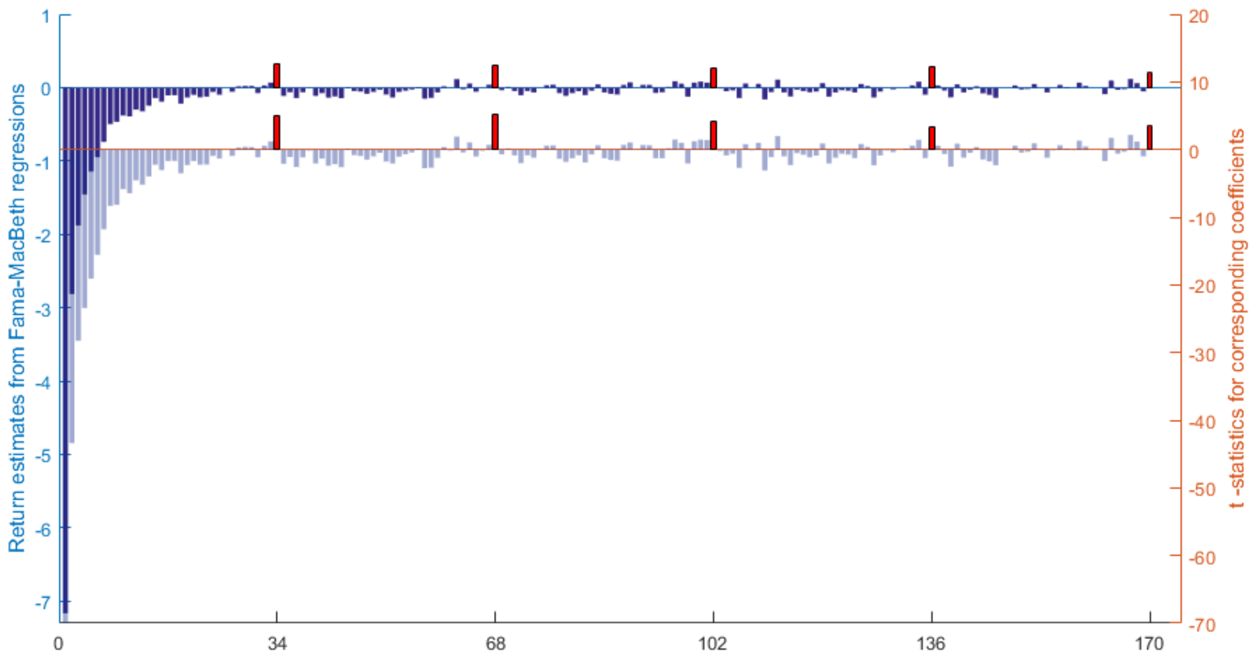

Figure 3: Time-series averages of return responses. The figure demonstrates results from (2): average return responses and corresponding t-statistics. A trading day is divided into 34 disjoint intervals, each containing fifteen minutes. For interval t and lag k, I run a simple univariate cross-sectional 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:

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

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 9 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 12 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

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

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 12 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.

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

[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.

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.

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

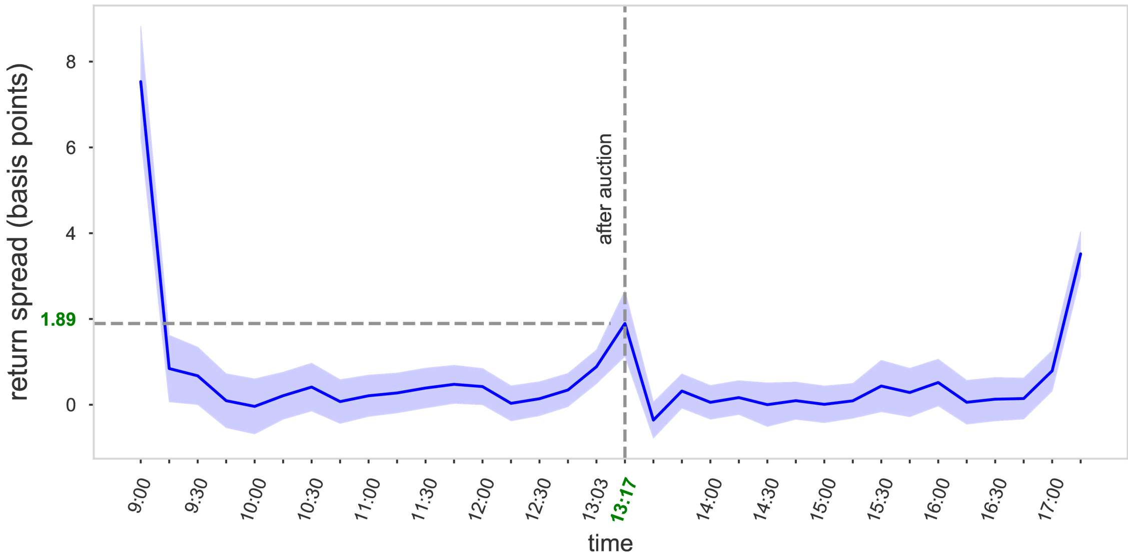

Figure 4: Average return spread of the daily momentum strategy. This figure shows the average return spread of the daily momentum strategy for each fifteen-minute interval during a day. The stocks are sorted based on their historical returns at the same interval one, two, three, four, and five days ago. 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 8 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

[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.

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 14 in Appendix).

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 13 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 8 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 9 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.

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.

	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.

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 10 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 11 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 13 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 onetoone 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

[25] Please refer to the Appendix 7 for the derivation of this proposition.

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.

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.

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.

[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*).

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 ChiX Europe evaporates at the time when Xetra switches to the daytime auction. As soon as the auction prices are defined, the ChiX 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

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

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.

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]

[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.

Small stocks. Degree of fragmentation	Returns	Price impact	Volume	Volatility
Low	✔	✔	✔	✔
Middle	✔	✔	✖	✖
High	✖	✖	✖	✖
Large stocks. Degree of fragmentation	Returns	Price impact	Volume	Volatility
low	✔	✖	✔	✔
mid	✖	✔	✖	✖
high	✖	✖	✖	✖

Table 5: Features of the model of infrequent rebalancing for small and large stocks This table demonstrates whether the estimated indicators for three different portfolios of small/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 small/large stocks with the highest share of trading value happening on the Xetra. Orange tick for volume of large stocks means that its value is high but insignificant. The line in the middle related to the model indicators for a portfolio of small/large, but with a lower trading share on the Xetra, higher trading on other markets(s). Similarly, the lower line shows measures for small/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.

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

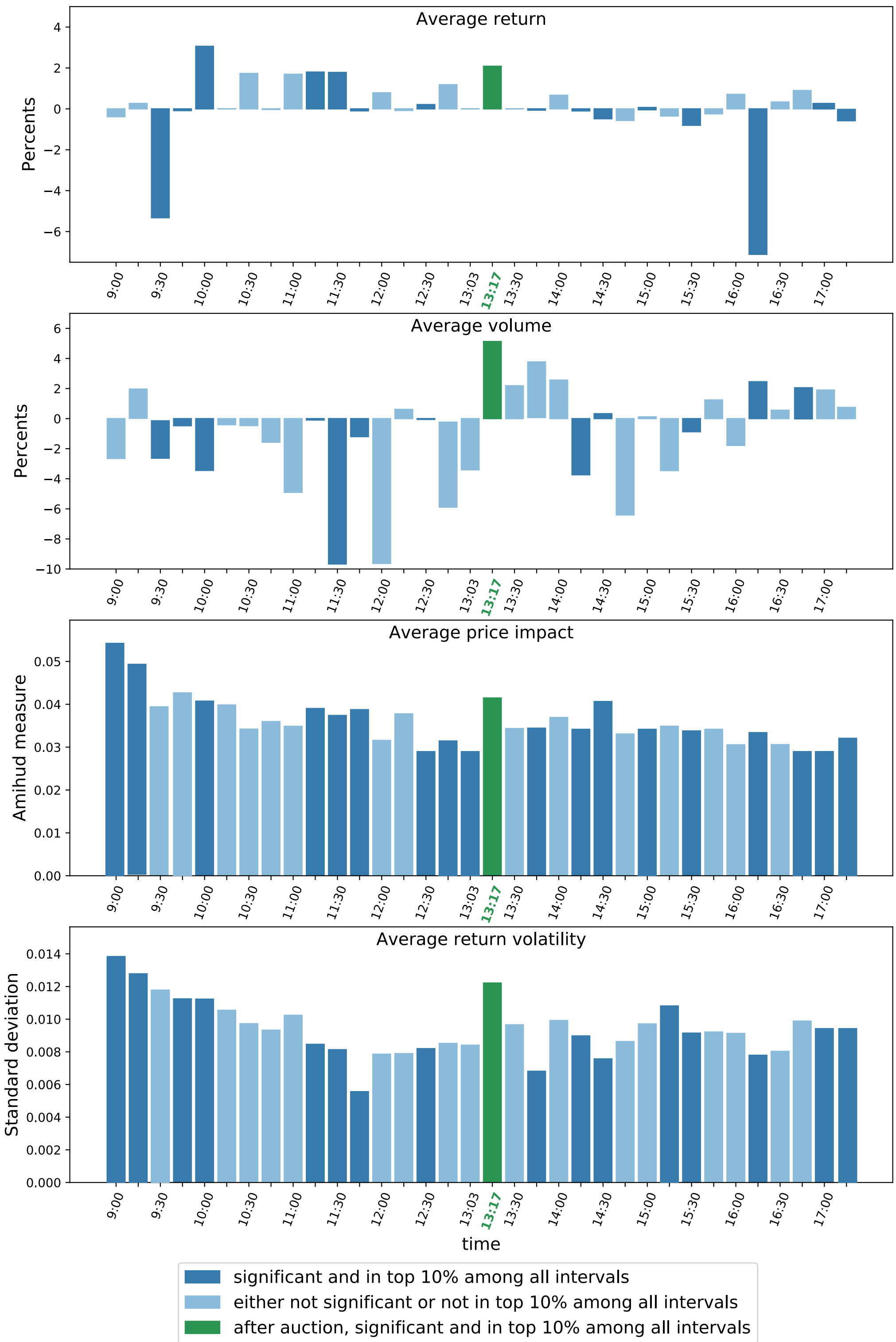

Figure 5: Features of the model of infrequent rebalancing for small low-fragmented stocks. Average returns and average volumes are defined as μ_k from (7). Coefficients are average returns adjusted for the standard deviation; the price impact is based on the Amihud measure from (6); return volatility 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 preUS 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.

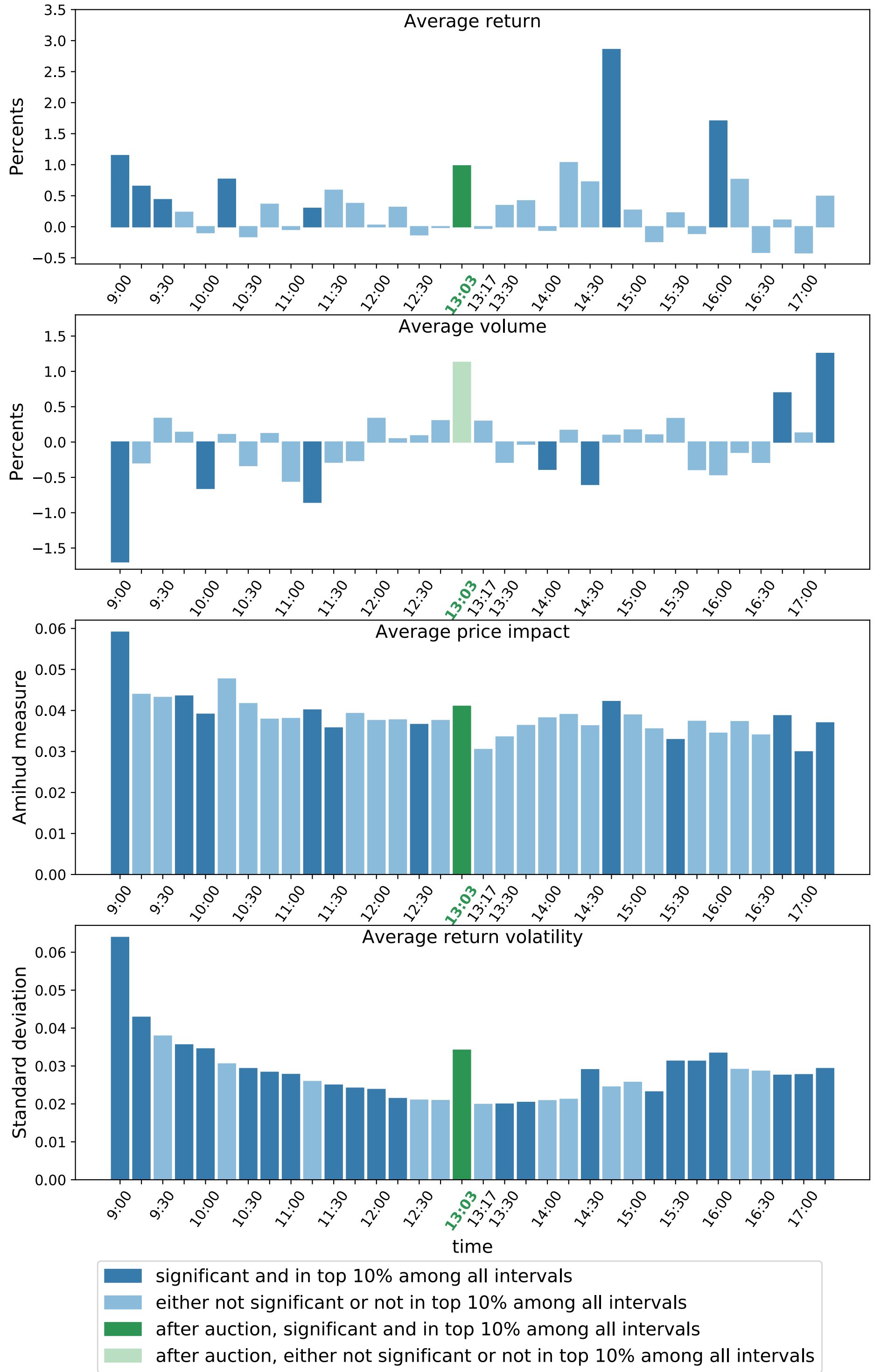

Figure 6: Features of the model of infrequent rebalancing for large low-fragmented stocks. Average returns and average volumes are defined as μ_k from (7). Coefficients are average returns adjusted for the standard deviation; the price impact is based on the Amihud measure from (6); return volatility 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 fifteenminute 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 afterauction 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 lateinformed 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 valueweighted 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 afterauction fifteen-minute returns on day t, T is the total number of trading days.

I find that postauction 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 6). 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 afterauction 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	...
α_τ	-0.001	0.000	-0.000	-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**	
	(0.42)	(0.12)	(0.54)	(1.57)	(-0.14)	(1.04)	(-0.85)	(2.08)	

...	15:30	15:45	16:00	16:15	16:30	16:45	17:00	17:15
	-0.001	-0.001	-0.001	-0.000	-0.000	-0.001	0.000	0.000
	-1.45	0.32	5.81	**5.36**	0.45	2.57	-2.84	**4.25**
	(0.63)	(0.15)	(1.29)	(2.32)	(0.24)	(0.97)	(-1.18)	(2.01)

Table 6: 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 timeseries 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

[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.

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, 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).

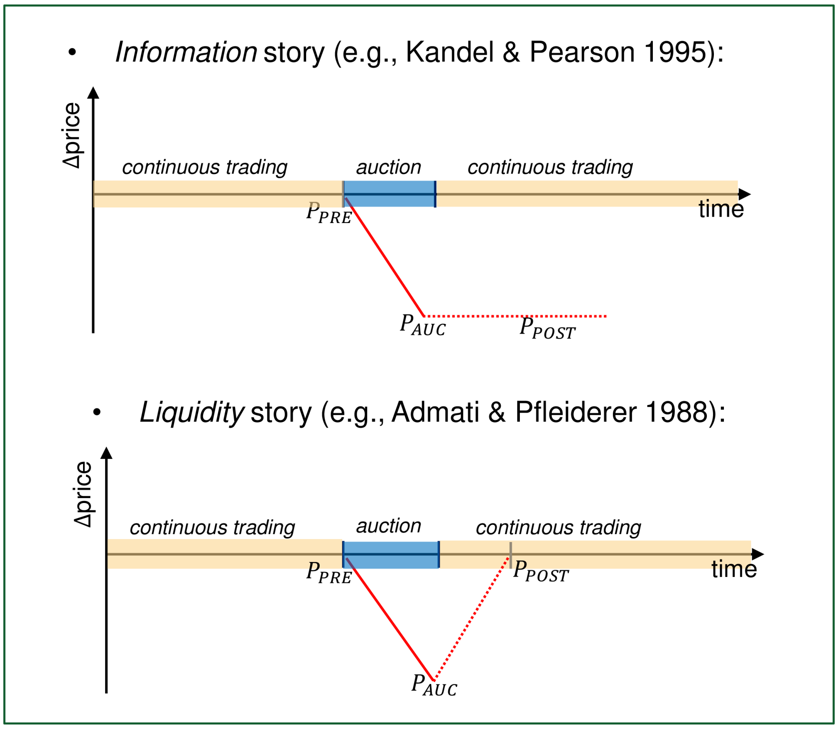

Figure 7: Price behaviour consistent with informational and liquidity models. The figure represents the dynamics of stock prices after intraday auctions implied by two different market microstructure models. The upper graph corresponds to the price dynamics according to Kander and Pearson 1995. The bottom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

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Appendix A

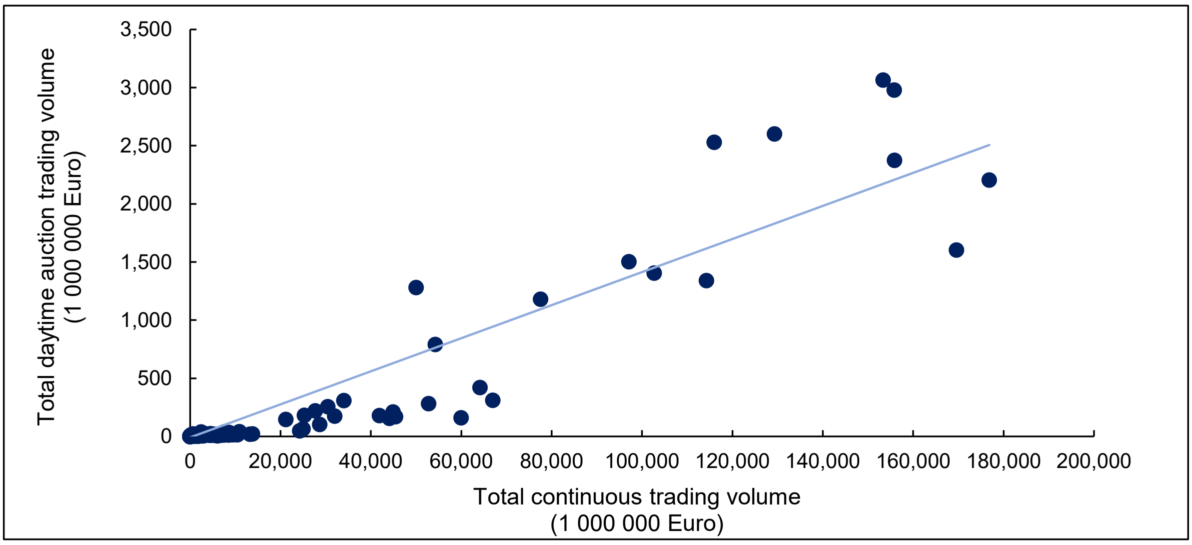

Figure 8: Relationship between volume in daytime stock auctions and in continuous trading. The figure plots the stock size, measured as the total daily total volume versus its daytime auction volume, both in Euro. Volume is defined as price of a given stock multiplied by the number of stocks traded. 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.

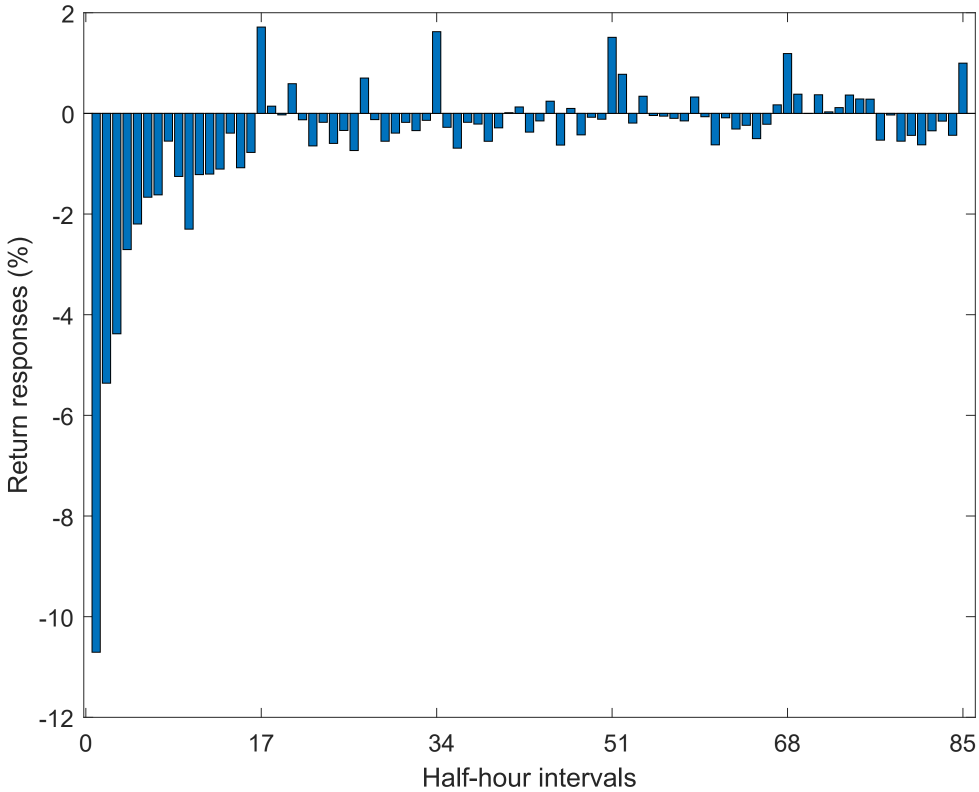

Figure 9: Time-series averages of return responses. Half-hour sampling frequency. The figure demonstrates results from (2): average return responses and corresponding *t*-statistics. A trading day is divided into 17 disjoint intervals, each containing thirty minutes. For interval *t* and lag *k*, I run 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.

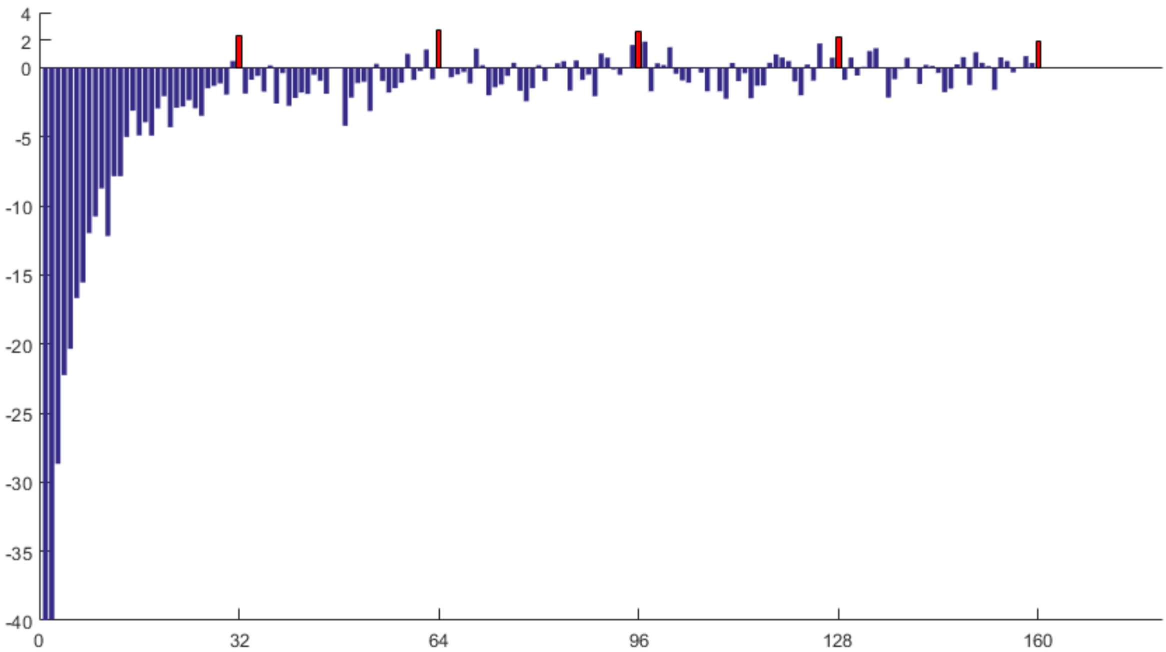

Figure 10: *t*-statistics of averages return responses without market open and close intervals. The figure demonstrates results from (2): average return responses and corresponding *t*-statistics. A trading day is divided into 32 disjoint intervals, each containing fifteen minutes. For interval *t* and 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.

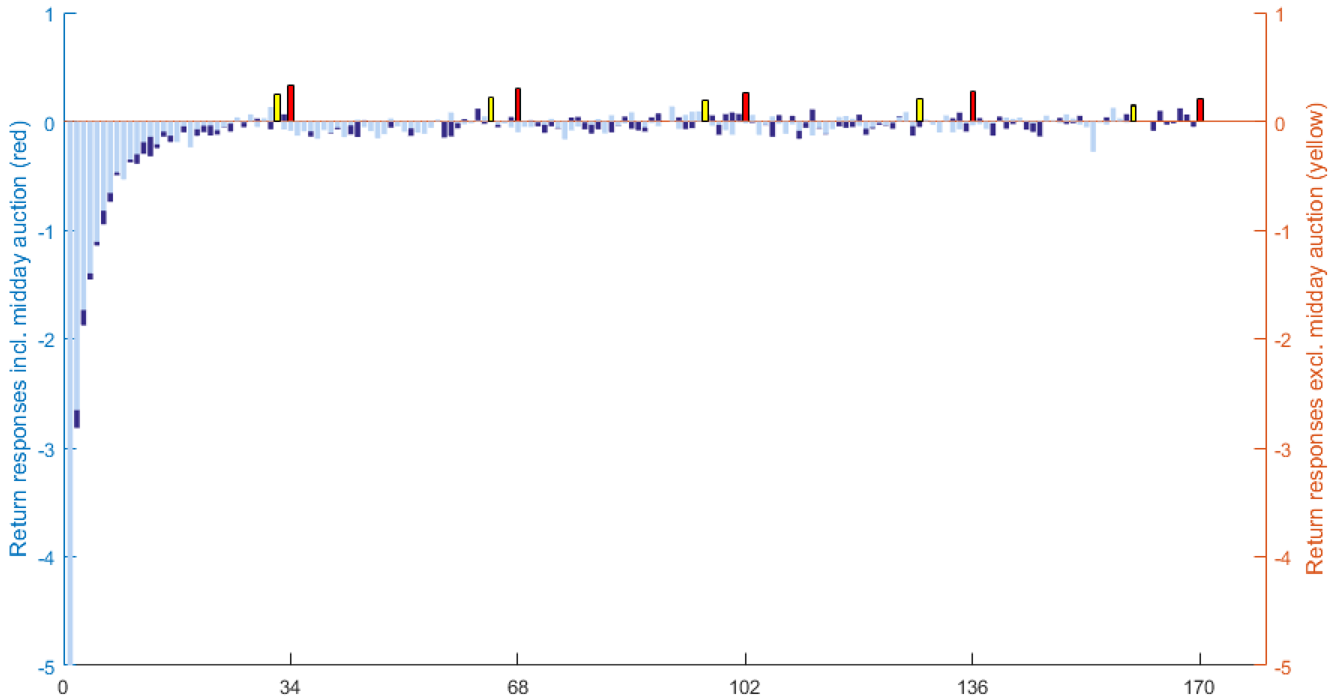

Figure 11: Time-series averages of return responses with and without daytime auctions. The figure demonstrates results from (2): average return responses and corresponding t-statistics. A trading day is divided into 34 disjoint intervals, each containing fifteen minutes. For interval t and lag k, I run 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 7: 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.

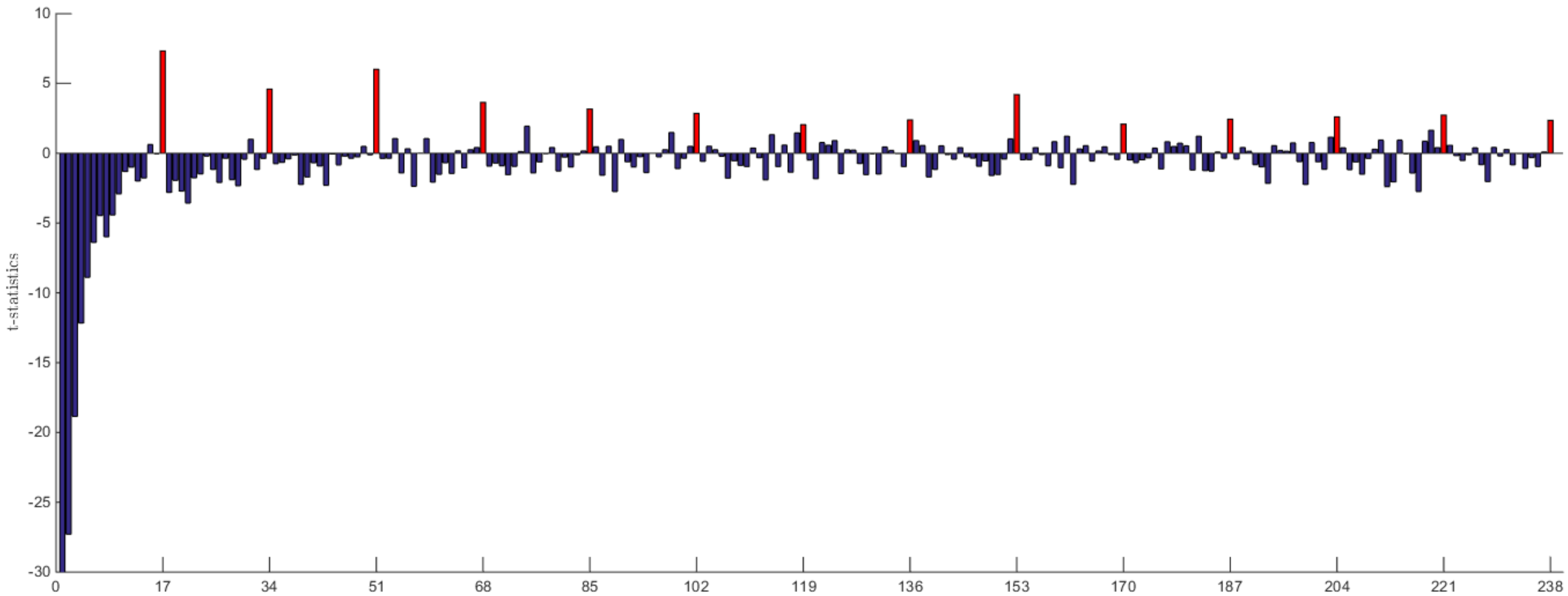

Figure 12: *t*-statistics of the return spread of long-short portfolio based on momentum strategy *k* days ago. The figure represents t-statistics of the return spread of momentum strategy that is built on the revealed daily return periodicity. Stocks are sorted based on their returns k intervals ago ($k \in [1, ..., 238]$), 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).

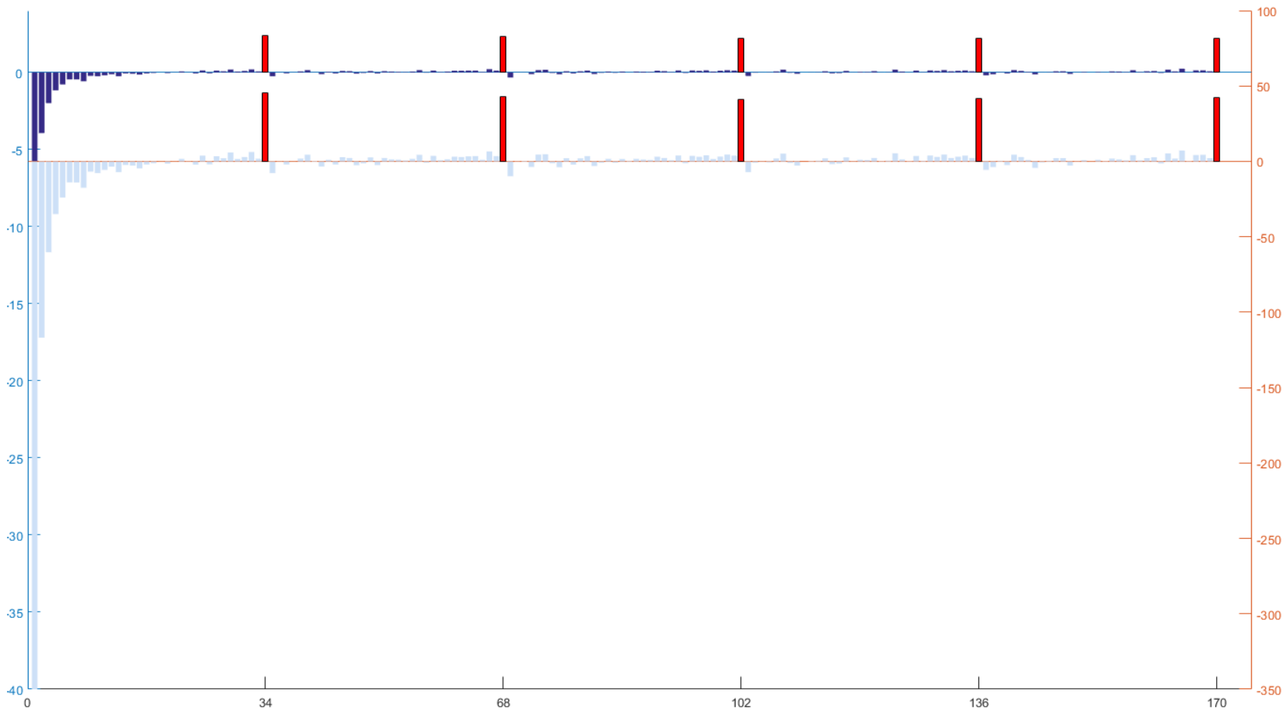

Figure 13: Average time–series volume change responses coefficients from cross–sectional regressions. The figure demonstrates results from (2): average volume changes and corresponding *t*-statistics. A trading day is divided into 34 disjoint intervals, each containing fifteen minutes. For interval *t* 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 8: 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 9: 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 10: 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 11: 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.

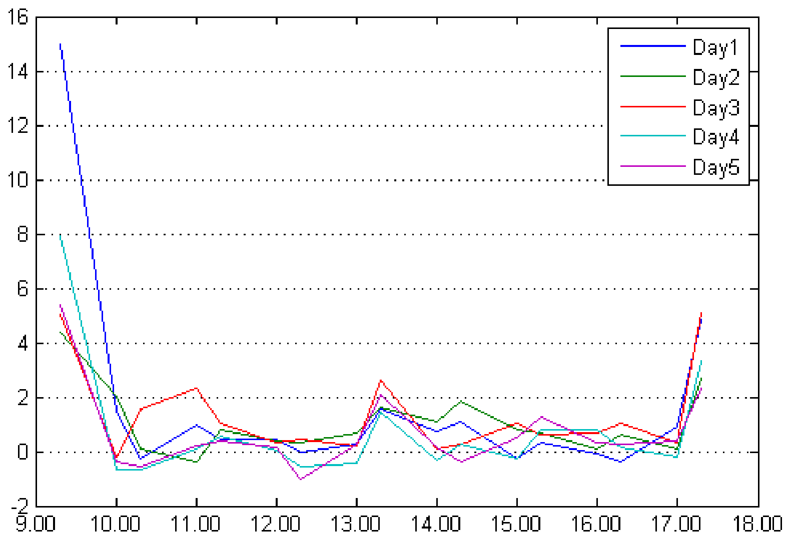

Figure 14: The intraday distribution of return spreads of the daily strategy for each day of the week

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 12: Two-week performance of a daily momentum strategy based on *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 13: 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.

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:

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

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.

Time for Dinner? No, for Risk Contraction*

Albert J. Menkveld† Ekaterina Serikova‡

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ABSTRACT

The study sheds light on how financially constrained traders allocate the risk of their equity portfolios during a trading day. They tend to contract risk before the market close, providing a central clearinghouse (CCP) with a ”natural hedge”. During this interval, traders sell and buy those stocks that decrease the total risk of their portfolio the most. As our measure of portfolio risk corresponds closely to the CCP estimation of daily margin requirements, these most traded stocks have the largest impact on the potential margin requested from CCP members on a daily basis. We therefore conclude that the risk-contraction behavior is driven by traders' reluctance to provide end-of-day margin contributions to the CCP. These trading volumes in the direction of risk contraction distort closing stock prices: for the top 10% most traded stocks, a pricing error at the close reaches 58 basis points.

JEL-Code: G10, G14, G15

Keywords: Intraday risk, institutional investors, trading patterns, price distortions, clearing

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†Albert J. Menkveld is with the Vrije Universiteit Amsterdam, School of Business and Economics, De Boelelaan 1105, 1081 HV, Amsterdam, Netherlands, albertjmenkveld@gmail.com, and Tinbergen Institute

‡Ekaterina Serikova is with the School of Finance at the University of St.Gallen (HSG), s/bf-HSG, Unterer Graben 21, CH-9000, St.Gallen, Switzerland, ekaterina.serikova@unisg.ch.

1 Introduction

Since the implementation of the Dodd-Frank Act in 2010, the systemic importance of central clearinghouses (CCP) was widely recognized and acknowledged. The Act, among other regulatory provisions, contained supervisory arrangements aimed at improving transparency and resilience of clearinghouses. Admitting the systemic importance of clearinghouses, the Act challenged authorities to improve and better coordinate the oversight of these institutions. To put the macroprudential approach into effect, regulators were called upon identifying and analyzing the complex risk linkages among clearinghouses and between clearinghouses and the financial firms that rely on and support them.

Where do these risks come from? Clearinghouses are there to lower the costs associated with clearing and settlement by centralization and standardization of trades. CCPs act as a counterparty of each trade, being a buyer to every seller and seller to every buyer – such intermediation helps to reduce the credit and liquidity risks of a counterparty. There is, however, the other side of such centralization - it generates the accumulation of sizable financial and operational risks in just a few institutions. For example, there are only nine equity clearing houses in Europe as of June 2018.[1] A failure of one of them might create a loss of trust and uncertainty across all clearinghouse participants and customers, or even trigger a further failure of other clearinghouses. Such risk can concentrate either in a set of closely connected entities, as well as within a particular CCP. For example, if a large trading partner defaults or fails to meet its contractual obligations, this could create considerable financial losses for a clearinghouse, especially if stock markets are highly volatile. Moreover, the default of a trading partner might even intensify stock market volatility.

These risks need to be addressed. The paper provides important insights for CCP risk management by studying how clearinghouse members allocate the risk of their equity portfolios during a trading day. We use the dataset from one of the largest European equity CCP that

[1] Wyman, O. *The future of clearing*. 2019. World Federation of Exchanges.

allows us to track the changes in individual stock portfolios. Firstly, we find a pervasive pattern that traders shrink risk by the end of a trading day, right before the CCP revises a margin on a per-trader basis. Understanding the risk behavior and the risk profile of each clearinghouse participant can help identify and forecast potential sources of the CCP risk and contribute to its operational efficiency and resiliency. We then define how aggregate market factors relate to the direction of trader's risk change during the upcoming intraday interval. These insights provide a CCP with a better intraday risk supervision and might potentially help to form policy decisions on intraday margining.

Shifting from the CCP perspective of the analysis to a larger question of price formation, we show that the end-of-day risk-contracting trading influences closing stock prices. The impact of (sizable) trading flows on stock prices is a crucial question of asset pricing and market efficiency. Moreover, traders, financial institutions, and regulators extensively use closing prices as a reference point for investing and regulatory decisions. In particular, stock closing prices are used to compute mutual fund net asset value or the performance of a large number of investment strategies. Also, prices at the close often determine the expiration value of derivative instruments and directors' options (Comerton-Forte and Putnins 2009). Therefore, evidence on price manipulation reported in research is not surprising. For example, Carhart et al. 2002 report that fund managers in the U.S. manipulate prices, so that price inflation is localized in the last half hour before the close and is more intense on quarter-end days. Stoll and Whaley 1991 show that large positions in derivatives on the underlying stock were extensively used as a way to manipulate closing stock prices.

To conclude, the motivation of the study is hence two-fold: the results bear policy and regulatory implications, as well as provide a fresh piece of evidence on the relationship between margins and stock price distortions. The paper contributes to the considerable body of literature on the topic, which we introduce below.

Related literature. This paper is related to three main directions of the existing research.

Recent policy-oriented studies have also become worrisome about the systemic nature of the potential clearinghouse risk. However, data on CCPs, especially, on a trader level, are rare. Several studies assess the impact of the CCPs introduction on trading quality of the market (Menkveld, Pagnotta, and Zoican 2015, Duffie et al. 2015, etc.). Further research analyzes the optimal design of the CCPs and the settlement process. Biais, Heider, and Hoerova 2012 show that the main advantage of centralized clearing is the mutualization of idiosyncratic risk and that making centralized clearing a mandatory procedure is Pareto improving. Correspondingly, Khapko and Zoican 2019 develop the model that shows that faster settlements benefit impatient traders but increase borrowing needs. Another direction of CCP-related research questions includes the assessment of margin sufficiency, collected by a CCP compared to the CCP risk exposure (Jones and Perignon 2013, Menkveld 2017). This paper adds to that literature by zooming on the risk behavior of CCP members on a trader portfolio level. This approach is appropriate from the perspective of CCP margin management because margins apply on a per-trader basis. It provides CCPs with a profound overview of intraday risk behavior and its consequences.

Intraday risk dynamics, aggregated from individual traders' portfolios, is per se rare evidence. Current literature has demonstrated the intraday dynamics of different market-wide risk measures such as volatility (starting from Chan, Chin, and Karolyi 1991, Foster and Viswanathan 1993, and later), trading volume (Hillion and Suominen 2004 and others), and different liquidity and illiquidity measures (Lee, Mucklow, and Ready 1993, McInish and Wood 1992, etc.). To the extent of our knowledge, no empirical findings have reported the aggregate risk dynamics of the market using individual trader portfolios. This study aggregates the market risk from the risk of individual portfolios of clearing members. Under such a setting, the analysis of commonality or heterogeneity in risk behavior across market participants becomes possible. This granularity is necessary from the perspective of CCP risk management.

The second line of related literature investigates the effect of trading flows on asset prices.

In particular, it was found that a large selling or buying pressure can influence prices: it creates temporary pricing errors and diverts prices from their fundamental values. For example, several studies (Lou 2012, Khan, Kogan, and Serafeim 2012, etc.) reveal the effect of mutual fund flows on the formation of distortions in stock prices. As a specific case, fire sales create temporary trade imbalances that convert further into stock price distortions (Coval and Stafford 2007). We bring in further evidence of stress-trading impact on stock prices on the intraday basis. Evidence on distorted closing prices rises further questions on using them for regulatory and investment decision purposes.

As all CCP members are subject to margin requirements, the literature about financially constrained investors is the third part of relevant research. It has been acknowledged that the behavior of investors, who are bound by financial constraints, can have an impact on the aggregate market dynamics and, eventually, on asset prices. In particular, fear of liquidity shocks, as well as liquidity shocks themselves, can motivate investors to sell more intensively (Chowdhry and Nanda 1998, Bernardo and Welch 2004). Alternatively, it has been shown that myopic decisions drive the behavior of investors who are close to default (Jensen and Meckling 1976). Related to that, Allen and Gale 2000 conclude that when agents borrow in order to invest, they largely shift their risk allocations. We contribute by proposing fresh evidence on the link between margin requirements and price distortions.

Main results. The most remarkable result is the phenomenon of the "natural hedge" that evolves on the market by the end of a day. In particular, CCP participants shrink the risk of their portfolios by the time when a CCP reassesses the margin for each member (every day, after the market close). As our measure of risk portfolio corresponds with the one, which the CCP uses for its internal margin estimations, the risk-contracting behavior can help traders evading end-of-day margin contributions to the CCP. This finding is favorable from the CCP perspective because it works like a shield against the immense risk accumulation in the portfolios of clearing members. The natural hedge is driven by (1) trading in the direction of risk contraction, especially by large traders, and (2) by changes in the covariance matrix of stock returns around the close. Secondly, focusing on the risk-contracting trades, we find that CCP members sell those stocks that have the highest marginal impact on the risk of their portfolios and buy stocks that decrease the risk of their portfolios the most per dollar. Further, we demonstrate how traders, being constrained by daily margining from the CCP, affect stock prices. Their risk-contracting end-of-day trading flows distort closing stock prices: for the top 10% most traded stocks, the pricing error at the close reaches 58 basis points.

The paper is structured as follows. Our methodology and the results on the natural hedge are presented in Section 2. Section 3 deepens into traders' behavior to a stock level. Each section concludes with the robustness tests. Pricing impact implications are shown in Section 4. Section 5 concludes.

2 Intraday risk dynamics and the natural hedge

2.1 Data

We use a dataset from one of the largest European equity clearing house, European Multilateral Clearing Facility (hereafter EMCF).[2] It clears transactions for almost all exchanges that trade Danish, Finnish, and Swedish stocks. The dataset contains information on spot transactions filed by clearing members (trader id,[3] stock id, quantity, price, trade direction, market id, timestamp, account type: house/client). As a trader id is stable across the period covered by the dataset, we can reconstruct open positions inside each trader's portfolio at any point in time. The dataset includes 242 stocks traded over 228 days from October 19, 2009 through September 10, 2010.

[2] In 2013, EuroCCP and EMCF merged to create Europe's largest cash equities clearing operation entity under the name of "European Central Counterparty N.V."

[3] Members are anonymized in the data and assigned a two-digit code (random numbers between 0 and 100).

Traders. The sample consists of 55 active clearing members, who are financial firms, e.g., international brokerage firms, local firms, and high-frequency traders. These clearing members are termed as traders in the paper. Each trader conducts trades either from its own ("house") account or by acting as an intermediary for clients' trades ("client" account). There are totally 226 accounts in the sample: 87 house and 139 client accounts. For the analysis, we use all trades submitted via both house and client accounts by each trader, because clearing members are charged for the margin based on the risk of their total portfolio. Therefore, we end up with the cross-section of 55 clearing members. In the sample, 28 out of 55 traders have 1-2 client accounts, 16 operate only from their own (house) accounts, 8 traders clear trades for 3-4 clients and only 3 traders have 15, 27, and 32 client accounts respectively.

During the sample period, house accounts trade more actively than client accounts: the average daily volume is 1.6 million shares versus 819 000 shares accordingly. Trading volumes vary substantially across traders: the average daily volume (hereafter ADV) is 1.2 million shares with the standard deviation of 2.3 million shares. In terms of traded value, €25 million is on average traded from the house accounts and €11 million - from the client accounts. For a more detailed statistics of the dataset, please refer to Menkveld 2017.

Markets. The dataset covers equity trading on 8 Nordic markets: BATS Europe, Burgundy, Chi–X, Nasdaq Europe, NOMX Copenhagen, NOMX Helsinki, NOMX Stockholm, and Quote MTF. The largest market in terms of the ADV is the NOMX Stockholm, followed by the NOMX Helsinki, but with more than two times lower ADV (Table 14). NOMX Copenhagen is the third-largest market, with an ADV close to the one of Chi-X. For the three largest markets, the trading volume of house accounts considerably exceeds that of client accounts. For smaller platforms, except the Burgundy, the ADV of house accounts is close to the ADV of the client accounts. In terms of traders' diversity, NOMX Copenhagen, Stockholm, and Helsinki attract the largest daily number of traders (34 out of 55). The least popular market in terms of traders' coverage is the Quote MTF, with only 2.3 traders per day.

Market	ADV (€1 000)	House accounts	Client accounts	Number of traders	Volume share before 17:00	Volume share after 17:00
(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
BATS Europe	166 303	50%	50%	20.8	4.2%	2.9%
Burgundy	106 070	86%	14%	10.7	2.7%	1.3%
Chi-X	532 344	59%	41%	26.4	13.6%	8.2%
Nasdaq Europe	28 789	41%	59%	18.4	0.7%	0.4%
NOMX Copenhagen	525 307	80%	20%	37.8	14.5%	0%
NOMX Helsinki	718 598	62%	38%	31.8	16.4%	24.3%
NOMX Stockholm	2 057 518	70%	30%	33.5	47.9%	62.7%
Quote MTF	895	49%	51%	2.3	0.1%	0.1%
Total	**4 135 827**	**68%**	**32%**		**87.1%**	**12.9%**

Table 14: Descriptive statistics per market. The table represents summary statistics per day: average daily trading volume (ADV), split between house and client accounts, the average daily number of unique traders, and average trading volume before and after 17:00 (the close of the NOMX Copenhagen). Average values are equal-weighted. Percentages in columns (6-7) are calculated based on the total euro trading volume before and after 17:00: the total values for these columns represent 100% for both.

All markets operate from 9:00 until 17:30 (after accounting for different time zones), except for the NOMX Copenhagen that closes at 17:00. As shown in the last two columns of Table 14, a share of trading volume of NOMX Helsinki and NOMX Stockholm increases by 50% and 30% correspondingly after the close of the Danish market, which might indicate a shift of volumes from an earlier close of the Copenhagen market.

Margin. Each CCP has its own risk model for margin calculations. Initial margin is usually calculated for all open positions in the portfolio and takes into account a range of stress and historically observed scenarios. Variation margin (usually for derivative CCPs) or initial margin adjustment (usually for equity CCPs) are generally based on the marked-to-market positions on a daily basis and is collected at the end of a trading day. For example, members may be required to provide an additional margin in form of cash to cover concentration risk of positions, especially in illiquid stocks.

The EMCF calculates margins according to their in-house Correlation Haircut Model. The methodology is proprietary and not available in the public domain. However, the EMCF reports that the model (1) takes into account the correlation between various products that are part of a trader's portfolio, (2) determines the risk factors that have the greatest impact on the portfolio, (3) shifts these components to find the worst-case scenario. The mechanics of margin estimation is as follows. Suppose a clearing member j acquired a position in stock i yesterday. Since settlement, the legal transfer of the asset, will only occur three days later (due to T+3 settlement cycle), the clearinghouse ensures all members against the default of j in the next three days. In case of default, the CCP automatically takes over j's trading positions and therefore also the potential trading loss (or gain) in its unsettled portfolio. It is, consequently, a standard practice to make the clearing member pay a margin that is proportional to the maximum loss on the existing portfolio.

2.2 Methodology

Intraday intervals. It is well known from the early market microstructure literature that trading volumes are exceptionally high at the market open and the market close. For example, 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 rather a J-shaped pattern (Kissel 2014). Consistent with this literature, the ADV in our sample is high at the market open and the highest around the market close. It first hikes before the Copenhagen market close around 17:00 and then spikes further before the close of other markets around 17:30 (Figure 15). As we wish to concentrate on the risk analysis independently of its seasonal components, the data should be transformed in such a way that results are not contaminated by this intraday seasonality.

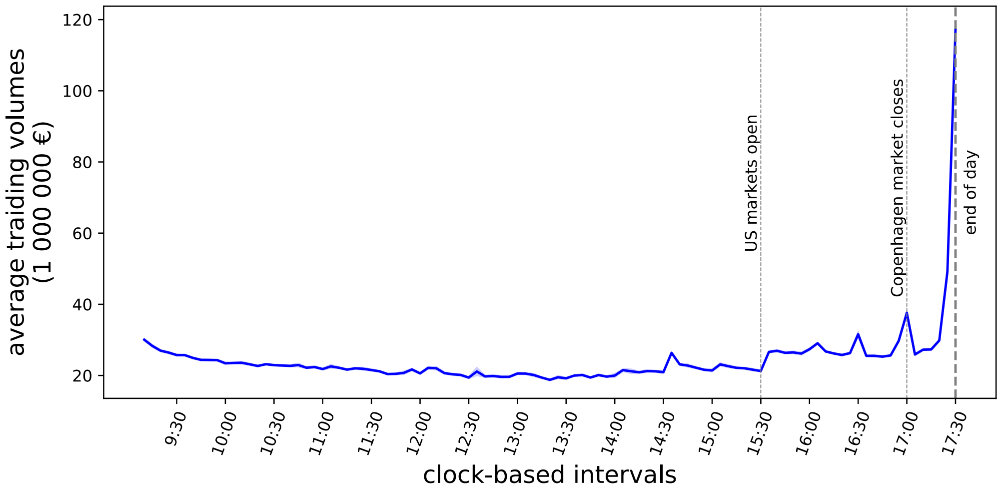

Figure 15: Intraday trading volume. The figure shows the average trading volumes at a five-minute frequency aggregated among all traders. Intervals are formed on time-clock intraday time intervals. Average values are equal-weighted. Boundaries represent the 1% confidence level. The sample consists of 55 traders and covers the period between September 2009 – October 2010.

Motivated by these intraday trends, the recently established market microstructure literature suggests to retract from splitting a trading day based on the usual clock time intervals. The same duration of five minutes contains trading volumes close to zero (e.g., around the mid-day) or spikes enormously (e.g., around the market close). To be able to analyze such data and keep some necessary statistical properties, a division of a trading day into activity-based intervals was suggested. In particular, Easley, de Prado, and O'Hara 2012 demonstrate that working with volume-based time has significant statistical advantages. Firstly, such transformation eliminates most intra-session seasonal effects. Secondly, it allows partial recovery of normality and the assumption of identically distributed returns. Finally, sampling in a volume-clock metric addresses the problem of random and asynchronous transactions, which is a major concern when computing correlations on high-frequency data. In support, Kyle and Obizhaeva 2019 develop a model of market microstructure invariance that is based on a similar idea that business time passes "faster" for more actively traded stocks. Specifically, the authors suggest bet size, bet volume, and bet volatility as alternatives of time-clock intervals for volatility and volume.

We compare three options for the activity-based intraday split: (1) according to the number of trades, (2) according to the number of stocks or (3) according to the euro volume traded. Taking a five-minute frequency as a benchmark,[4] with a regular trading day lasting between 9:00 and 17:30 and excluding overnight hours, we eventually have 102 intervals a day. Under this setting, every day is sliced so that each interval contains the same fixed number of trades, stocks, or euro volume traded. For example, if we choose a number of trades as a basis for a split, each interval contains the same number of transactions. This number is calculated as the total number of transactions across the whole sample period divided by 102 intervals and further divided by 228 days. Thus, the maximum number of intraday intervals is 102, with a lower number on the days with low number of trades. In order not to lose observations at the market close even for the days with low trading volume, we start slicing each trading day from the end (e.g., from 17:30). Therefore, interval 1 corresponds to the end of the day, while the interval 102 relates to the market open. we repeat the same procedure and create intervals that contain the same number of stocks and the same euro volumes traded.

Figure 16 provides a comparison of these three different approaches to the intraday split. When we divide according to the number of trades, we end up with the highest number of intervals per day on average. However, this approach (1) may catch an overall trend of of the increased intensity of trading activity, which might be influenced by higher activity of high-frequency traders on the market, (2) may reflect the fact that trade size has become smaller with time (Easley, de Prado, O'Hara 2012). The other two options that represent the split according to the number of stocks and euro volume traded, produce almost identical results. The number of stock-based intraday intervals is somewhat higher at the beginning of the sample; however, the number of volume-based intervals surpasses the latter during latest months. We chose to stick to the euro volume intervals as a baseline case for intraday intervals in the rest of the

[4]Swiss clearinghouse considers a five-minute interval an appropriate period to collect collateral to ensure counterparty risk *(SIX, 2014)*

analysis. Each interval thus contains the average traded euro volume of €2.5 million traded (total ADV divided by 102 intervals and by 228 days).

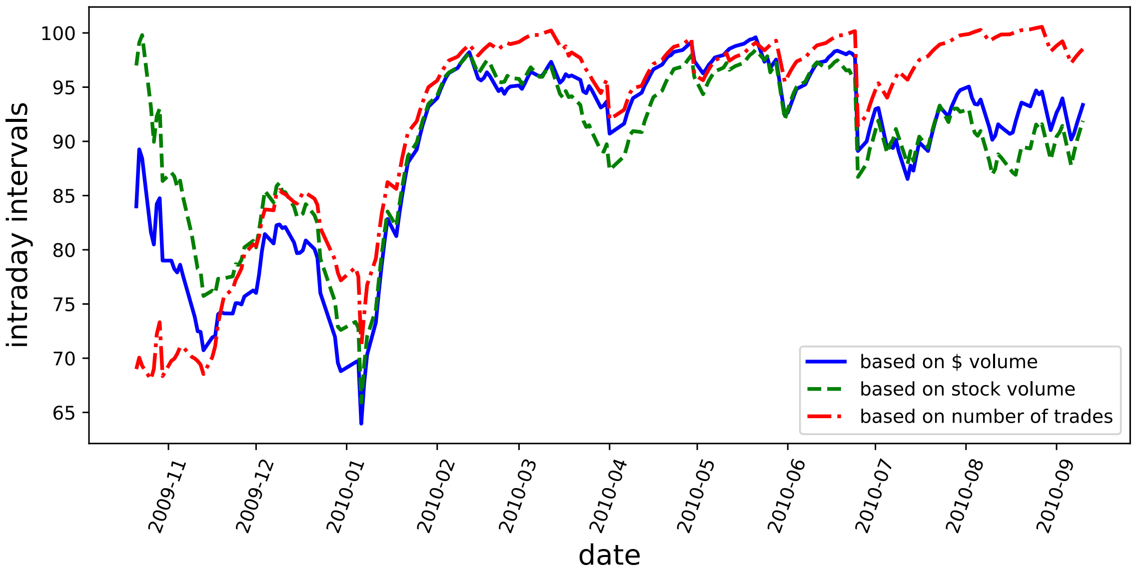

Figure 16: Average number of intraday intervals per split option. The figure shows the average daily number of intraday intervals according to three activity-based approaches: based on fixed euro volume per interval, based on the fixed number of stocks per interval, or based on the fixed number of transactions per interval. Each option takes the aggregate measure for the whole sample period that is divided by 102 and further divided by 228. The resulting number represents threshold inside each interval. The sample consists of 55 traders and the period between September 2009 – October 2010.

Measure of risk. Consider **I** securities with normally distributed returns

$$R \sim \mathcal{N}(0, \Omega) \tag{1}$$

Let **X** be a vector of trader's *j* P&L portfolio. If *n* is a vector of yet-to-settle trade portfolio of that member, then:

$$X \sim \mathcal{N}(0, \Sigma) \tag{2}$$

where X is normal with mean zero and Σ is a variance-covariance matrix of stock returns:

$$\Sigma = N'\Omega N \tag{3}$$

The risk of the portfolio held by member *j* at time *t* is measured as the standard deviation at each volume-clock time cutoff *t*:

$$\sigma_{j,t} = \sqrt{N'_{j,t}P'_t\Omega_t N_{j,t}P_t}, \tag{4}$$

where $N_{j,t}P_t$ is a set of the open (unsettled) marked-to-market dollar positions held by trader *j* at *t* and Ω_t is a covariance matrix of returns. The covariance matrix is estimated for each upcoming interval as an exponentially weighted moving average (hereafter EWMA) of the outer product of historical returns. Thus, risk of a given portfolio at *t* incorporates positions accumulated in a trader's *j* portfolio by time *t* and the best estimation of return volatility is taken from from the EWMA, based on historical information until *t*. The risk estimation from (4) serves as a decent proxy for the internal CCP methodology of daily margin calculations. The methodology used to estimate the inputs, portfolio positions and the covariance matrix of stock returns, is explained below.

One can claim that our definition of a trader's portfolio is mostly relevant for CCPs and not so relevant from the investors' point of view. However, the settlement cycle has to be carefully taken into account by investors because the discrepancy in settlement cycles among assets in a portfolio may bear costs for them. In particular, stocks, bonds, mutual funds, and equity traded funds currently use a T+3 settlement period. However, some other investment classes in investor's portfolio can have a T+1 cycle, with the settlement right on the next business day. These include T-bills, high-interest saving accounts, and money market funds. It means that if a trader sells one asset and buys another one with a different settlement cycle, his trades could settle out of order.

Estimate of covariance matrix. A dynamic covariance matrix of stock returns is estimated according to the MSCI RiskMetrics approach. For an upcoming interval, we calculate an exponentially-weighted moving average of the outer product of past returns, allowing for time-varying volatility. Following the standard practice (e.g., RiskMetrics and EMCF), we estimate the decay parameter as follows. RiskMetrics applies a coefficient of 0.94 for daily returns; in our case, a trading day comprises 102 five-minute intraday intervals. If we choose the parameter so that the half-life of a shock corresponds to the half-life of a daily shock in RiskMetrics, then it should satisfy $\lambda_{5min}^{102} = 0.94$. We exclude overnight intervals, as we apply volume-based intervals for an intraday split: including intervals with no trade would mechanically lower the covariance matrix during the first (morning) intervals. This implies the five-minute decay parameter of 0.9994. Consequently, the corresponding covariance matrix is:

$$\begin{aligned} \Omega_t &= (1 - 0.94) \times \sum_{\tau=0}^{\infty} (0.94)^{\tau} r_{t-1-\tau} r'_{t-1-\tau} \\ => \Omega_t &= 0.0006(r_t r'_t) + 0.9994\Omega_{t-1}, \end{aligned} \tag{5}$$

where r_t are volume-clock logarithmic returns.

Before estimating the aggregate risk for the whole market, we first look at how heterogeneous it is across traders. As mentioned in Section 2, average trading volumes vary substantially among 55 traders. In order to verify whether this heterogeneity is also present for risk, we look at the average trader's portfolio risk versus the size of a trader. Average risk is the average of the trader's portfolio standard deviation calculated as in (4); the average size of a trader is his average daily trading volume. Figure 17 clearly shows that larger traders accommodate more substantial risk. The pattern does not differ for all intraday intervals versus only end-of-day period.

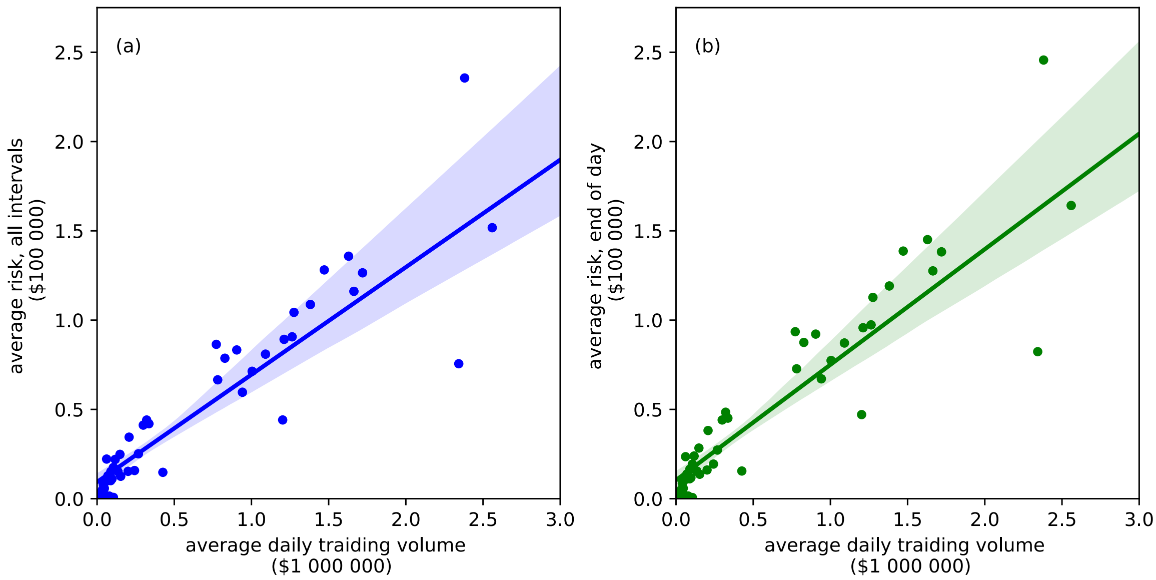

Figure 17: Average risk versus trader size. The figure shows the relationship between trader's size and the average risk of his portfolio. Average risk is estimated per trader as in (4), trader size is the ADV for each trader. Average values are equal-weighted, lines represent the for of a linear regression, boundaries show the 5% confidence level. The sample consists of 55 traders and the period between September 2009 – October 2010.

Looking at the aggregate risk measures, it is worth to notice that its dynamics pertains momentum. In particular, its autocorrelation at the first lag is positive and statistically significant across traders. A predictive panel regression $\Delta\sigma_{j,t} = \alpha_j + \gamma\Delta\sigma_{j,t-1} + \epsilon_{j,t}$ produces $\gamma = 0.42$ with t-statistics of 20.075. It means that if portfolio risk was increasing during the previous volume-based interval, it is expected to increase further during the upcoming interval.

2.3 Intraday risk dynamics

The risk measure used for margin calculation and defined in (4) can change because of a change in its inputs: positions and/or a covariance matrix. We start from an aggregate view of risk dynamics and then focus on its "active" part - when portfolio risk changes due to the changes in portfolio positions.

To capture the risk dynamics, we select the intervals, in which portfolio risk has changed. Next, we define a risk-contraction dummy as follows:

$$d_{contr}|\Delta\sigma_{j,t} \neq 0 := \begin{cases} 1, & \text{if } \Delta\sigma_{j,t} < 0 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

For a complete representation, risk expansion intervals are the opposite of risk contraction: risk of portfolio shrinks during these periods. The intraday dynamics of risk varies during a trading day, as shown in Figure 18. It is at the lowest level right after the first interval, follows relatively the same level during the day with small variations, but starts to drop sharply starting from interval 20. The decrease lasts until the end of the trading day, and the average risk contraction reaches 65% compared to 46% before the start of risk shrinkage. We refer to that period as a natural hedge. This finding is favorable from the CCP perspective because it works like a shield against the immense risk accumulation in the portfolios of clearing members.

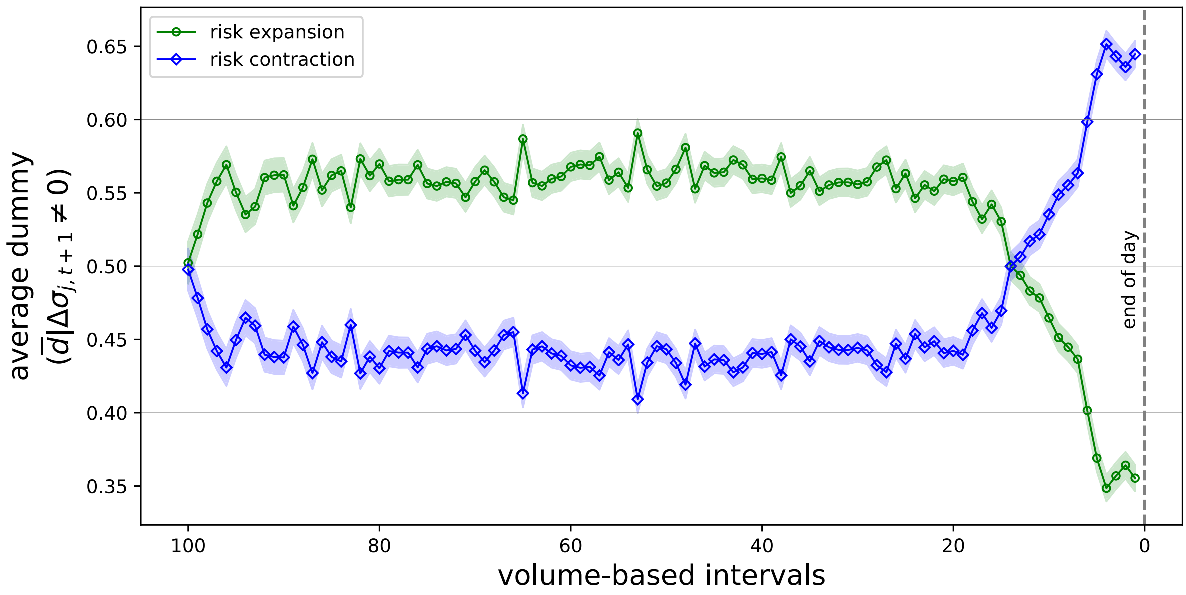

Figure 18: Dynamics of total risk contraction and risk expansion. The figure shows average values of risk contraction dummy defined in (6). Risk expansion is defined as the opposite of the risk contraction dummy. Average values are equal-weighted, boundaries show the 99% confidence level. Volume-based intervals are calculated according to the number of Euro trading volume, interval 0 corresponds to 17:30 (market close) and interval 102 corresponds to 9:00 (market open). The sample consists of 55 traders and the period between September 2009 – October 2010.

The Danish market closes earlier than other, at 17:00. To net out its possible mechanical effect on risk contraction, we add another condition to the risk contraction dummy - a change in weights, meaning that at least one portfolio constituent has to be changed. As the changes in portfolio positions captures the trader's decision to trade, this dummy captures an active part of risk dynamics. Otherwise, the risk contraction can reflect the changes in the covariance matrix instead of risk *behavior*. It is worth to clarify that even when the Danish market is closed, a Danish part of traders' portfolio is not blocked and can still be traded. In particular, Danish stocks are transacted on other markets – there is no stock that is traded exclusively on the Danish market and cannot be bought or sold because of the closed Danish market.

The dynamics of intraday dummy is shown in Figure 19. The risk contraction is high at morning intervals demonstrates the development of the natural hedge by the end of a trading day: the average values of risk-contraction dummy spike by about 8%, starting from volume-based interval 7. In terms of clock time, the natural hedge is present at the market for 20 minutes before the close, starting from about 17:07.[5]

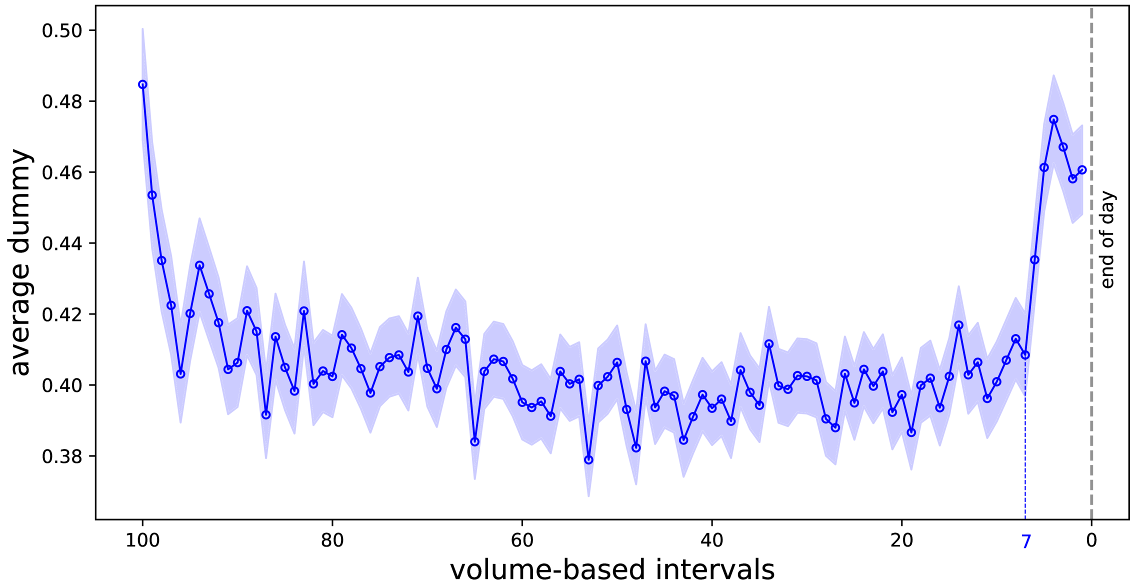

Figure 19: Intraday dynamics of risk contraction. The figure shows average values of risk contraction dummy conditional on a trade. Average values are equal-weighted, boundaries show the 1% confidence level. Volume-based intervals are calculated according to the number of Euro trading volume, interval 0 corresponds to 17:30 (market close) and interval 102 corresponds to 9:00 (market open). The sample consists of 55 traders and the period between September 2009 – October 2010.

Next, we deepen further into the separation of the risk dynamics of the natural hedge into trade-related and price-related effects. Daniel 1973 introduces a one-factor-at-a-time (OFAT) approach, which helps decomposing several-factor interactions by varying only one factor at a time. Portfolio risk, as defined in (4), has a price-related ($N_{j,t}P_t$) and trade-related (Σ_t) factors. The OFAT method changes these two factors sequentially from their values at $t-1$ to t. We first update the price effect because it identifies a pure price effect and shows what the change of portfolio risk would have happened had traders' portfolios stay the same as in the previous

[5]On 85% days interval 7 corresponds to the clock time of 17:07

period. Thus, the steps are:

$$\begin{aligned}\Delta std\_var\_only_{j,t} &= \sqrt{N'_{j,t-1}P'_t\Omega_t N_{j,t-1}P_t} - \sqrt{N'_{j,t-1}P'_{t-1}\Omega_{t-1}N_{j,t-1}P_{t-1}} \\ \Delta std\_posi\_only_{j,t} &= std_{j,t} - \Delta std\_var\_only_{j,t},\end{aligned} \tag{7}$$

where $\Delta std\_var\_only_{j,t}$ is a change in portfolio risk of member *j* at interval *t* driven only by price changes. N_j denotes *stock* positions of trader *j* at time *t*, P_t is the price of a corresponding stock at time *t*, Σ_t is a covariance matrix at time *t*, $std_{j,t}$ is the portfolio total standard deviation (risk) as in (4), $\Delta std\_var\_only_{j,t}$ is a change in portfolio risk of member *j* at interval *t* driven only by change in portfolio positions (trades).

In order to define which of these factors contribute to the end-of-day risk contraction, the following regression is estimated for the volume-clock intervals starting from interval 16:

$$\Delta\sigma_{j,t} = \alpha_j + \gamma_1 \log\_std\_var\_only_{j,t} + \gamma_2 log\_std\_posi\_only_{j,t} + \epsilon_{j,t}, \tag{8}$$

where regressors correspond to the variables defined in (7).

Results in Table 15 uncover several insights. First, changes in both a covariance matrix and in positions contribute to the end-of-day risk reductions: an increase of the portfolio risk is associated with a positive change of the covariance matrix and risk due to portfolio positions. Second, risk change contributed by positions rebalancing is more robust than that contributed by a covariance matrix. In particular, the latter is robust in all three specifications and significant at 99% level, while changes in covariance matrix are only significant at 10% level when time fixed effects are added (column (2) in Table 15).

Dependent: risk change $\Delta\sigma_{j,t}$	(1)	(2)	(3)
$log\_d\_std\_var\_only_{j,t}$	0.49**	0.46*	0.48**
	(2.1)	(1.8)	(2.0)
$log\_d\_std\_posi\_only_{j,t}$	1.07***	1.06***	1.06***
	(17.6)	(17.7)	(17.1)
Constant	-0.87***	-0.87***	-0.88***
	(-17.3)	(-17.1)	(-17.3)
Trader fixed effects	yes	no	yes
Time fixed effects	no	yes	yes
Number of observations	53 504	53 504	53 504
R^2	0.47	0.46	0.48

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 15: Results of panel regressions. The table demonstrates results from regression (8), with risk change as the dependent variable, according to which risk contraction dummy in (6) is defined. Both independent variables are defined in (8). The coefficients show the effect of an increase in risk on $x_i - min(x) + 1$, due to the transformation of negative values for using log. The standard errors are Newey-West standard errors. Values in brackets are *t*-statistics.

This section introduced the notion of the natural hedge and concluded that traders' actions significantly contribute to it. Further in the paper, we will focus on further analysis of the risk contraction, starting from the robustness of the first results.

2.4 Robustness

Several robustness tests show that evidence for the natural hedge holds under various settings.

Weighting. First, we address a potential concern of averaging the risk contraction dummies using equal weights across traders.[6] Given heterogeneity between the traders' size, such an approach tends to overweight the impact of small traders and make the results biased towards them. Figure 20 demonstrates the findings for a case when dummies are weighted according to the trading volume of each trader. A natural hedge is a market-wide pattern that is still clearly

[6] Hou et al. 2017 replicate 447 published stock anomalies from the existing literature and show that many studies overweight microcaps with equal-weighted returns. After the authors control for microcaps and use value-weighted instead of equal-weighted returns, 286 anomalies (64%) become insignificant at the 5% level.

present: end-of-day risk contraction has the same magnitude as the benchmark case with equal weights. Moreover, there is no more risk contraction of the dummy conditional on no trade, while the decrease still holds for an active part of the natural hedge period.

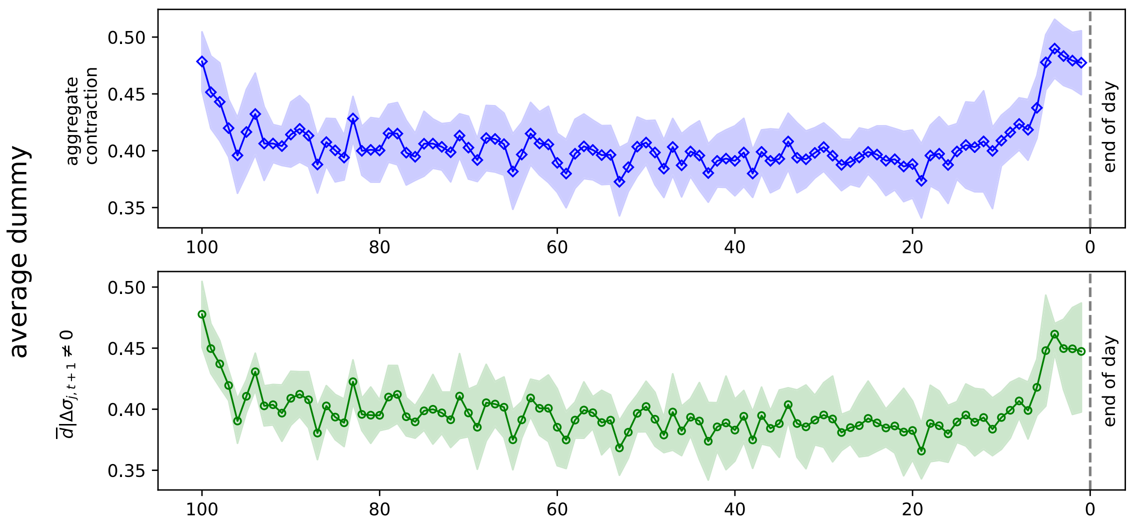

Figure 20: Value-weighted risk contraction. This figure shows the average values of risk contraction dummies. Aggregate contraction is the aggregate average across all intervals when risk changed (incl. no trading intervals), active part denotes to the average risk contraction dummy conditional on a trade. Averages are value-weighted, based on the trading volume of each trader. Confidence intervals represent the 1% confidence interval, standard errors account for cross-trader correlation. The sample consists of 55 traders and the period between September 2009 – October 2010.

Taken into consideration traders' heterogeneity, we select twenty traders whose trading volume comprises 90% of the total trading volume. The natural hedge is much more pronounced for them than for the whole market (Figure 21).

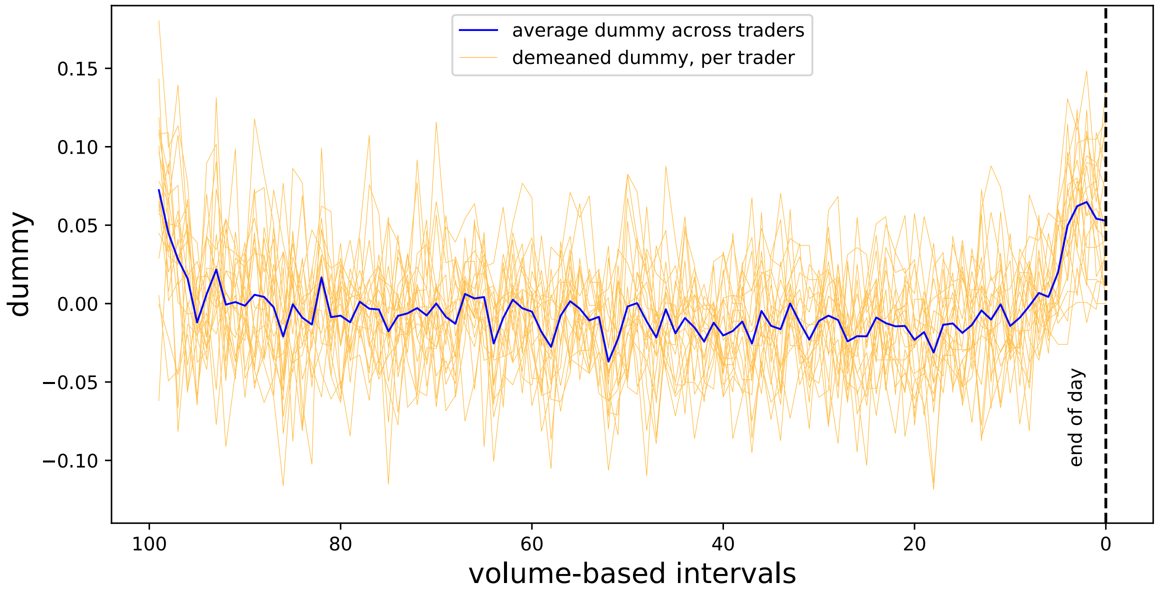

Figure 21: Risk contraction for largest traders. This figure shows average values of an active part of the risk contraction dummy, calculated according to (6), conditional on a trade. The average is equal-weighted. Confidence intervals represent the 1% confidence interval, standard errors account for cross-trader correlation. The sample is 20 traders whose trading volume covers 90% of the total trading volume. Volume-based intervals are calculated according to the number of Euro trading volume, interval 0 corresponds to 17:30 (market close) and interval 102 corresponds to 9:00 (market open). The sample period is between September 2009 – October 2010.

Mechanical effects. The earlier close of the Copenhagen market provides us with an advantage to conduct further robustness tests. Firstly, as the natural hedge and the earlier close of the Danish market are close to each other in terms of clock time, the pattern of risk contraction might be contaminated by potential effects connected to this earlier close. In particular, the risk might be dropping, because some traders simply cannot trade parts of their portfolios on this closed market. We select traders who do have *none* of Danish stocks during the whole sample and are thus not affected by an earlier close of the Copenhagen stock exchange. There are fifteen such traders, for whom this earlier close should not matter because no stock in their portfolios is dependant on it. They are mostly middle-size traders, with average daily trading volumes of €9[7], which comprises about 7% of the total ADV. As further in the paper we mostly concentrate on an active part of the natural hedge, Figure 27 in the Appendix shows that the

[7]The total ADV across all traders is €37 million.

magnitude of the active risk contraction is comparable with the benchmark case. Starting from the highest risk contraction at the start of the trading day, this subset of traders accumulate risk slower in the morning but have the same risk contraction by the market close as the whole market.

Argumentation. Clearing members are aware that they are eligible for potential margin charging at the end of each day. Risk reduction around the market close is a rational strategy because it helps them avoiding to contribute additional collateral. One of the alternative explanations comes from evidence reported in previous research and related to a different trader behavior when he trades from his own or client's account. In particular, Fecht et al. 2018 study the conflict of interest that arises when banks conduct proprietary trading together with its retail services. This setting is close to our dataset - clearing members are also institutional entities, who can trade either from their own accounts or on behalf of their clients. The authors provide strong evidence showing that banks tend to push some of the stocks that they sell from their proprietary trading portfolio onto their retail customers. This finding is further supported by a causal relationship between equity sells of the banks and the buys of the same equities by banks' retail clients, especially for illiquid stocks. EMCF members might also shrink risk only of their own portfolios, shifting less liquid stocks to client's accounts. Repeating the analysis for house accounts only, we do not see the difference in risk contraction between house and client accounts. Splitting a sample into house and client types of accounts, the natural hedge exists for both house and client accounts, with almost the same magnitude and statistical significance as for the case of using both types of accounts.

There is also a particular type of traders who tend to reduce end-of-day risk to a greater extent than others. In particular, high-frequency traders (HFTs) are a type of market participants who tend to unload their portfolios by the end of the day and not to hold any overnight risk.[8] Menkveld and Zoican 2013 identify such traders in the EMCF dataset based on three criteria,

[8] The US Securities and Exchange Commission (2014) presented a list of five characteristics that often are attributed to HFT. One of these characteristics is "ending the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions overnight)"

following Kirilenko, Kyle, Samadi, and Tuzun 2017. The authors identified only seven CCP members, who have a pronounced HFT profile compared to the rest of the traders. The identified HFTs account for 5.43% of the total NASDAQ OMX volume (denominated in Euro), with one particular account being strongly dominating (4.91% of the total NASDAQ OMX volume and the third trader in the market by volume, as well 90% of the total HFT volume). So, the observed effect is not driven by HFTs, it is instead a pattern generated by large clearinghouse members (Figure 21).

Danish stocks. As the Danish market closes earlier than the other seven markets of the sample, it is worth to have a look at this market traders and stocks separately and study whether they demonstrate similar patterns. There are nine traders, whose portfolios consist only from Danish stocks. The data do not demonstrate evidence on risk contraction by these traders: there is no risk contraction before the Danish market close (Figure 22). Two reasons can provide further insights on why this does not happen. First, end-of-day margins are charged "marked-to-market", meaning that the portfolio risk is estimated using the prices at the time of calculation, which is 17.30 for the EMCF. As all Danish stocks are cross-listed on the other seven markets, their covariance matrix continues to update even after the market is closed. Given that their ADV between 17:00 (Danish market close) and 17.30 (all markets close) reaches 13% of the total ADV per stock, this might lead to a significant change of the covariance matrix by the time of margin reassessment. Second, these traders comprise only 1% on aggregate of the total ADV across the sample, while we are mostly interested in broad market patterns.

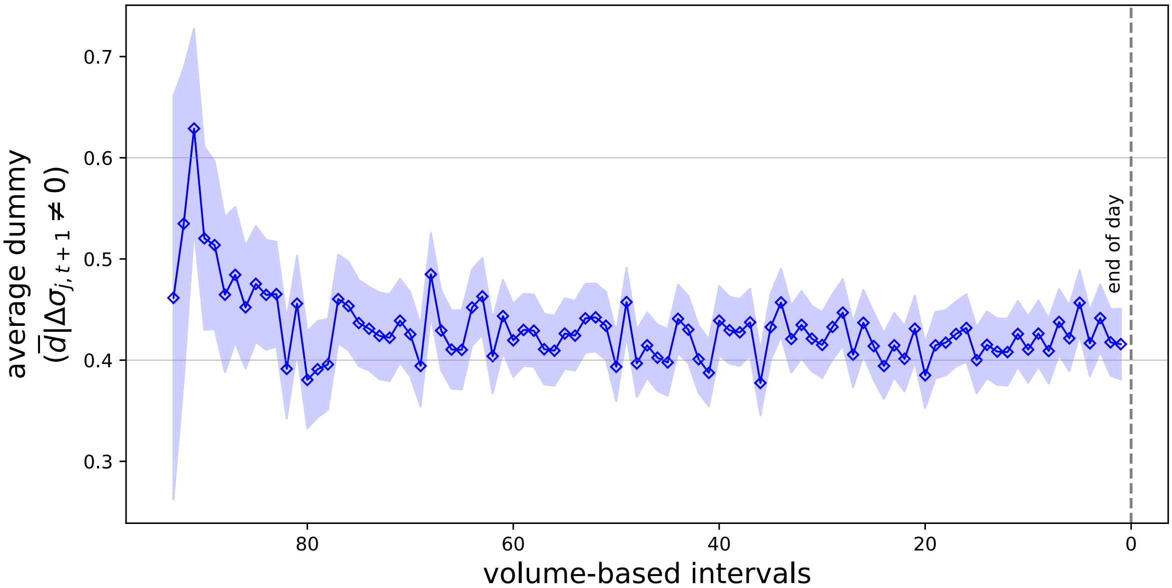

Figure 22: Risk contraction for traders with only Danish stocks. This figure shows average values of the risk contraction dummy, calculated according to (6), conditional on a trade. Volume-based intervals are calculated according to the number of Euro trading volume, interval 0 corresponds to 17:30 (market close) and interval 102 corresponds to 9:00 (market open). Confidence intervals represent the 1% confidence interval. The sample is 9 traders who have *only* Danish stocks in their portfolios throughout the whole sample period between September 2009 – October 2010.

This section provides empirical evidence on the existence of the natural hedge by the end of a day. The hedge is driven by traders, who adjust their portfolios in the direction of risk contraction, and by changes in the covariance matrix of returns. In the rest of the analysis, we concentrate on the active part of the natural hedge, deepening into the risk contraction behavior of CCP members.

3 Risk contraction under the lens

3.1 Natural hedge and stock riskiness

Existing research has found various patterns on how financially constrained investors behave under different external shocks. For example, they might demonstrate myopic behavior and sell randomly large amounts of stocks under panic. Alternatively, they can mostly trade those stocks that have the highest per euro effect on their portfolio risk. We believe that the daily margin assessment by a CCP after the market close can trigger similar incentives for traders as other shocks. The reason is that additional cash collateral can be costly for them (Biais, Heider, and Hoerova 2016). Reluctance to provide it tends to motivate CCP members to reduce the risk of their portfolios.

To determine which stocks are the most traded during natural hedge interval, we define a measure that represents a per-euro effect on margin for each stock, a marginal risk contribution of a stock. "Marginal" refers to the incremental risk change of a portfolio for a given change in stock positions. In other words, this measure shows how the total portfolio risk would change if the weight of given stock changes. Therefore, a stock with a high MR_i has high per euro effect on the margin.

The marginal risk contribution is a derivative of the portfolio's standard deviation, with respect to the position in a given stock:

$$MR_i := \frac{dstd_p}{dw_i} = \frac{\left[\sum\limits_{i=1}^{n} w_i^2\sigma_{ii} + \sum\limits_{i=1}^{n}\sum\limits_{k=1,k\neq i}^{n} w_i w_k \sigma_{ik}\right]^{1/2}}{dw_i} = \frac{w_i\sigma_{ii} + \sum_{k=1,k\neq i}^{n} w_i\sigma_{ik}}{std_p}, \tag{9}$$

where w_i is the dollar position of stock i in portfolio p, σ_{ii} is the variance of stock i, σ_{ik} is the covariance between stock i and stock k.

This derivative shows (1) a sign of individual stock effect to the overall portfolio risk, e.g., a negative/positive sign of MR_i indicates that a change in stock position decreases or increases the risk of the currently held portfolio; (2) magnitude of a margin effect, by which the risk potentially increases/decreases if an additional piece of stock is bought/sold. For example, if the value of $MR_i = -0.034$ for a portfolio of trader *j* at interval 8 of a given day, it means that if a trader buys stock *i*, this trade decreases the total standard deviation of his portfolio by 0.034.

As the natural hedge is observed starting from volume-clock interval 8,[9] MR_i is estimated at the very last interval before the traders start to contract risk. We analyze whether stocks with different marginal risk are traded in a different manner during the *risk-shrinking* intervals between the start of the contraction and a market close. These periods are defined conditionally on whether a particular interval *was* risk-contracting or risk-expanding for a particular trader (based on risk dummy from (4)). We hypothesize that during the risk-contracting intervals, stocks with the highest marginal risk contribution are traded the most. This is in line with the literature saying that, under a pressure of financial constraints in the form of margins, one fire-sells the riskiest assets, so that it would be possible to make the required compensating cash payment or avoid posting additional collateral. The hypothesis is supported by Biais, Heider, and Hoerova 2016, who call upon policy attention by showing that variation margins lead to a pecuniary externality in the forms of fire sales. Related to that, Brunnermeier and Pedersen 2009 detect "flight to quality" behavior, which refers to the episodes when risky securities become especially illiquid. In their model, capital deterioration induces them to mostly provide liquidity to those securities that do not use much capital (e.g., low-volatility stocks with lower margins). This capital effect means that illiquid securities are predicted to have more liquidity risk. In the setting of our analysis, traders can treat liquid and illiquid stocks differently and switch from the former to the latter when contracting the risk.

We allocate each stock in a given portfolio into one of eight bins, based on its MR_i at the

[9]On 85% days interval 8 corresponds to the clock time intervals starting from 17.07

last interval before the start of risk contraction. The bins are assigned based on MR_i defined in (9), and there are four bins for positive values of marginal risk and four - for the negative ones. In particular, each "positive" bin includes 25% of positive MR_i in ascending order. Stocks from each risk bin are matched to their corresponding trading volumes during natural hedge risk-contracting intervals. An aggregate change in trading volumes during the risk contraction per bin is shown in Figure 23.

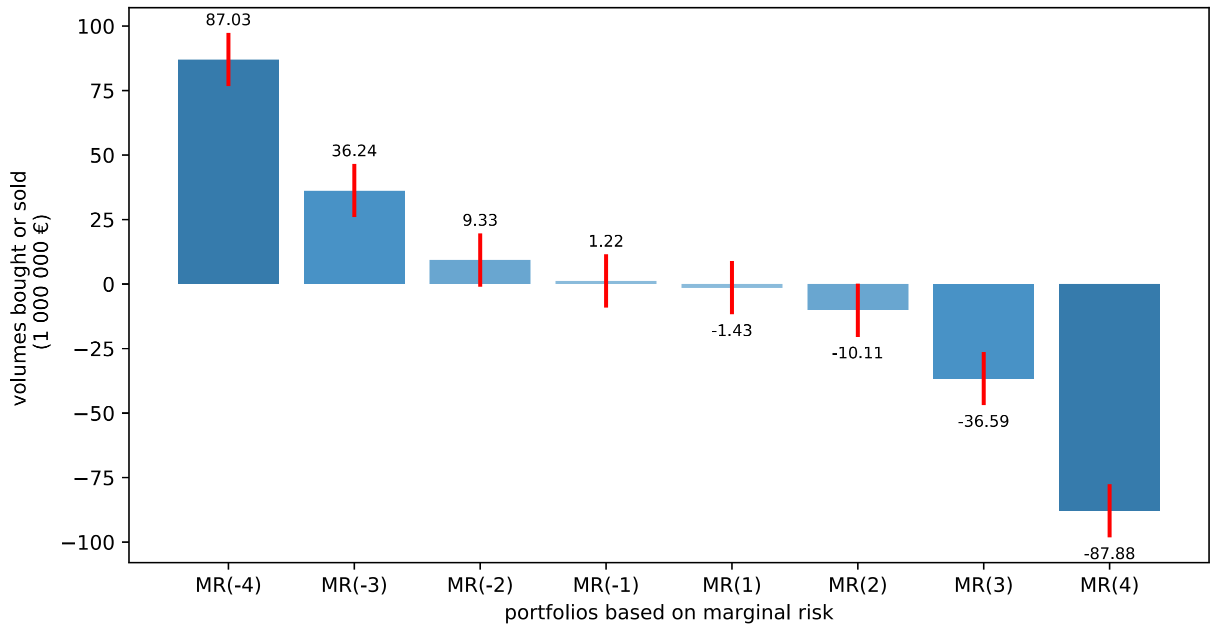

Figure 23: Trading volumes for different stock risk bins. The figure shows Euro position changes between the start of end-of-day risk contraction until the market close for eight different portfolios. The stocks were divided into eight bins based on MR_i defined in (9) so that negative and positive bins contain the same number of stocks. Positive volume values on the y-axis denote purchases, negative values represent sells. Error bars are indicated on the top of each bar. The sample consists of 55 traders, 242 stocks, and the period between September 2009 – October 2010.

First, we found a striking pattern of the relationship between marginal risk and stressed trading volume. When shrinking risk, traders largely buy stocks that reduce the overall risk of their portfolio the most. An aggregate stressed purchasing volume of these stocks is \$87,032,900 (the left bar mr(-4)). For stocks with weaker per dollar risk effect, the trading volume is much lower, but still positive (bins from mr(-3) to mr(-1)). The pattern is mirrored for the four positive bins (mr(+1) – mr(+4)). Starting from low negative trading volumes, a selling power of stocks with the highest marginal risk reaches $87,877,500. Therefore, the most trading activity arises in stocks that have the lowest and the highest per dollar marginal risk. This trading activity demonstrates a gradual pattern: risk-contracting trading volumes for the stocks with the smallest risk effect are ten times lower than those of the extreme bins. The purchasing volumes decrease with a marginal risk for negative MR_i, and their selling volumes increase with a higher positive marginal risk.

Second, the pattern is symmetrical: $ 87,032,900 of bin mr(-4) is bought on aggregate, and almost the same volume at the other extreme risk side mr(+4) is sold. Taking into account the fact that all positions belong to the same clearinghouse and add up to zero, similar values of buys and sells for the extreme risk portfolios implies the heterogeneity across traders' portfolios before they start to reduce risk. Such diverse composition of initial portfolios allows traders having a counterparty for risk-contracting trades, e.g., for selling stocks with the highest risk and for buying stocks with the most negative marginal effect. Traders find a counterparty due to their portfolio diversity before the risk contraction, and therefore a symmetry of trading volumes arises during the natural hedge.

Third, the regression results support the findings of the negative relationship between higher risk and stressed trading. The following regression is estimated on a stock level:

$$\begin{gathered} \Delta vol_i = -81.8 - 10.2 mr_i + \epsilon_i \\ (-5.3)\ (-6.5) \end{gathered} \tag{10}$$

The results demonstrate that a unit increase in the logarithm of the marginal risk is associated with additional selling pressure of 10.2 in the logarithm of volume, significant at 1% confidence level.

Moreover, regressions on a per-trader basis reveal that this pattern is supported by *most* traders and is not driven by some exceptional cases (Table 17 in the Appendix).

Robustness. If traders shrink their portfolios by trading stocks with the highest marginal risk due to their reluctance to provide a clearinghouse with additional cash, then the effect should be stronger for periods when it is more expensive to borrow cash. As clearinghouse members are mostly institutional investors, a spread between three-month USD LIBOR and Federal Funds rate is used as a proxy for the cost of cash collateral. In particular, we define days when the spread exceeds 90th percentile of the sample period as collateral-costly. Rerunning regression (10) only including these days, we get the coefficient of -0.89 comparing it to -0.07 when including all days of the sample and -0.05 when including ”cheap” the rest of the days.[10]

3.2 Natural hedge and stock liquidity

According to the prior research, stock liquidity can, under some circumstances, have an impact on investor behavior. Brunnermeier and Pedersen 2009 suggest that the impact of funding liquidity to market liquidity ought to be strongest for relatively less liquid assets. This finding is later supported by another study that focuses on hedge funds that used bank Lehman Brothers Inc. as a prime broker before the crisis in 2008. Aragon et al. 2012 confirms the downward spiral phenomenon and concludes that shocks to agents' funding liquidity caused a decline in market liquidity of the assets traded. The effect is particularly large and significantly strong for stocks with lower initial liquidity. In the setting of the stressed trading at the market close, we expect agents to trade more actively those stocks, which are more liquid prior to a natural hedge period. Such stocks can be favorable due to their execution immediacy, as might be wished by traders at the market close.

The measurement of market liquidity has shown to be complex in market microstructure research. In particular, Ranaldo 2011 demonstrates the multidimensional nature of market liquidity and its close relationship with market efficiency. We proceed with looking at liquidity

[10]For the full regressions' specification, see Table 16 in Appendix.

from the market depth perspective, using trading volume as liquidity estimator. We apply independent double sorting and sort stocks based on their liquidity, which is proxied by the average daily trading volume across the whole sample. Therefore, aggregate ADV of each liquidity portfolio comprises one-fifth of the total ADV. The stocks are substantially heterogeneous, with a minimum ADV of \$4.6 and a maximum of \$346,146,892 for Nokia Corporation. With a total average ADV of \$2,047,082, 79% stocks (191 firms) comprise the first bin, followed by 9%, 5%, 4%, and 3% correspondingly in each bin.

After allocating stocks in five liquidity bins, keep the split based on the marginal stock contribution to a portfolio (mr_i). The average stressed trading volumes during risk-contraction intervals of the natural hedge mainly concentrates in the most extreme risk bins across all liquidity portfolios (Figure 24). Trading volumes for extreme risk bins are higher, and standard errors are lower for portfolios of more liquid stocks. Reasonably, the trading volume of the most liquid stocks is several times higher than of the other bins. Therefore, trading based on a marginal risk is not driven by liquidity. Robustness section will deepen further into it.

These findings are in line with the banking literature that evolved following the financial crisis in 2008. Being under financial constraints and having limited access to funding liquidity, market participants at that time could be a relevant proxy for the behavior of clearinghouse participants before margin assessment. The earlier mentioned study by Aragon et al. 2012 finds that stocks held by the funds connected to the Lehman Brothers Inc. experienced more severe declines in market liquidity after the bankruptcy than other stocks. The effect was larger for ex-ante illiquid stocks and persisted into the beginning of 2009. Related to this literature, a few studies (e.g., Goldberg and Hudgins 2002, Karas et al. 2013) document that experiencing events such as bank failures can lead to a wake-up call among depositors. They examine the balance sheets of banks and provide evidence that distressed banks experienced stronger deposit outflows during financial crises at different times. Our results say that being under pressure of the potential margin contributions, traders get rid of the riskiest stocks and are interested in buying those that would decrease the portfolio risk the most, especially liquid stocks. This is in line with existing findings and adds up further evidence on the stock liquidity and its effect on the margin.

In this section, we showed that the phenomenon of natural hedge evolves by trading the stocks that affect the portfolio risk the most. Traders sell stocks that decrease their total risk portfolio most and buy stocks, whose marginal risk would decrease the risk of their portfolios. This pattern is driven by the largest traders present on the market and not driven by stock liquidity, which is shown next.

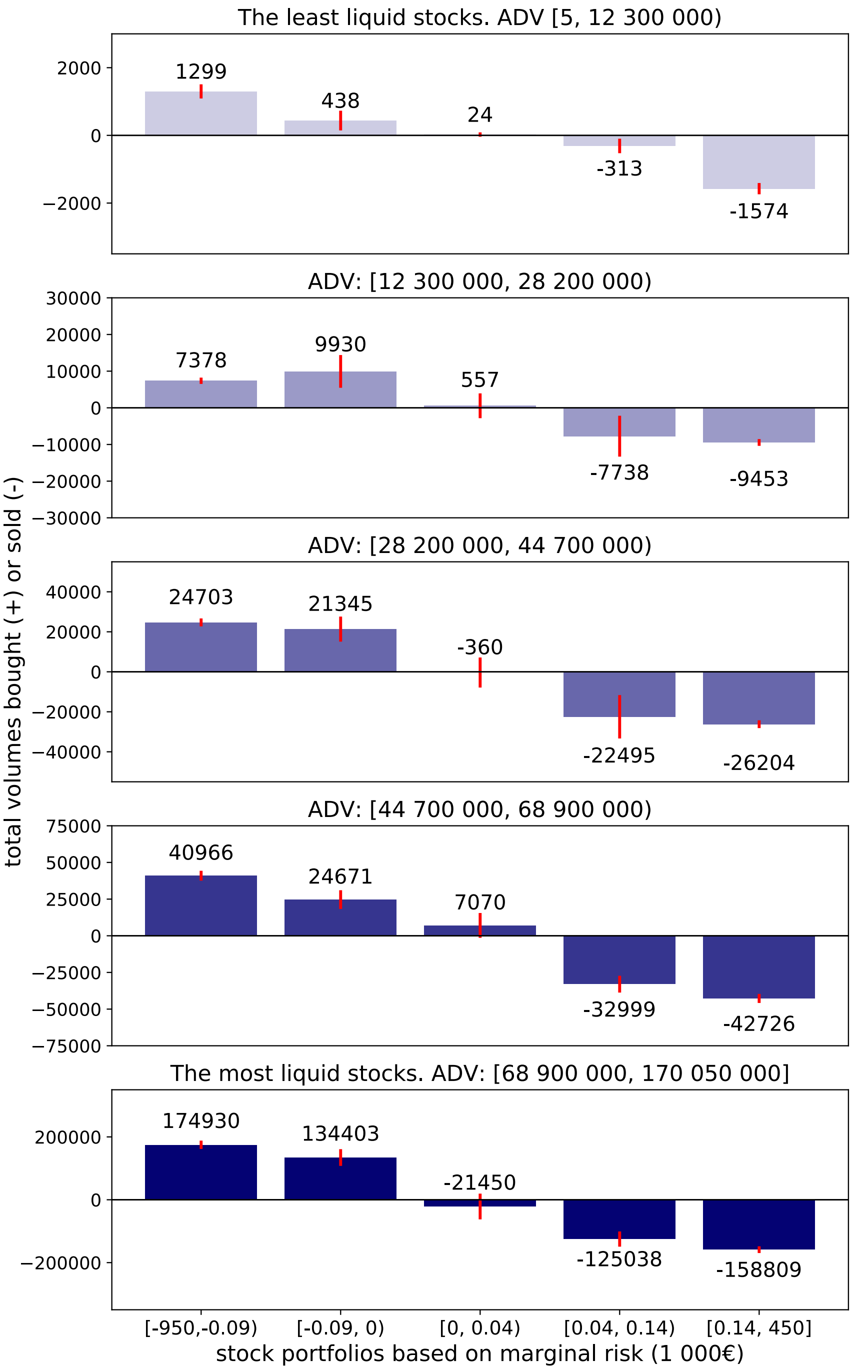

Figure 24: Trading volumes for different stock risk bins. The figure shows Euro position changes between the start of end-of-day risk contraction until the market close for 25 portfolios. Stocks are allocated based on the ADV so that the ADV of each bin equals 1/5 of the total ADV. Each subplot represents a liquidity category. Numbers above show the minimum and maximum values of the bin. Stocks are further divided into portfolios based on MR_i from (9), so that negative and positive bins contain the same number of stocks. Red lines are the standard errors. The sample consists of 55 traders, 242 stocks, and the period between September 2009 – October 2010.

3.3 Robustness

Sorting. The pattern is even stronger for the case when stocks are divided into bins with the same number of stocks according to their liquidity. For this alternative case, we further take the most liquid portfolio and divide it further into five risk bins. If the results are driven by liquidity, stocks inside this bin would be traded just randomly, not depending on their marginal risk bin, rather than keeping a pattern. Figures 28 and 29 in Appendix demonstrate that the results hold both across all liquidity portfolios and inside the most liquid portfolio as well.

In order to observe how general is the trading pattern across agents, we run the following fixed-effect regressions, one for each risky bin, for a period of risk contraction during the natural hedge period:

$$\Delta Vol_j = \sum_{k=1}^{K} 1_{t,j} + \epsilon_j, \tag{11}$$

where $1_{t,j}$ is a dummy variable that takes the value one if interval t belongs to risk-contracting natural hedge period k and zero otherwise. Estimating this regression is equivalent to finding averages trading volumes per bin for each trader. The results show that about 90% volume of the extreme bins are traded in an expected direction and magnitude and are statistically significant. These volumes are driven by 24 traders who buy the stocks with the most negative marginal risk and by 20 traders who sell the stocks with the highest marginal risk. Stocks with the lowest marginal risk per dollar are the least actively traded across the market: only 20% of the traded volumes of these bins are statistically significant. The largest 15% of traders represent high volumes and support the pattern (marked bold in column 1). A market-wide nature of trading stocks with highest per dollar risk impact supports the argument of diverse portfolios across traders before the risk contraction period around the close.[11]

The pattern of trading the most risk-expensive stocks is not only covered by the largest

[11] Please see the details in Appendix Table 17.

traders but is also almost identically distributed across volume-clock intervals inside a natural hedge period. For the extreme risk bins, about one-eighth of the total volume is traded inside each volume-clock interval. The largest volume of \$16,444,410 bought and \$15,086,550 sold is traded during volume interval 5[12], which is the very last interval before the market close.

4 Negative externalities of the natural hedge

The question of how traders' access to funding liquidity affects asset prices is one of the fundamental questions in financial economics. Furthermore, if asset liquidity is a priced risk factor, shocks to the market liquidity might raise expected returns by lowering prices (e.g., Amihud and Mendelson 1986, Pastor and Stambaugh 2003). These shocks can initiate a temporary price impact and distort closing stock prices. Kraus and Stoll 1972 investigate price effects accompanying block trades at the close. In a less than perfectly efficient market, short-run liquidity effects produce such price impact, under which the expected rate of return is shifted only temporarily since the price is expected to go back to equilibrium reasonably quickly. Their findings imply that the pressure of institutional trading is a significant factor of temporary price effects of block trades. Conceptually, such price impact described is different from that produced by differences in investor preferences. The latter involves a change in equilibrium price associated with a change in the expected rate of return and is not implicitly a temporary effect. By contrast, under the price impact produced by stressed risk-shrinking trading, expected returns are shifted only temporarily, and prices are expected to go back to equilibrium fairly fast. The stressed trading before potential margin calls is likely to generate the same effects, especially for the most traded stocks (equivalent for block trades). We show that the created price impact is transitory, as the price rebounds once the market opens the following day.

The ideal conditions assume that the value of stock follows a random walk, meaning that

[12] On 85% days interval 5 corresponds to the clock time interval 17.19–17.29

buy and sell orders are equally probable and serially independent (Roll 1984). We estimate the first-order serial covariance in price changes for three intervals: between a start of the natural hedge to the market close, between the close to the next day's open, and between the close to the next day's after-open interval. We show that such covariance between returns at the close and the next day open is negative and statistically significant. Similarly, Roll 1984 shows that such first-order serial covariance is inversely related to the effective bid-ask spread. He infers a bid-ask spread from the transformed serial covariance by $2\sqrt{-cov}$.

Transitory price error of the natural hedge is then calculated as the scaled autocovariance:

$$\rho_i = \sqrt{-cov(R_{h,c}, R_{c,o})}, \tag{12}$$

where $R_{h,c}$ is a vector of each stock return between its last price before a natural hedge period and its closing price, and $R_{c,o}$ is a vector of each stock return between its closing price and the opening price on the next day.

Keeping the liquidity split, we further divide stocks into three portfolios: stressed sold (stocks that are sold during risk-contraction at the close), stressed bought (stocks that are bought during risk-contraction at the close), and zero-volume (stocks that are not traded during risk-contraction at the close). The third portfolio serves as a control reference because it allows comparing the price effect associated with trading (stressed bought/sold portfolios) to the price effect without trading (zero-volume portfolio). Figure 25 shows the pricing errors for 15 stock portfolios formed according to liquidity and trading volumes during risk contraction interval at the close. The largest pricing error of 33-34 basis points is generated among less liquid stocks (bins 1-2). Given that these bins contain the largest number of stocks (because it is formed so that one-fifth ADV is in each bin), the effect is largely present. It disappears for the most liquid stocks. In terms of asymmetry, stressed sells distort stock prices stronger than stressed buys.

The price effect measure for the top 10% most-traded stocks across all bins (during risk-shrinking intervals) is 58 basis points and 86 basis points for top 5% most traded stocks, and both are significant at 5% level.

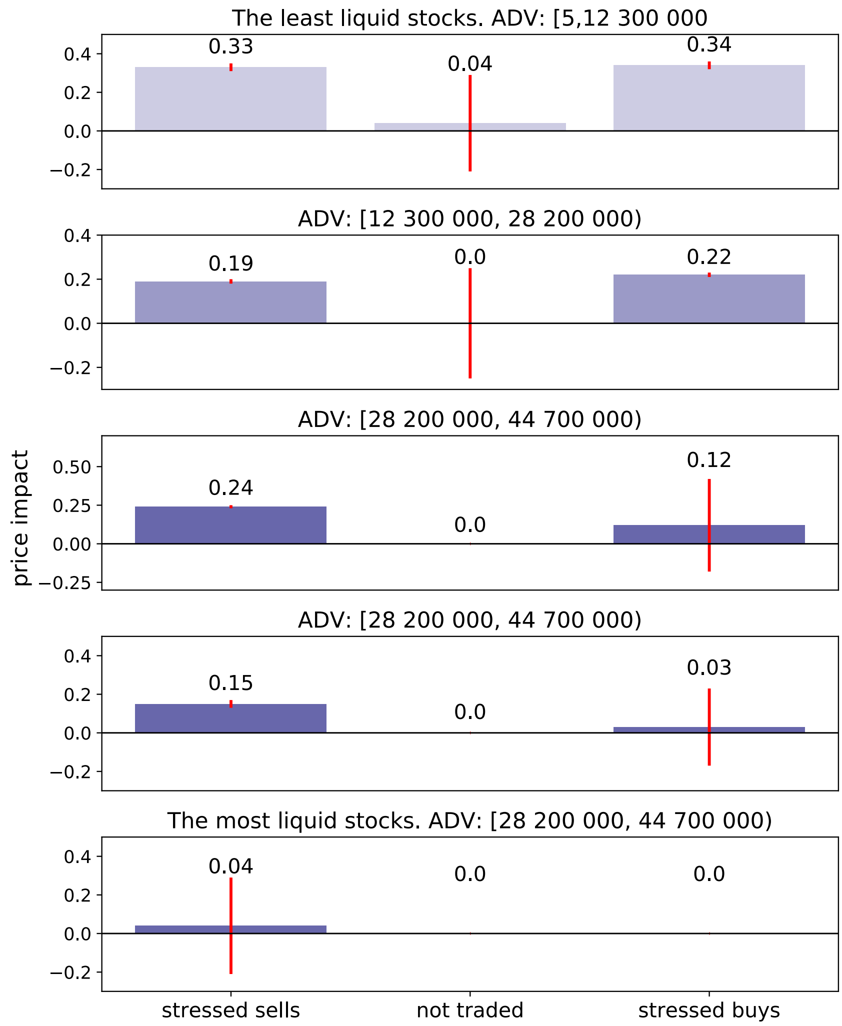

Figure 25: The price effect of the natural hedge period. The figure shows the price effects for 15 different portfolios. The values on top of bars are in percentage points and are calculated as the scaled autocovariance of the series of returns as in (12). Values are in percents. The sample consists of 55 traders, 242 stocks, and the period between September 2009 – October 2010.

To test the relation between size of risk-trading and size of price effect on a more general level, we run a panel regression with time fixed effects: the absolute value of the dollar transaction volume in the risk contraction intervals of the natural hedge until the end-of-day on the previous date is regressed on the product between the stock's return at the end of the day and return on the next day. The absolute value of volume allows to capture both risk-shrinking sells and buys during risk-contracting intervals. In the results shown below, $|\Delta Vol_{i,co}|$ is a change in trading volumes between the start of natural hedge period and the market close, measured in dollars; $\sqrt{-(R_{i,hc} * R_{i,co})}$ is in 1/100 of basis points, and the numbers in parentheses are values of t-statistics.

$$\sqrt{-(R_{i,hc} * R_{i,co})} = \gamma_t + 0.018|\Delta Vol_{i,h-c}| \tag{10.82}$$

The estimation shows that €1 of stressed trading during the end-of-day risk-shrinking intervals increase the reverse price "bounce" in the opening by 1.8 basis points.

Price effect conclusions show that trading pricing error plays against traders - they buy stocks more expensive and sell cheaper than they would do at usual time periods. Traders would do so if the costs of borrowing cash exceed the "cost" of trading at the price bounce during the natural hedge. The literature provides evidence that the collateral might be indeed costly (Biais, Heider, and Hoerova 2016). The reluctance to provide it tends to motivate CCP members to reduce the risk of their portfolios.

These results are consistent with Meier and Servaes 2018, who find that firms buying distressed assets in fire sales earn excess returns. Coming back to Aragon and Strahan 2010, they similarly show that the overall price impact of the stocks held by Lehman's hedge fund clients prior to the bankruptcy rose more than other stocks following the bankruptcy, as well as their bid-ask spreads.

4.1 Alternative explanations for risk contraction

Risk hedge on the other markets. Clearing members is our sample are mostly institutional entities who have an access to numerous other markets and assets. They thus have various opportunities to hedge the risk of their stock portfolios that we study on some other markets. One of the natural way to protect themselves from possible portfolio price fluctuations is to pursue a perfect hedge via the options to a market index. In order to analyze whether the CCP members exploit such opportunities, we tackle the following problem.

Take trader *j* at time *t*, whose weights in the various stocks is captured by vector $\underline{\mathrm{w}}_{j,t}$ with the corresponding returns $\underline{\mathrm{r}}_{i,t}$ for each stock *i* inside the portfolio. Suppose, we add securities to this portfolio: for example, the market futures $\lambda_{j,t}$ with returns $r_{m,t}$. To be effectively hedged, a trader solves the following optimization problem:

$$\sigma\_post_{j,t} = \underset{\lambda}{\text{minimize}}\, \text{var}(\underline{\mathrm{w}}_{j,t}\underline{\mathrm{r}}_t + \lambda_{j,t} r_{m,t}), \tag{13}$$

where $\sigma\_post_{j,t}$ denotes the variance of the trader's *j* portfolio that includes his current stock portfolio and the market futures.[13] The variance of "non-hedged" (current) portfolio is defined as:

$$\sigma\_pre_{j,t} = \text{var}(\underline{\mathrm{w}}_{j,t}\underline{\mathrm{r}}_t) \tag{14}$$

The hedging ratio is then defined as:

$$\frac{\sigma\_pre_{j,t} - \sigma\_post_{j,t}}{\sigma\_pre_{j,t}} \tag{15}$$

If traders use the market index for hedging their portfolios, we would detect that the weights are tilt toward the index weights by the end of the day. As intraday data on indices are not available from the open data sources for our sample period, we construct the value-weighted

[13] For the details regarding the optimization problem, please see Appendix B 5

market index from all existing stocks available in the sample. The weight of each stock in the index is calculated as number of outstanding stocks multiplied by the average price during the sample. The correlation of returns of the constructed index with the STOXX Nordic Total Market Index is 91.9%, with MSCI Nordic Index – 92.9%, with the OMX – 92.1%, which indicates that the combined index is a decent proxy for the Nordic indices actually available on the market.

The optimization problem was approached through two methods: analytically (via matrix derivations) and numerically and converged to the same results.[14] Both methods do not detect any special patterns neither for alpha nor for the hedging ratio, represented in Figure 26.

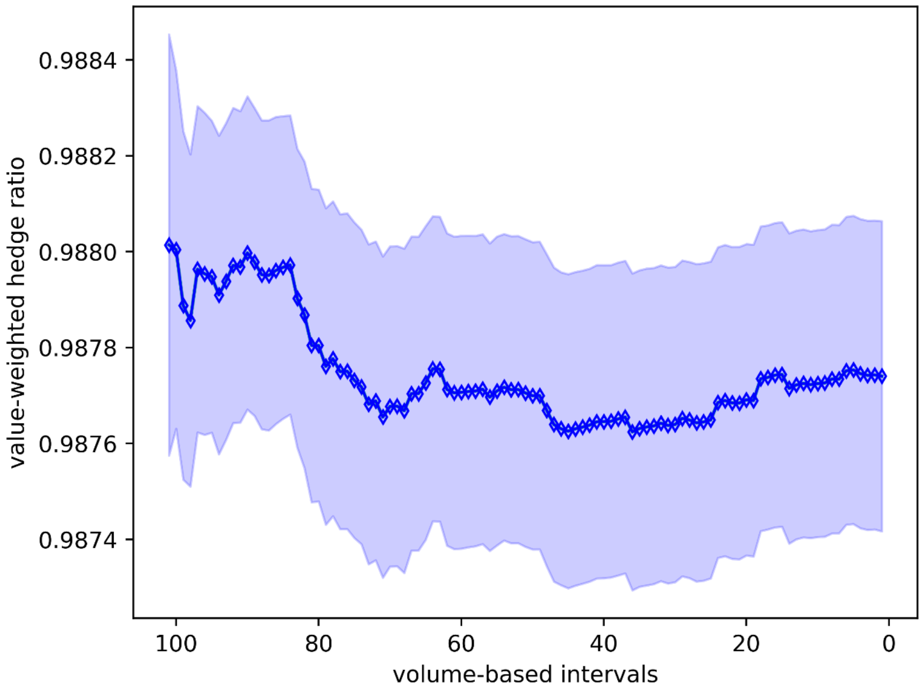

Figure 26: Portfolio hedging using the market index futures. The figure shows the value-weighted average hedging ratio calculated as in (15) at each volume-based interval. The average is value-weighted, depending on the trader's average daily trading volume across the sample. Volume-based intervals are calculated according to the number of Euro trading volume, interval 0 corresponds to 17:30 (market close) and interval 102 corresponds to 9:00 (market open). Confidence intervals represent the 1% confidence interval. The sample consists of 55 traders, 242 stocks, and the period between September 2009 – October 2010.

[14]The details of each method are in the Appendix B.

Cross-listed stocks. In Section 3, we show that CCP members tend to sell those stocks that has the highest marginal risk per dollar of their holding portfolio. Such behavior allows them decrease the overall risk of their portfolios and avoid contributing the daily margin to the CCP. Another potential reason to sell such stocks could be switching to another market. For example, traders can sell *cross-listed* stocks by the end of a trading day because another market (e.g., the US exchanges) opens around this time and traders may wish to switch to the market where the trading is open, closing all positions in the stock on the soon-to-be closed market.

To approach this issue, we sort stocks based on their aggregate selling volume during the risk-contraction period at the end of the day. We then match the stock's tickers from our dataset to its corresponding ISINs in the *Thomson Reuters*, and define the company's home country of domicile based on the ISIN code.

It occurs that among 90% of the total selling pressure none of the stocks is US (Table 18 in the Appendix). The actively sold stocks are mostly Swedish companies. Eight stocks are Finnish, and one is British.

5 Conclusion

The paper analyses the risk behavior of traders subject to financial constraints. We use the dataset from one of the largest European equity CCP that reassesses margins on a per-participant basis at the end of each trading day. By using a relevant proxy for margin estimations, we show that traders contract risk of their portfolios at the market close, providing a CCP with a natural hedge. This behavior is common across the market and is more pronounced for large traders. Agents trade in the direction of risk contraction by selling stocks with the highest marginal risk and buying stocks that decrease the overall portfolio risk the most. The pattern is stronger on days when the borrowing costs of cash are at the highest level. Such risk-contracting end-of-day trading distorts closing stock prices: for the top 10% most traded stocks, a pricing error at the close reaches 58 basis points. This result might be of interest for policy regulators, investors, and asset managers, who use the closing prices as a benchmark for investment and performance decisions.

The results are shown to be robust across various robustness checks. As the market close is a special intraday period in terms of market behavior, we also check other potential channels of the risk contraction. The findings are neither driven by high-frequency traders, nor by a specific small subsample of traders. Being common across the market, the pattern of selling the riskiest stocks do not relate to cross-listed firms. Moreover, no increased hedging is detected by the end of a trading day.

The study suggests a fresh perspective on the channel between stressed trading volumes and their impact on closing stock prices. For the direct detection of this link, the dataset that would contain the already collected margin would be of use. More data on borrowing costs per trader would also help to better define whether obtaining cash externally is more expensive than the negative externalities of the natural hedge.

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Appendix A

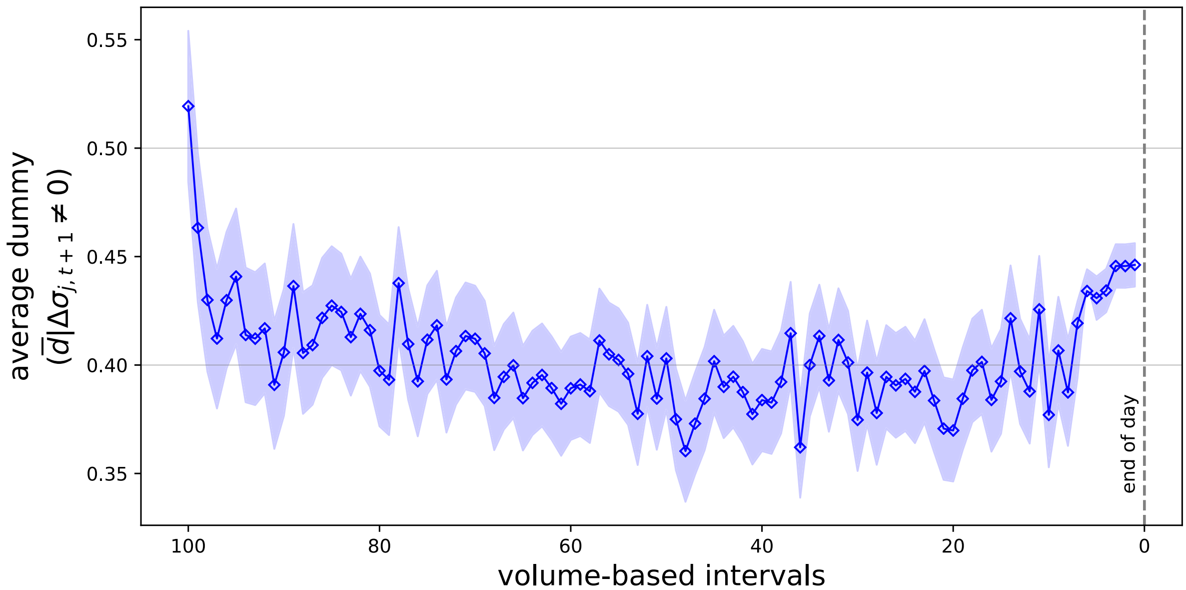

Figure 27: Risk contraction for traders without Danish stocks. This figure shows average values of an active part of the risk contraction dummy, calculated according to (6), conditional on a trade. The average is equal-weighted. Confidence intervals represent 99%, standard errors account for cross-trader correlation. The sample is 15 traders who do not have any Danish stock in their portfolios throughout the whole sample period. Confidence intervals represent the 1% confidence interval. The sample consists of 55 traders and the period between September 2009 – October 2010.

Dependent: volume changes Δvol_i	all days	"costly" days	"cheap" days
	(1)	***(2)***	***(3)***
mr_i	-0.07***	-0.89***	-0.05***
	(-5.1)	(-7.9)	(-4.3)
Constant	16.17***	8.17***	16.24***
	(13.8)	(7.6)	(13.4)
Number of observations	197 808	27 220	170 588
R^2	0.009	0.029	0.008

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 16: Results of cross-section regressions. The table demonstrates results from regression (10), with a change in volumes during risk-contraction end-of-day intervals as a dependent variable. Independent variable is a stock's marginal risk contribution defined in (9) for the last interval preceding the risk contraction. The coefficients show the effect of a unit change in the logarithm of volume change to change in the logarithm of marginal risk, because values were transformed by adding a constant and taking logarithm. "Costly" days are the days when a spread between 3-month LIBOR and Federal Fund rate was above 90th percentile, "cheap" days are all the rest observations. Values in brackets are *t*-statistics. The sample consists of 55 traders, 242 stocks and the period between September 2009 – October 2010.

Trader ID	negative marginal risk				positive marginal risk			
	Most negative mr	mr(-3)	mr(-2)	mr(-1)	mr(+1)	mr(+2)	mr(+3)	Most positive mr
10000	25,940***	13,620***	1,958	-1,079	-2,391***	-3,418***	-9,349***	-23,660***
20000	16,550***	8,642***	1,895	1,554	-766	-1,149	-2,084	-11,370***
30000	11,270***	4,172*	91	-370	-801	-2,792**	-12,040***	-13,920***
40000	1	0.4331	-	-	-	-14	143	-659
50000	113	-40	4'.8	-	-	-1,234	624	-1,418
60000	38,570***	15,090***	565	3,322***	-1,413***	-2,125	-15,010***	-25,320***
70000	311	-285	201	705	17	-7	-20	-14
80000	2,823	1,108	453	-249	-11	-919	-1,948	-5,042
90000	22,600***	7,690***	-4053***	467	-980	2,466	-8,273***	-30,090***
100000	1,097	-520	349	-16	-893	-1,345	-249	-1,282
110000	9,520***	985**	289	-	-	-	157	-2,897***
120000	22,520***	13,840***	3,165***	1,458	-878	-5,483***	-7,993***	-26,760***
130000	4,378	2,277	459	-43	-261	-1,262	-2,828	-9,418***
140000	10,310***	5,502***	2,677***	235	-52	-4,188***	-7,406***	-15,170***
150000	24,630***	10,400***	5,240***	627	979	41	-21,390***	-36,910***
160000	20,530***	6,878***	4,994***	-5,310***	-13	-3,465***	-7,054***	-17,620***
170000	154	-30	319	-	-	-	-	-62
180000	825	117	48	8	-40	-99	-63	-1,834
190000	614	275	82	-13	-0.3	-112	-1,043	-515
200000	4,999	1,351	1,944	1,712	57	-4,626	-3,880	-2,519
210000	809	2,007	157	149	-181	-265	-129	-1,975
220000	232	-3.87	38	-	-103	-22	-192	-341
230000	3,446	5,033***	253	364	64	-833	-2,575	-5,686
240000	2,191**	222	17	113	-259	-721	-1,334	-4,601
250000	29,300***	12,700***	2,759***	346	-325	-5,264***	-13,320***	-24,060***
260000	1,283	39	65	5	-74	-1,527	-411	-544
270000	3,005	25	-	1,211	353	-	108	-4,868
280000	1,316	127	29	-57	-129	-163	-232	-2,936
290000	377	293	48	74	99	140	8	-244
300000	14,620***	2,886	484	446	-183	-377	-1,645	-9,971***
320000	1,677	940	376	93	-67	-497	-1,186	-2,793
330000	6,683***	963	384	-321	-795	-214	-1,506	-7,329***
340000	801	481	243	-18	-21	-270	-308	-2,010
350000	5,683***	594*	54	-	-	-	-90	-3,786***
360000	188	6.6	43	89	0	-6	4	442
370000	1,690	758	385	935	-203	-201	-1,526	-1,762
380000	1,895***	674	290	-	10	-	-66	-657
390000	25,110***	10,510***	2,180	1,048	1,051	-837	-13,870***	-25,140***
400000	4,601	4,241***	466	479	90	190	-4,523***	-6,206
410000	31,540***	11,270***	7,730***	1,254	1,339	-1,143	-8,162***	-22,300***
420000	-36	-60	107	7	14	-184	-144	-262
430000	10,740***	2,274	890	177	-583	-2,829*	-5,824***	-15,900***
440000	12,860	-587	-1,320	5,551	-196	-10,050	1,039	-2,247
450000	20,840***	5,749***	4,160***	-310	-46	-2,656*	-4,461***	-21,940***
460000	34,410***	6,803***	2,594**	-27	-609	-3,504***	-7,276***	-28,400***
470000	909	371	206	-19	10	-125	-309	-276
480000	4,349	3,984*	47	-37	-90	-562	-1,857	-9,297***
490000	138	15	17	-8	-1	-5	-8	-90
500000	2,533	-274	202	151	-	-	499	-742
510000	606	25	22	-	-97	-	-213	-187
520000	84	-335	374	20	-11	-251	-361	-1,173
530000	12,180***	7,756***	2,286*	277	-160	-2,527*	-4,914***	-5,534*
540000	6,587***	6,513***	1,134	539	660	-1,343	-2,965	-4,032
550000	54	36	-	-	-	-	-	29
560000	4,349**	2,789*	-	276	-	-1,356	-879	-2,789**
number of traders significant at 1%	24	18	9	2	2	6	16	20
% of volume, significant at 1%	92%	87%	62%	27%	21%	34%	82%	88%

Table 17: Average trading volumes for different risk bins per trader. Trading volumes for different risk bins per trader. The figure shows results of regressions $\Delta Vol_j = \sum_{k=1}^{K} 1_{t,j} + \epsilon_j$. Risk bins are defined based on the marginal risk contribution per stock, MR. Three stars indicate statistical significance of corresponding values at 1% confidence interval and are indicated in green color for extreme bins. Bold trader id indicates that a trader belongs to the largest 15% of traders. The sample consists of 55 traders, 242 stocks, and the period between September 2009 – October 2010.

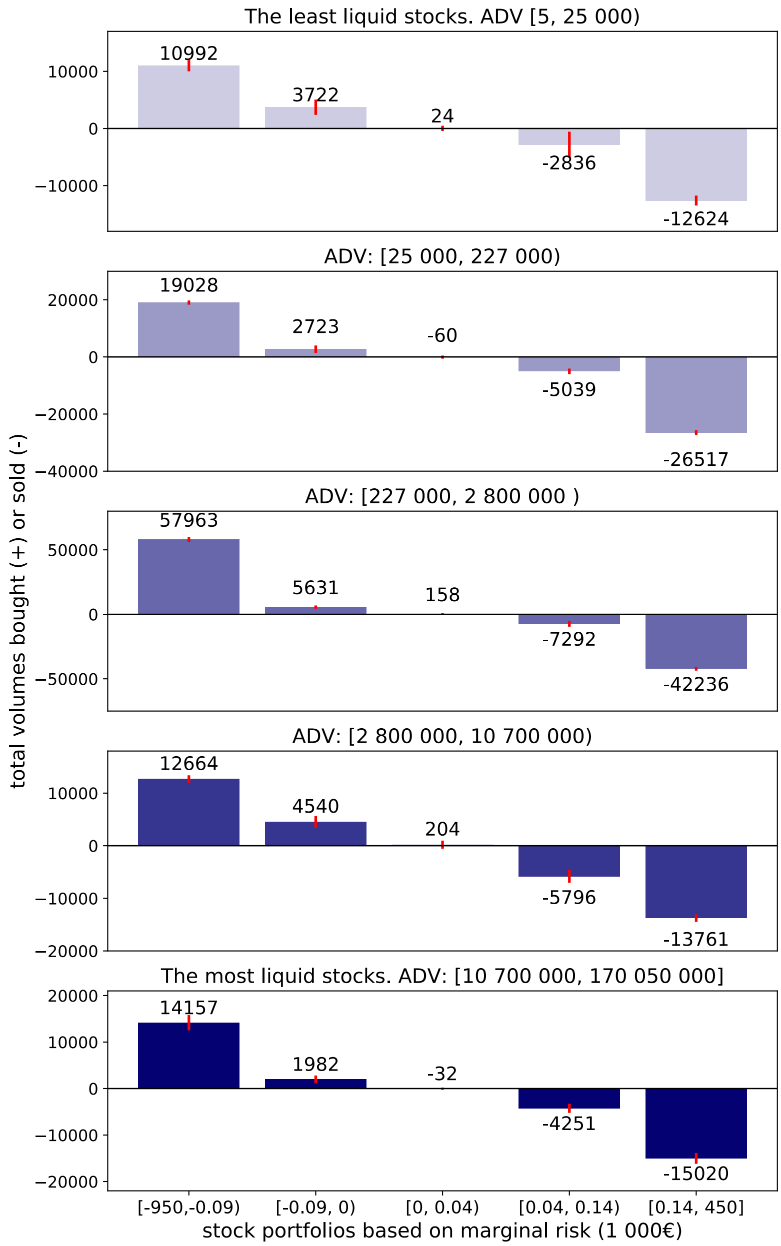

Figure 28: Trading volumes for different stock risk bins. The figure shows Euro position changes between the start of end-of-day risk contraction until the market close. Stocks are allocated into five portfolios based on the ADV, so that the number of stocks is the same across bins. Each subplot represents a liquidity category. Stocks are further divided into bins based on MR_i from (9), so that negative and positive bins contain the same number of stocks. Red lines are the standard errors. The sample consists of 55 traders, 242 stocks, and the period between September 2009 – October 2010.

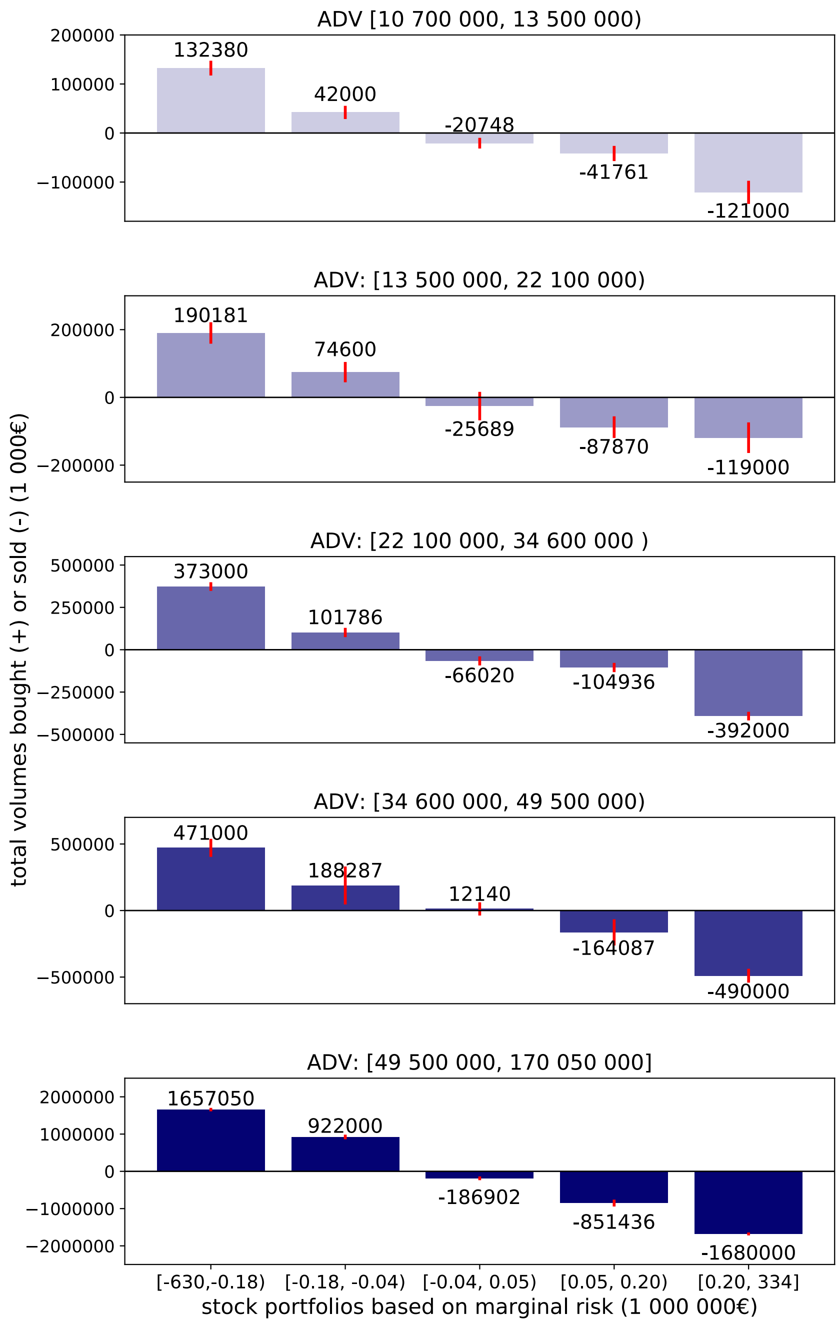

Figure 29: Trading volumes for the most liquid stock portfolios. The figure shows the total Euro position changes between the start of end-of-day risk contraction until the market close. Stocks with the largest ADV are allocated into five portfolios based on the ADV. Stocks are further divided into bins based on MR_i from (9), so that negative and positive bins contain the same number of stocks. Red lines are the standard errors. The sample consists of 55 traders, 242 stocks and the period between September 2009 – October 2010.

Stock ticker	Selling volumes	ISIN	Country of domicile
HMB	-61,057,050	SE0000106270	Sweden
SEBA	-36,431,882	SE0000148884	Sweden
SKFB	-34,010,736	SE0000108227	Sweden
SEN	-30,565,274	FI0009003305	Finland
ER	-25,008,516	SE0000108656	Sweden
SAND	-24,977,747	SE0000667891	Sweden
VOLB	-23,725,049	SE0000115446	Sweden
TIEN	-17,454,346	FI0009000277	Finland
ALFA	-16,154,554	SE0000695876	Sweden
NBH	-15,350,872	SE0000427361	Sweden
UPM1V	-14,969,286	FI0009005987	Finland
SKAB	-14,691,692	SE0000113250	Sweden
ATCOA	-14,280,038	SE0000101032	Sweden
ASSAB	-13,425,801	SE0000255648	Sweden
TLS1V	-11,457,999	SE0000667925	Sweden
ZEN	-10,282,005	GB0009895292	Great Britain
SCVB	-9,876,241	SE0000308280	Sweden
NOR1V	-9,813,581	FI0009005318	Finland
SHBA	-8,069,650	SE0000193120	Sweden
MEO1V	-7,567,467	FI0009007835	Finland
KC4	-7,563,958	FI0009013403	Finland
SCAB	-5,955,127	SE0000112724	Sweden
STERV	-5,497,356	FI0009005961	Finland
ORION	-5,181,814	FI0009014377	Finland
HUSQB	-4,888,255	SE0001662230	Sweden
ORI	-4,320,886	SE0001174889	Sweden
FSPAA	-4,050,097	SE0000242455	Sweden
INVEB	-3,583,502	SE0000107419	Sweden
SSABA	-3,579,867	SE0000171100	Sweden

Table 18: The most sold stocks. The figure shows 90% of selling volumes during the risk-contraction interval at the end of a trading day. Stock ticker is a ticker for a corresponding stock in the dataset. Selling volumes are the aggregate selling volumes across all traders and all days (only risk contraction intervals are taken). ISIN is a corresponding ISIN retrieved from the *Thomson Reuters*. Country of domicile is the country of stock based on the stock's ISIN. The sample consists of 55 traders, 242 stocks and the period between September 2009 – October 2010.

Appendix B

Take trader *j* at time *t*, whose weights in the various stocks is captured by vector $\underline{\mathrm{w}}_{j,t}$ with the corresponding returns $\underline{\mathrm{r}}_{i,t}$ for each stock *i* inside the portfolio. Suppose, we add securities to this portfolio: for example, the market futures $\lambda_{j,t}$ with returns $r_{m,t}$. To be effectively hedged, a trader solves the following optimization problem:

$$\sigma\_post_{j,t} = \underset{\lambda}{\text{minimize}}\, \mathrm{var}(\underline{\mathrm{w}}_{j,t}\underline{\mathrm{r}}_t + \lambda_{j,t} r_{m,t}) =>$$

$$\mathrm{var}(\underline{\mathrm{w}}_{j,t}\underline{\mathrm{r}}_t + \lambda_{j,t} r_{m,t}) = (\underline{\mathrm{w}}_{j,t} + \lambda_{j,t}\underline{\mathrm{w}}'_{j,t})\Sigma(\underline{\mathrm{w}}_{j,t} + \lambda_{j,t}\underline{\mathrm{w}}'_{j,t})' = 2\underline{\mathrm{w}}_{j,t}\Sigma\underline{\mathrm{w}}'_{j,t} + \lambda^2_{j,t}\underline{\mathrm{w}}_{j,t}\Sigma\underline{\mathrm{w}}'_{j,t},$$

where Σ is an exponentially weighted moving average covariance matrix.

$$\text{FOC: } \underline{\mathrm{w}}_{j,t}\Sigma + \lambda_{j,t}\underline{\mathrm{w}}_{j,t}\Sigma\underline{\mathrm{w}}'_{j,t} = 0$$

$$\lambda_{j,t} = -\frac{\underline{\mathrm{w}}_{j,t}\Sigma}{\underline{\mathrm{w}}_{j,t}\Sigma\underline{\mathrm{w}}'_{j,t}}$$

The optimization problem was solved via two approaches. The first approach applied corresponding $\underline{\mathrm{w}}_{j,t}$ and Σ matrices from the sample. The second approach is numerical: the optimization method of Broyden-Fletcher-Goldfarb-Shanno was used to find the $\lambda_{j,t}$ for each trader's portfolio at each interval *t*. Both methods yield very similar results, consistent with Figure 26. The resulting weights of the market futures from the optimization (λ_t), averaged across time periods, is represented in Figure 30.

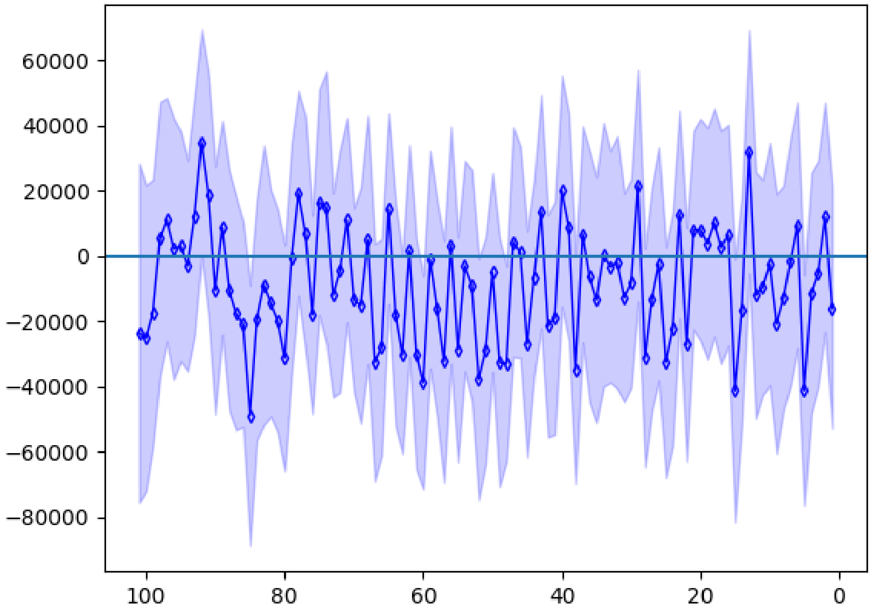

Figure 30: Weights in the potential market futures. The figure shows the average $\lambda_{j,t}$ at each volume-based interval during a trading day, from optimization problem defined in (13).

The Winner should take it all: How Academic Research Helps to Separate Winners from Losers in the Market for Actively Managed Funds

Sebastian Müller* Ekaterina Serikova † Florian Weigert ‡

This version: June 2019

Prior research has proposed numerous variables to differentiate between well performing and poorly performing active equity funds. We combine eight prominent representatives of these measures to obtain a composite, aggregate fund predictor. While only three of the eight individual variables are significant predictors of future fund performance in a multivariate setting, the composite predictor has strong forecasting power. A hypothetical quintile-based long-short strategy based on the composite predictor realizes a four-factor alpha of 5.4% per year. The performance spread is robust to different regression specifications, is similar for different size classes and investment styles, and persists over time. Our results point towards inefficiency in the market for actively managed equity funds.

JEL-Code: G11, G14, G20, G23

Keywords: Mutual funds, performance prediction, combined predictor

*German Graduate School of Management and Law. *Address:* Bildungscampus 2, 74076 Heilbronn, Germany. *E-mail:*sebastian.mueller@ggs.de

†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.

‡University of St.Gallen (HSG). *Address:* s/bf-HSG, University of St. Gallen, Unterer Graben 21, CH-9000 St. Gallen, Switzerland. *E-mail:* florian.weigert@unisg.ch.

”For me, the most direct and most convincing tests of market efficiency are direct tests of the ability of professional fund managers to outperform the market”.

Burton G. Malkiel

1 Introduction

What is the value of active fund management? Arguably, few questions have received more attention in academic capital market research. Given the practical importance of the asset management industry, and the implications for the efficient market hypothesis, an extensive amount of research devoted to this question is not surprising. Researchers and investors, who rely more and more on index funds and ETFs, seem to have a consensus that active management is a zero-sum game before fees (Malkiel (2003)). However, conflicting views still exist on whether successful active funds can be differentiated from underperforming funds ex-ante.

Several studies point to the inherent problem to separate skill from luck with a limited history of performance data (see e.g., Barras et al. (2010); Busse et al. (2010); Fama and French (2010); Hunter et al. (2014)). Moreover, even if skill can be identified a-priori, it is not clear if skilled managers eventually outperform unskilled managers in the future.[1] On the other hand, many researchers have proposed sophisticated measures that seem to be able to predict future fund returns. Examples include measures on fund activity (see, e.g., Amihud and Goyenko (2013); Cremers and Petajisto (2009); Kacperczyk et al. (2005)), measures on trading activity (see, e.g., Kacperczyk et al. (2008); Pastor et al. (2017); Wermers (2000)), or measures on managers’ preferences for certain stocks (see, e.g., Cohen et al. (2005); Kacperczyk and

[1]For instance, in the model of Berk and Green (2004) active fund managers possess different capacities to generate alpha. Investors compete with each other by providing ceteris paribus more money to skilled managers up to the point at which differences in expected alpha between skilled and unskilled managers disappear.

Seru (2007); Fang et al. (2014)).

The goal of our paper is to suggest a new and distinct approach to assess managers' skill, by aggregating individual fund return predictors into a composite score. Despite extensive existing research on mutual funds, we are not aware of any systematic attempts to collect, compare, and synthesize different available predictors of fund returns. However, without this work, we are unable to conclude which of the predictors provide independent information about future returns, how easy or hard it is to separate winners from losers based on the collective academic wisdom, and how efficient is the market overall for actively managed funds. Our work is inspired by the recent meta-studies on return predictors in the stock market (see, e.g., Hou et al. (2015); Harvey et al. (2016); Green et al. (2017); Jacobs and Müller (2017)) and on the influential calls to address the "zoo of factors" that has been discovered by researchers over time (see, e.g., Cochrane (2011); Harvey (2017)). While this zoo is considerably larger for individual stocks, we believe it is now the time to perform a similar exercise for mutual funds. In addition to its connection to meta-studies on stock return predictors (in particular Green et al. (2017)), our paper is related to a recent working paper of Jones and Mo (2017). They show that the degree of predictability, as measured by alpha spreads from quintile sorts or by cross-sectional regression slopes, falls by around 75% after academic publication of the effect. In contrast to this paper, we have a different approach of combining the predictors and the performance of our new multi-signal predictor is relatively stable over time.

In line with most prior work, our analysis focuses on actively managed, broadly diversified US equity funds with a sample period covering January 1985 to December 2010. We select eight prominent predictors that are shown to significantly predict fund future returns, requiring that each measure can be entirely calculable from the CRSP Mutual Fund Dataset (hereafter: CRSP) and Thomson Reuters Mutual Fund Holdings (hereafter: Thomson Reuters) databases. The predictors are introduced in Table 19 and are the following: *Active Share* (Cremers and Petaijisto (2009), low values deliver high performance), *Carhart Alpha* (Carhart (1997), high values deliver high performance), *Characteristic Selectivity* (Wermers (2000), high values deliver high performance), *Characteristic Timing* (Wermers (2000), high values deliver high performance), *Expense Ratio* (low values deliver high performance), *Fund Turnover* (Pastor et al. (2017), low values deliver high performance), *R-Squared* (Amihud and Goyenko (2013), low values deliver high performance), and *Return Gap* (Kacperczyk et al. (2008), high values deliver high performance).

[TABLE 19 IS ABOUT HERE]

By choosing these predictors, we address the key aspects of predictability available in the existing research. In particular, a stock-picking ability of a fund manager is targeted in the *Carhart Alpha*, *Active Share*, and *Characteristic Selectivity* predictors; an ability to time the market is captured in the *Fund Turnover* and *Characteristic Timing*. *R-Squared* and *Return Gap* aim to catch the combination of both, while the *Expense Ratio* corresponds to a group of predictors based on internal fund features.

We start our analysis by investigating the impact of each of the respective predictors on future performance in univariate portfolio sorts and regressions. In line with the previous literature, we find that four-factor alphas of a hypothetical strategy of going long the quintile portfolio of funds with predictor values promising high performance and going short the quintile portfolio of funds with predictor values promising low performance yields positive future monthly returns and alphas for seven individual predictors. However, we also find that the long-short spread for the Carhart (1997) four-factor alpha (as our baseline performance measure) is statistically significant only for six out of the eight predictors with economic magnitudes ranging from 0.10% (for the R-Squared forecasting measure) to 0.20% (for the Carhart Alpha forecasting measure) per month. These values translate into marginal spreads between 1.2% and 2.4% per annum, and it is questionable whether investors should use the individual predictors to select successful active equity funds from an ex-ante point of view.

We then dig deeper and investigate the incremental information of a predictor variable for future fund performance. We first observe that the correlations among the different predictors are moderate: they range from -0.255 for the relation between *Active Share* and *R-Squared* to +0.168 for the relation between *Active Share* and *Expense Ratio*. Hence, we conclude that multicollinearity is not an issue in the multivariate analysis and that combining predictors could be potentially beneficial in forecasting performance based on diversification gains. We conduct Fama-MacBeth (1973) regressions on the fund level of returns and alphas in month *t+1* on the eight fund predictors measured in month *t*. Our results indicate that three out of eight predictors remain statistically significant at least at the 10% level (*Carhart Alpha*, *Expense Ratio*, and *Turnover*), while the remaining predictors do not display statistical significance in the multivariate setting.

The main contribution of the paper is the formation of the new joint predictor. To obtain a composite predictor for the future fund performance based on the individual variables, we follow the econometric method suggested by Green et al. (2017) and Lewellen (2015). First, we examine the historical relations between fund returns and the eight individual predictor variables in multivariate regressions using a rolling estimation window of 36 months. Second, we map the estimation coefficients to the current values of the individual fund predictors in order to obtain a composite forecast for the funds one-month-ahead returns. We show that this multidimensional composite predictor has strong predicting power for future fund performance. Specifically, a hypothetical strategy of investing in the top quintile of funds based on the composite predictor outperforms the bottom quintile of funds by 0.45% per month or annualized 5.4% using the Carhart (1997) four-factor alpha as a performance metric. This spread is statistically significant at the 1% level with a *t*-statistic of 6.34. Moreover, the spread remains substantial and statistically significant at least at the 5% level when we evaluate fund performance over the future 2-month, 3-month, and 6-month ahead periods.

We carefully examine whether this outperformance can be explained by different risk factors developed in the recent academic literature. For this purpose, we regress the long-short portfolio that is based on our composite predictor on the risk factors of the Fama and French (2015) five-factor model, the Hou et al. (2015) four-factor model, the Fama and French (1993) three-factor model extended by short-term and long-term reversal factors, as well as the risk factors of the Carhart (1997) four-factor model extended by the Pastor and Stambaugh (2003) liquidity risk factor, the Frazzini and Pedersen (2014) betting-against-beta factor, the Baker and Wurgler (2006) sentiment index, the Bali et al. (2017) lottery factor, and the Chabi-Yo et al. (2018) tail risk factor. Our results indicate that the return spread of the long-short portfolio remains strong and statistically significant when adjusting for all these different risk factors.

We conduct several robustness checks to show that our results are not sensitive to several choices that we make in our empirical analysis. First, our composite predictor strongly forecasts future fund performance when we apply alternative rolling horizons to estimate fund alphas and to compute historical relations between fund returns and the eight individual predictor variables. Second, our results are stable and robust when we divide our full sample period into two equivalent sub-periods: from January 1985 to December 1997 and from January 1998 to December 2010. Third, we show that our composite predictor strongly forecasts future performance for funds of different size (small/medium/large) and funds of distinct investment strategies (value/growth/other).

Finally, we check which individual predictors provide the largest additional benefit in the forecasting power of the composite predictor. To do so, we perform regressions of the long-short return spread of the composite predictor on the respective long-short spread of the individual predictors. As expected, we observe that the long-short return spread of the composite predictor is significantly related to the return spreads of *Carhart Alpha*, *Expense Ratio*, and *Fund Turnover* (which came up as statistically significant fund predictors in the univariate regressions). However, we surprisingly find that the long-short return spreads of *Carhart Alpha*, *Expense Ratio*, and *Fund Turnover* are not able to explain the outperformance of the composite predictor. Controlling for *Carhart Alpha*, *Expense Ratio*, and *Fund Turnover*, the long-short return spread of the composite predictor amounts to 0.30% per month (3.6% per annum) and is significant at the 1% level when evaluated according to the Carhart (1997) four-factor alpha as performance metric. Hence, our results suggest that combining mutual fund predictors adds value in the selection process for active equity funds. Broadly spoken, our paper finds that the "collective" wisdom of academic research is helpful to separate winners from losers in the market for actively managed funds.

The remainder of this paper is as follows. Section 2 describes the data and introduces the individual fund predictors. In Section 3, we present empirical results for individual predictors as well as the composite predictor and future fund performance. Section 4 concludes.

2 Data and Fund Predictors

2.1 Data

For the empirical analysis, we merge the CRSP and the Thomson Reuters databases. The CRSP contains fund performance information on a monthly basis: fund total and net returns, total net assets as well as fund characteristics, such as investment style, fee structure, and asset allocation information. Thomson Reuters includes quarterly fund portfolio holdings. We merge these two datasets using *Mutual Fund Links*. For constructing holding-based predictors, we also use the CRSP US Stock database. Our sample spans between 1985 and 2010, covering 25 years.

The meta-analysis nature of our study involves the replication of several measures from existing research. In order to pursue a synthesized approach, several decisions on consolidating the data were made. To enable others to replicate and expand our work, we start by explaining our filtering procedure, which is unified for all predictors. We do recognize that for several predictors, this choice may divert from the initially identified and tested predictors from the original papers.

Initially, we start with the universe of all mutual funds from the CRSP for a period between 1980 and 2010. We follow Kacperczyk, Sialm, and Zheng (2008) and select domestic equity funds that invest primarily in stocks. Thus, we eliminate balanced, bond, money market, international, and sector funds, as well as funds not invested primarily (less than 80%) in equities. We select the funds according to the objective codes and on the disclosed asset compositions.[2] As a double-check and because the objective code does not always clearly show if a portfolio of the fund is balanced, we also check the type of assets the fund invests in and exclude those that hold less than 80% or more than 105% in stocks on average.

The CRSP database includes information on all mutual funds, including those who terminated their existence. Thus, our sample is free from the potential survivorship bias. However, Evans (2004) addresses a survival bias in the CRSP database, which results from a strategy used by fund families to increase their return histories. In particular, these funds would report publicly only the history of the surviving incubated funds. To address this issue, we exclude funds that do not have fund names in the CRSP and funds that have observations before the reported fund-starting year. In the last step, after the merge of the two databases, we exclude funds that have fewer than ten disclosed stocks in a given year and funds that did not disclose their holdings during the last year. As a result of such sample selection, the number of distinct funds in our analysis is 2,815, with 420,175 monthly observations on average. Our original dataset spans from 1980 until 2010, but as some predictors require a history of up to three years, we end up with a sample that covers a period between January 1985 and December 2010.

Our analysis takes place on the portfolio level; hence, we aggregate observations for different share classes into one portfolio fund. For the total net assets (hereafter: TNA) under

[2]First, we leave those funds that have the following objectives based on the ICDI classification: AG, GI, LG, or IN. In case a given fund lacks any of the mentioned ICDI objectives, we apply the following Strategic Insight objectives: AGG, GMC, GRI, GRO, ING, or SCG. If a fund has neither of the two described strategies, we proceed with the Wiesenberger Fund Type Code, selecting the following objectives: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. If still none of the objectives exists for a fund and it has a Common-stock policy, we leave that fund. We also recheck and eliminate funds having the following Investment Objective Codes: municipal bonds/international/bond/preferred/balanced.

management, we sum up the TNAs of the different share classes.

The dynamics of our sample is represented in Table 20. The number of funds has increased from almost 400 in the year 1985 to the peak of 2,185 funds in the year 2005 and then dropped to 1,674. There are 2,815 distinct funds in our sample universe, with an average of 1,431 funds per year.

[TABLE 20 IS ABOUT HERE]

Summary statistics shown in Table 21 report that our mutual funds invest 94.2% in stocks and fewer proportions in cash (4.6%) and bonds (0.6%). The percentage of holdings in other assets is also relatively small (only 0.6%). Average monthly excess (after-fee) returns are 0.7%. Funds are 12 years old on average, with a turnover ratio of 88.1%. The sample includes funds of different size, with an average TNA of $941 million and a standard deviation of 4,326$ million. Table 29 in the Appendix contains a more detailed summary statistics for each size portfolio. When splitting the sample into three groups with the same number of fund-month observations, the number of distinct funds inside each varies from 1,136 for a subsample of large funds (average TNA of $2,825 million) up to 2,478 of small funds (average TNA of $12 million).[3]

[TABLE 21 IS ABOUT HERE]

2.2 Construction of Predictors

In this section, we explain the construction of each of the eight predictors in detail.

Active share (hereafter: *AS*). This measure aims to represent the share of fund portfolio holdings that differ from the holdings of the benchmark index. Cremers and Petajisto (2009) show that funds with the highest *AS* significantly outperform their benchmarks, both before

[3]The number of distinct funds for each size group does not add to the total number of funds from Table 20, because fund's TNA is not a fixed number and it changes, sometimes often.

and after expenses and exhibit strong performance persistence. Thus, the measure provides information about a fund's potential for beating its benchmark index. The logic is the following. When a fund overweights a stock relative to its weight in the index, it has a long position in this stock. To the contrary, when a fund underweights a stock compared to the index or does not buy it at all, it has an active short position in it. One may decompose each portfolio of fund holdings into two parts: a static portfolio that holds securities in the weights close to the fund's benchmark index and a zero-net-investment long-short portfolio that holds securities in weights different from the benchmark, in its attempt to outperform it. The size of this active long-short part is the idea behind the *AS* predictor. The larger the discrepancy between the constitutes of the fund and the benchmark, the greater the *AS*. The benchmark index is defined to be the index with the lowest active share to a given fund. As mutual funds almost never take actual short positions, their *AS* will always be between 0 and 100%.

Our construction of the measure until 2009 is based on the publicly available data from Antti Petajisto's website. After 2009, we replicate the measure using data on indices (index returns and ETF holdings) from *Morningstar direct*. Quarterly ETF holdings are merged with the CRSP for additional information about stocks. When holdings are reported only semi-annually, the missing quarters are filled up by using the information of the latest previous quarter. We do not calculate *AS* if less than 95% of positions for the benchmark could be identified. *AS* is calculated as the sum of the absolute value of the differences between the weights of the stocks in a portfolio and their weights in the fund's benchmark:

$$\text{Active Share} := \frac{1}{2}\sum_{i=1}^{N}\left|w_{fund,i} - w_{index,i}\right|, \tag{1}$$

where $w_{fund,i}$ and $w_{index,i}$ are the portfolio weights of asset i in the fund and the index, and the sum is taken across all assets.

Three-year Carhart Alpha (hereafter: *CA*). This predictor relates to the past mutual fund performance. Carhart (1997) shows that funds with high past three-year alphas from the four-factor model demonstrate relatively higher alphas and expected returns in subsequent periods. *CA* is estimated as the one-month abnormal return from the four-factor model, where factor loadings are estimated over the previous three years:

$$\alpha_{it} := R_{it} - RF_t - \hat{b}_{1it-1}RMRF_t - \hat{b}_{2it-1}SMB_t - \hat{b}_{3it-1}HML_t - \hat{b}_{4it-1}PR1YR_t, \quad (2)$$

where $RMRF_t$, SMB_t, HML_t, $PR1YR_t$ are Fama-French risk factors (market, size, value, and momentum) at month *t*, $R_{i,t}$ is a return of fund *i* in month *t*. Following the original paper, we estimate alphas on a monthly rolling-window basis for every fund that has a minimum of thirty observations. Specifically, for each fund at each date, we use the previous 36 months to estimate the betas on the Fama and French (1993) and Carhart factors. We then use those betas in (2) to calculate α_{it}. Mutual funds with high alphas demonstrate above-average alphas in the next period and large expected returns in subsequent periods. This can also be seen as a shred of supportive evidence on funds' performance momentum.

Characteristic selectivity (hereafter: *CS*). Wermers (2002) decomposes mutual fund returns into several components. One of them is the stock-picking ability of the fund manager, after controlling for a particular style used by that manager (initially developed by Daniel et al. (1997)). This measure helps to detect whether portfolio managers can successfully select stocks that outperform a peer stock with the same characteristics. The characteristic-based benchmark portfolios are constructed according to three dimensions – size, book value of equity to market value of equity ratio, and a prior-year return of a stock. To construct benchmark portfolios, we conduct the following three-step procedure. First, all stocks are ranked by their market capitalization at the end of June each year. The resulting quintile portfolios are divided further into book-to-market quintile portfolios, based on their book-to-market values at the end of December preceding the ranking year. Finally, the resulting 25 portfolios are divided further based on the past twelve-month stock returns through the end of May of the ranking year. Eventually, each of these portfolios represents a unique combination of different size, book-to-market, and momentum features. They are re-balanced in June each year. Thus, a characteristic-adjusted return for a given stock is computed as the buy-and-hold stock return minus the buy-and-hold value-weighted benchmark return during the same quarter.

The *CS* predictor is thus calculated as:

$$CS_t := \sum_{j=1}^{N} \widetilde{w}_{j,t-1}(\widetilde{R}_{j,t} - \widetilde{R}_t^{b_{j,t-1}}), \tag{3}$$

where $\widetilde{w}_{j,t-1}$ is the portfolio weight on stock j at the end of quarter $t-1$, $\widetilde{R}_{j,t}$ is the quarter t buy-and-hold return of stock j at the end of quarter $t-1$, $\widetilde{R}_t^{b_{j,t-1}}$ is the return on the characteristics-based benchmark portfolio matched at the end of quarter $t-1$. The *CS* is shown to predict future mutual funds' returns positively.

Characteristic timing (hereafter: *CT*). In the same paper, Wermers (2000) investigates whether portfolio managers successfully *time* their portfolio weightings on the same three characteristics as in the *CS* – size, book-to-market, momentum. Indeed, if these three characteristic-based strategies have time-varying expected returns, a manager can exploit this time variability and potentially generate additional returns to a fund. *CT* thus measures the manager's ability to time different stock characteristics. It is constructed as:

$$CT_t := \sum_{j=1}^{N} (\widetilde{w}_{j,t-1}\widetilde{R}_t^{b_{j,t-1}} - \widetilde{w}_{j,t-5}\widetilde{R}_t^{b_{j,t-5}}), \tag{4}$$

where $\widetilde{w}_{j,t-1}$ is the portfolio weight on stock j at the end of quarter $t-1$, $\widetilde{R}_t^{b_{j,t-1}}$ is the return on the characteristics-based benchmark portfolio matched at the end of quarter $t-1$ or $t-5$.

In the estimation, we deduct returns at t based on matching characteristic portfolio of quarter $t-5$ (weights are also belong to quarter $t-5$) from the return at t based on matching portfolio of quarter $t-1$ (weighted at the end of quarter $t-1$). Intuitively, *CT* will be high for those fund managers who increase the fund's weight on stock j before the payoff to the stock characteristics is the highest. The *CT* is found to positively predict future mutual funds' returns in the paper of Wermers (2000).

Expense ratio (hereafter: *Exp*). Gil-Bazo and Ruiz-Verdu (2009) introduce another predictor by uncovering the puzzle of a negative relationship between fund performance and fees charged by a fund. Although expense ratios were already tested in Carhart (1997), the above-mentioned authors rather concentrate on a before-fee performance and show that funds with worse before-fee performance charge higher fees. In general, mutual funds charge fees for the services they provide to investors. Because the main service supplied by a mutual fund is portfolio management, the fees should reflect funds' risk-adjusted performance. These management fees are typically computed as a fixed percentage of the value of assets under management. They are also a part of other operating expenses such as custodian, administration, accounting, registration, which all comprise the fund's expenses and are deducted on a daily basis from the fund's net assets by the managing company. Expenses are expressed as a percentage of assets under management known as the expense ratio and are taken from the CRSP.

Fund turnover (hereafter: *Turn*). The study by Pastor et al. (2017) finds that high fund turnover is associated with high future fund returns. To show this, they use the following regression with fund fixed effects:

$$R_{i,t} := \alpha_i + bX_{i,t-1} + \epsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ is the funds benchmark-adjusted return in month *t*, and $X_{i,t-1}$ is the funds turnover in period *t-1*. This is a lagged fund-adjusted predictor that explores the hypothesis that a fund trades more when it perceives greater profit opportunities and can exploit such ”alpha-producing” opportunities. The authors also note that it is important to control for the general level of trading activity by a fund, suggesting that funds with above long-term average volumes are skilled. As this approach uses the whole period for in-sample regressions, the findings from the original paper cannot be implemented as a trading strategy.

To capture the idea from the paper and to build a strategy based on the results, we calculate an "excess turnover". This is the fund's turnover in month *t* minus the fund's average turnover over five recent years. Such a measure can be used in a trading strategy because all information is known. We thus standardize turnover at the fund level using its previous history and require a fund to have at least five years of historical data.

R–squared. Amihud and Goyenko (2013) propose the measure of active fund management. It stems from the R^2 obtained from a regression of fund returns on the four-factor model. The measure is estimated on a rolling basis over 24 months preceding the test month. The low R^2 indicates that a fund manager deviates from standard factor models and significantly predicts better fund performance in the next month.

Return gap (hereafter: *RG*). This measure is claimed to be evolved from the unobserved actions of mutual fund managers. Such actions might potentially appear from the difference between returns on the fund's portfolio holdings and the returns reported by a fund. For example, there can be the specific timing of trades due to informational advantage and, correspondingly, their transaction costs. Kacperczyk et al. (2008) report that this deviation of the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings can predict future fund performance. Although a monthly measure of RG is on average close to zero, the authors find significant cross-sectional heterogeneity across funds. It suggests that hidden costs are more important for some funds, while hidden benefits are more pronounced for others.

The measure consists of two parts. First, the net investor return of fund f at time t (RF_t^f) is calculated as:

$$RF_t^f := \frac{NAV_t^f + D_t^f + CG_t^f - NAV_{t-1}^f}{NAV_{t-1}^f}, \tag{6}$$

where NAV_t^f is the net asset value of the fund f shares in month t, including dividends (D)

and the capital gain (CG) in the corresponding month. The other constitute is the return on a hypothetical buy-and-hold portfolio that invests in the most recently disclosed fund's holdings, after subtracting expenses:

$$RH_t^f := \sum_{i=1}^{n} \widetilde{w}_{i,t-1}^f R_{i,t}. \tag{7}$$

After adjusting weights $\widetilde{w}_{i,t-1}$ for stock splits, RG aggregates the two parts (6) and (7):

$$RG_t^f := RF_t^f - (RH_t^f - EXP_t^f), \tag{8}$$

where EXP_t^f are the fund's expenses in month t.

After constructing all eight predictors, we winsorize each of them at 1% level for the whole sample period. Missing values are filled with cross-sectional means.

2.3 Summary statistics of constructed predictors

Table 21 (Panel A) contains summary statistics of eight mutual fund predictors. The total number of unique funds and the corresponding number of month-fund observations slightly varies, depending on the inputs required for replication of each predictor. On average there are 2,627 funds per predictor, with a maximum of 2,815 funds for the Exp measure and a minimum of 2,399 funds for the AS and CT predictors. For example, the measures that do not require mutual funds' holdings and long history of consecutive observations (CA, Exp, $Turn$, $R-squared$) have a higher number of observations than those that do. In particular, the CT predictor has fewer observations than the CT and other predictors, because of a so-called "active" part of its construction, for which we need to have the reported fund holdings, stock returns and corresponding benchmark returns available for a current month as well as for the previous 12 months. For those papers that report the average values of predictors, the means of each constructed predictor are consistent with the original sources. $Turn$ has the largest standard deviation of 0.917, indicating heterogeneity across funds' trading volume and trading activity. RG has only 158,674 fund-month observations due to its extensive dependency on both holdings, expenses, and return history.

As we intend to use all predictors in the multivariate setting, it is crucial to inspect cross-correlations among them. If the correlation is high, we face potential multicollinearity concerns. Even though multicollinearity does not lead to bias in estimated slope coefficients, it increases standard errors of the coefficients and might lead to inaccurate conclusions. Absolute pairwise Pearson correlations among predictors occur to be rather low, with the lowest value of -0.0002, between CA and AS, and the highest absolute value reaching 0.255 between $R - squared$ and AS. (Table 21 Panel *B*). This allows us to avoid a potential problem of multicollinearity and to use all predictors together in further analysis.

3 Empirical Analysis

In this section, we test the predictive power of the constructed predictors. We start with univariate analysis and check whether each measure demonstrates predictive power in portfolio sorts, OLS, and Fama-MacBeth regressions. Next, we shift to a multivariate setting and combine all predictors in order to reveal which of them demonstrate independent information in terms of future fund return predictability.

3.1 Univariate analysis

The univariate setting delivers two main goals: (1) it provides a sanity check on whether the predictors were correctly constructed, (2) we use the results from univariate estimations as the baseline to be compared with the performance of the combined predictor.

The differences between the results of the constructed measures and the ones from the original papers can arise from several caveats. First, each paper applies its filtering procedure on a fund universe, including different threshold requirements (e.g., on the size of a share of stocks for equity mutual fund), various objective codes, etc. We apply *identical* filtering steps for each of eight predictors, relying on a cleaning procedure from Kacperczyk et al. (2008). Second, there is a large number of methods on how to test the performance of a predictor. Currently, the methods used in the original papers are diverse, and it is upon the decision of authors to choose types of regressions, prediction horizons, etc. on data transformation and estimations. We mainly use two approaches to identify the ability of the measure to predict next month's fund excess returns: portfolio sorting and Fama-MacBeth regressions with a different combination of factors.

Because of these reasons, predictors may divert and have missing values. We avoid discarding some measures only because their values are missing in one or few fund-months. Instead, we follow Green et al. (2017) and replace empty values with the corresponding cross-sectional averages. We also winsorize predictors at the 1st and 99th percentiles for the entire sample period.

We start testing the predictors by applying one of the most common approaches used in the mutual fund literature on predictability – portfolio sorts. Every month the funds are sorted based on the value of the corresponding predictor up to month *t-1*. A given mutual fund is allocated into one of the five quintile portfolios: portfolio 5 includes funds with the predictor values that claim to predict higher future fund returns. We map these predictors to the next month excess returns on a fund-month basis. Then, we calculate equal-weighted excess returns of each resulting quintile portfolio in month *t*, adjusting for different risk factors, and compare results between the top and the bottom portfolios. If there is a pronounced difference, a trading strategy exploiting this difference should make a profit. So, we go long (buy) the portfolio with the highest predictor value (quintile 5 in our case) in the previous month and go short (sell) the portfolio with the lowest predictor value (quintile 1 in our case). The return spread between these two portfolios points at the ability of such strategy in generating positive future excess returns, and the predictive power of a given fund measure.

Table 22 (Panels *A*-*D*) shows return spreads of the strategy in the next month based on the predictor value in the previous month for each quintile portfolio. In general, results are consistent with the original papers, and predictors generate excess future returns that are robust to controlling for risk factors. Although raw excess returns do not everywhere present gradual changes in returns from bottom to top portfolios, the returns of the long-short strategy have expected signs and are significant for most measures. Returns for CS appear to be statistically insignificant for a trading strategy, which might be explained by the fact that the original paper constructs the across-fund CS, weighted by the total net assets of each fund. The long-short portfolio, based on CA earns the highest returns of 0.16% per month. $Turn$ shows the highest statistical significance with an average monthly return of 0.14%. We also test whether each long-short portfolio generates a positive alpha on top of common risk factors: the market, the Fama-French, and the Carhart factors (Table 22 Panels *B*-*D*, correspondingly). Most predictors continue to perform in the same manner as without the factors, with slightly changed coefficient magnitude. CA, CT, Exp, $Turn$, and $R-square$ stay significant independent on the set of risk factors included, keeping the expected sign and with a relatively small variation in the return values. CS becomes significant on the 5% level only when Carhart factors are included.

Panel *E* of Table 22 demonstrates results of a different approach of testing predictability: Fama-MacBeth regressions (*FMB* henceforth). There are mainly two reasons of why the FMB regressions are a robust and relevant approach from an econometric point of view for our purpose to identify independent predictors of funds' future returns. First, the FMB easily deals with the models in which the slope coefficients change over time. As this refers to the varying nature of our predictors, it is easier to apply FMB than time-series or cross-sectional regressions separately. The other advantage is that FMB properly handles big cross-sectional data, allowing entities to be correlated with each other. Fund trading is found to be correlated: Koch et al., 2016 find that trading of mutual funds are correlated because of the common ownership across funds and because the liquidity shocks are also correlated. As the correlation among fund in the cross0section would generate the correlation in the errors, the FMB regressions are the way to correct the standard errors.

[TABLE 22 IS ABOUT HERE]

Results of the FMB regressions are not always in line with the portfolio sorts. $Turn$ is the most statistically significant predictor in this setting, although with a rather low coefficient of 0.0006. This means that a portfolio weighted toward funds with high turnover tend to earn higher future excess returns than a portfolio of funds with low turnover. A trading strategy built on the expense ratio (Exp) is associated with the largest returns of 0.108 among all predictors. CA, Exp and $Turn$ remain significant with the expected signs of coefficients. This is not the case for AS[4], CT, $R - squared$, and RG that have no significance of their FMB coefficients.

3.2 Multivariate analysis

In this section, we combine the predictors into multivariate analysis. The main goal is to determine how many and which of eight predictors contain independent information on predicting future fund returns. Because of the properties mentioned in the previous section, we argue that the FMB approach enables us to most powerfully identify the *independent* determinants, those that would stay significant when the estimation is controlled for all other predictors.

Estimation results in Table 24 (Panel *A*) show that for the period from 1985 to 2010, only three predictors occur to be significant: CA, Exp, and $Turn$, all at 1% confidence level. These predictors are also robust to the inclusion of different risk factors: the coefficients vary narrowly, and significance does not drop.

The predictive power may be driven by a subsample of specific funds or a particular time pe-

[4] In the original paper, the performance of the AS is analyzed using the benchmark-adjusted returns. Having replicated the measure using benchmark-adjusted returns, we still do not observe the FMB regression to reveal the statistical significance of the AS predictor.

riod. To investigate this issue, we split the sample based on (1) fund characteristics such as size and investment strategy, and (2) time periods. Panel *B* of Table 24 shows the results of different subsample tests. The results are mostly stable over two equal time periods from 1985-1997 and 1998-2010 (columns 1-2); however, time variability of some predictors reveals interesting insights. CA is a better predictor for an earlier period of 1985-1997, while it becomes insignificant during 1998-2010.

The magnitude and statistical significance of Exp decreases from the earlier to the later sample period from -0.0956 to -0.1167, while $Turn$ performs well for both time periods. These predictors that yield to be insignificant in the FMB regressions (AS, CS, CT, $R - squared$) of the whole sample period do not become significant in either of the time subperiods. The only predictor that turns out to change its statistical significance across the two sub-periods is the RG: it significant at 10% level in an earlier subsample.

[TABLE 24 IS ABOUT HERE]

A cross-sectional fund split reveals some further insights. We first explore the portfolios based on the fund investment styles. There are three groups: value, growth, or other defined according to the fund objective code reported in the CRSP database. Growth funds are the funds that mostly hold growth stocks that are expected to grow faster than the overall market. Value mutual funds invest primarily in value stocks, which are stocks that, as investors believe, are selling at a lower price in relation to their earnings or other fundamental value measures. There are three characteristics in the CRSP database that help us to allocate a given fund into either *growth*, *value*, or *other* type of investment strategy. These are fields called Lipper Objective codes, Wiesenberger Objective codes, and Strategic Insight Objective codes. As the Lipper classification has the largest number of non-empty strategy flags, we first allocate funds based on these codes. Then we look at the Wiesenberger classification code and finally use the Strategic Insight Objective codes.[5] Funds with different strategy codes and those that do not have a

[5] A given fund is assigned into "value fund" portfolio when it has the following strategy codes: LCVE, MLVE,

strategy flag are assigned into a portfolio of ”other” investment strategies.

Finally, we have 1,822 growth, 704 value, and 1,378 funds with other investment strategies.[6] Interestingly, two measures that aim to tackle fund's stock selectivity (AS and RG) work better for value funds. This might indicate that value fund managers are skilled in identifying market inefficiencies, meaning that they identify the stocks that are traded at cheaper prices than they are actually worth. CA significantly predicts excess returns of growth and other-strategy funds, suggesting that returns of these funds are more persistent on a three-year horizon. Relatedly, the predictability of Exp is driven by value and other-strategy funds. $Turn$ performs well for growth and other funds at almost the same magnitude and loses power for value funds.

The power of predictors also varies across different fund sizes. CA, Exp, and $Turn$ perform well across funds of all sizes. AS works only for small funds, probably because small funds are the ones that can run active strategies by diverting from the index benchmarks more easily. This is also a case for RG that loses power for middle and large funds. This predictor also relates to the deviation of fund holdings from the benchmark, and the argument of small funds being more ready to deviate from the benchmarks is also relevant for RG. Other measures do not show up to be significant for any size portfolio.

3.3 Joint Predictor

As the statistical significance of individual predictors in multivariate FMB regressions does not necessarily imply substantial forecasting power for future performance, in this section, we conduct different tests focusing on measuring the magnitude of economic benefits by exploiting the full set of our eight predictors.

We follow the method suggested by Lewellen (2015) and Green et al. (2017) and create the joint

SCVE, MCVE. The ”growth fund” strategy codes are: ING, GRO, GRI, AGG, G, GI, LCGE, MCGE, MLGE, SCGE, MLGE, MCGE, SCGE, AGG, GRI, GCI, SCG, MCG, LTG, GRO.

[6] The total number of funds is larger than 2 815 from Table 20, because the strategy flag is not stable over time; i.e., it can change throughout the sample period.

fund return predictor as follows. We run FMB regressions of the excess returns in month *t+1* on the joint predictor in month *t*. This is done on a rolling basis with the fixed estimation window of 36 months: we use the estimation period from month *t-36* up to month *t* and excess fund returns in month *t+1*. The fitted values from these regressions are saved and used as a basis for creation of five quintile portfolios, on a monthly frequency of hypothetical rebalancing. The newly combined predictor is tested by portfolio sorting and FMB regressions, both also controlled for different risk factors models.

Table 25 shows the performance of our newly created variable under several specifications. Quintile portfolios with the lowest value of the combined predictor persistently show the lowest average returns ranging from -0.3% (on top of the CAPM risk factor) to 0.38% (raw returns without adjusting for risk factors). At the same time, portfolios with the highest combined predictor values generate positive and statistically significant returns ranging from 0.16% (on top of the Carhart risk factors) to 0.86% (raw returns without adjusting for risk factors). The long-short portfolio formed on a new prediction variable earns average raw monthly excess returns of 0.48% per month and statistically significant at the 10% level. Adjusting for the risk factors does not affect the results: the trading strategy still performs well and earns an average alpha of 0.48% per month when Carhart risk factors are included. Again the spread shows statistical significance at the 1% level.

[TABLE 25 IS ABOUT HERE]

In order to see further how stable and persistent the return-generating process of the trading strategy based on the combined predictor is, we calculate excess future returns with a horizon of two months. Panel *A* Table 25 present cumulative return for two months. The values are calculated as the natural log of one plus the cumulative mean portfolio returns starting after the month when sorting is made (columns 5). Returns of the portfolio built from the funds with the highest combined predictor are 1.71% for the following two months. The long-short trading strategy generates significant returns of 2.91% for an out-of-sample period lasting for six months.

Figure 31 represents the dynamics of cumulative returns for an extended duration of the whole sample period. Visual inspection of the figure indicates that: (1) cumulative returns increase on average throughout the time, (2) the mean returns for the portfolio slightly fell in early 2002 and sharply decreased in 2008. These declines both correspond to the stock market downturn in 2002 and the financial crisis of 2008. Such return decline during these periods can suggest that the new predictor is exposed to a market crash risk.

[FIGURE 31 IS ABOUT HERE]

Finally, we use our new combined predictor using the FMB specification. The predictor generates positive and significant coefficients on top of different combinations of risk factors and is statistically significant at the 10% level at all specifications of risk factors (Panel *B* Table 25).

To summarize, this section shows the results of identifying independent measures that predict funds' future returns in a multivariate setting. Combining the replicated predictors, we create the joint combined predictor. We show that this new predictor performs better compared to the baseline model of univariate predictor estimations in both portfolio sorting and FMB approaches. For example, the highest monthly return of the long-short portfolio spread on top of Carhart factors of 0.14% is found for CA, while the comparable value of the combined predictor is 0.45%. For FMB regressions, the predictor with the highest coefficient (also CA) amounts to 0.057 (with corresponding *t*-statistics of 3.51), while the same estimate of the new predictor is 0.940 (with corresponding *t*-statistics of 7.00).

3.4 Robustness

As our new variable performs better than benchmark specifications under all settings, this part focuses on different robustness tests. First, we check whether the inclusion of various risk factors weakens the predictability. Second, the predictability of the joint predictor is analyzed across different cross-sectional and time-series splits. Eventually, we disentangle the predictor and look closely on its potential drivers.

In the first robustness check, we check whether the predictive power of the new joint predictor depends on the inclusion of different risk factors found in the existing research. We apply the following additional risk factors: the market (MKT), small-minus-big (SMB), high-minus-low (HML) from Fama and French (1993), monthly premium on winners minus losers (UMD) based on Carhart (1997), market-wide liquidity (LIQUI) introduced by Pastor and Stambaugh (2003), long-run reversal effect (LTREV) found by De Bondt and Thaler (1985), factor that exploits the return reversal at horizon of one month (STREV by Jegadeesh (1990)), betting-against-beta (BAB) found by Frazzini and Pedersen (2014), and the quality-minus-junk (long high-quality stocks and shorts low-quality stocks) factor by Asness et al. (2013).

We regress the return spread, which is the return difference between the top and the bottom quintile portfolios based on the new combined predictor on these different risk factors. Table 26 shows that in all specifications, the long-short portfolio generates a significant alpha ranging from 0.39% (in the model that includes Carhart and LIQUI factors) up to 0.51% (in the model that includes only Carhart factors) on a monthly basis. In each specification, the alpha is statistically significant at the 10% level.

We also check whether the predictive potential of the new variable is driven either by a specific period or by a particular group of funds. For this purpose, we investigate the cross-sectional split on the fund size (small, middle, large), fund investment strategy (value, growth, other), and for the time period (1985-1997, 1998-2010). Table 27 (Panel *B*) shows that there is a slight decrease in alphas and FMB coefficients in the later period of 1998-2010, but the predictive power is still strong and statistically significant. The predictor is also stable across the subsamples of different fund size (Panel *C*) and investment styles (Panel *D*). In each subsample, estimations demonstrate positive significant alphas and FMB coefficients of the new combined variable.

[TABLE 27 IS ABOUT HERE]

We proceed with further analysis of the combined predictor variable. As its performance can be driven exclusively by those predictors that happen to be significant in a multivariate FMB regression, we disentangle further analysis in two parts. First, we estimate multivariate FMB by regressing the spread of the trading strategy based on each significant predictor (CA,Exp, $Turn$) on the return spread based on the new predictor. and then insignificant ones ($R - squared$, CT, CS, RG). Panel *A* of Table 28 indicates that no matter which risk factors are included and which time period is taken, the strategy still generates positive and statistically significant alphas. Interestingly, positive and significant alpha exists when the strategy is regressed on the set of insignificant predictors as well. We thus conclude that this is truly a *combination* of the eight distinct predictors that contribute to the performance of the joint predictor.

[TABLE 28 IS ABOUT HERE]

3.5 Limitations

While our study is the first to estimate the simultaneous predictive power of predictors of different nature on funds' excess returns, we admit several limitations of this study. First, we replicate and examine only about 40% of all predictors currently available in the literature. This might be a caveat in identifying truly independent predictors of funds' performance. Thus, it is also not correct to generalize our results to the whole universe of 25+ predictors, because we have not chosen predictors randomly from the population of all predictors. In particular, we concentrate on those measures that can be replicated with CRSP and Thomson Reuters databases that are available to us. Second, our treatment of missed values (replacing them with the cross-sectional average) might cause estimation inaccuracies. Third, the performance of a trading strategy created from the new combined predictor does not account for trading costs/fees of monthly rebalancing that might be relatively high.

4 Conclusion

The goal of our paper is to suggest a new and distinct approach for assessing a manager's skill by aggregating individual fund return predictors into a composite score. In line with most prior work, our analysis focuses on actively managed broadly diversified US equity funds using a sample period from 1985 to 2010. We select eight prominent predictors that are shown to significantly predict future fund returns, requiring that each measure can be entirely calculable from the CRSP and Thomson Reuters databases. We map the estimation coefficients to the individual fund predictors' current values to obtain a composite forecast for the funds' one-month-ahead returns. We show that this multidimensional composite predictor has strong predicting power for future fund performance. Specifically, a hypothetical strategy of investing in the top quintile of funds based on the composite predictor outperforms the bottom quintile of funds by 0.45% per month or annualized 5.4% using the Carhart (1997) four-factor alpha as a performance metric. This spread is statistically significant at the 1% level with a *t*-statistic of 6.34. Moreover, the spread remains strong and statistically significant at least at 1% level when we evaluate fund performance over the future 2-month, 3-month, and 6-month ahead periods. We conduct several robustness checks to show that our results are not sensitive to several choices that we make in our empirical analysis. Broadly spoken, our paper finds that the "collective" wisdom of academic research might be helpful to separate winners from losers in the market for actively managed funds.

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Figures and Tables

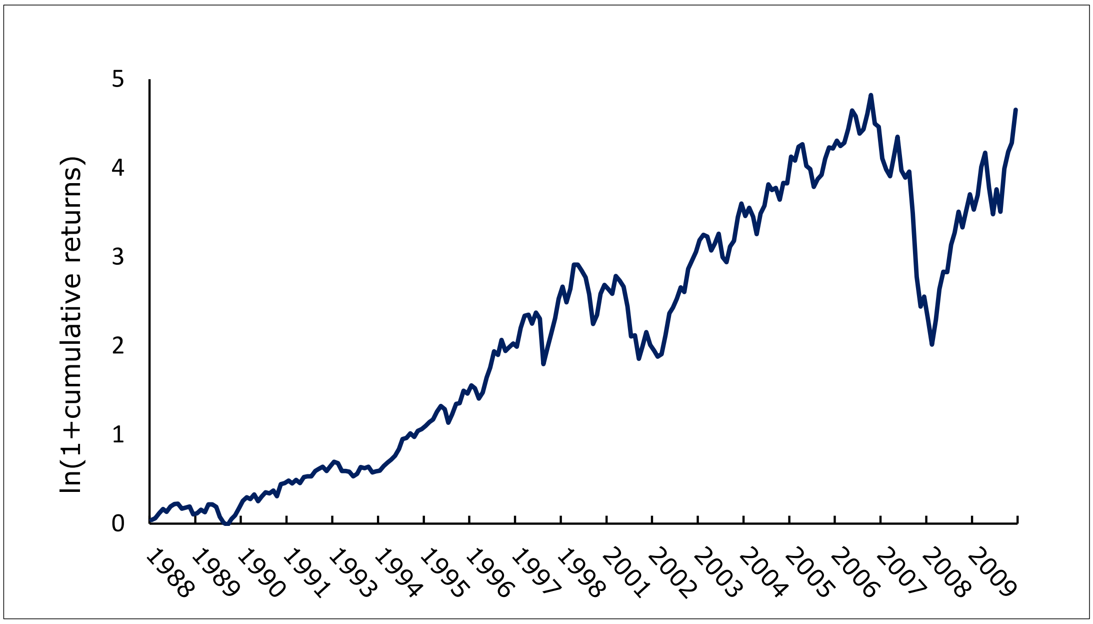

Figure 31: Cumulative return of the joint predictor. This figure plots ln(1+cumulative mean) of monthly long-short portfolio returns based on the joint predictor. The predictor was formed using the method suggested by Lewellen (2015) and Green et al. (2017). We run FMB regressions of the excess returns in month *t+1* on eight existing predictors in month *t*, on a rolling basis of 36 months. The fitted values from these regressions are saved and used as for five portfolios sorted, on a monthly frequency of hypothetical rebalancing. The sample covers US mutual funds over a period between 1985 and 2010.

Predictor	Abbreviation in the paper	Original source	Expected sign
(1)	(2)	(3)	(4)
Active share	AS	Cremers and Petaijisto (2009)	$+$
3-year Carhart alpha	CA	Carhart (1997)	$+$
Characteristic selectivity	CS	Wermers (2002)	$+$
Characteristic timing	CT	Wermers (2002)	$+$
Expense ratio	Exp	Gil-Bazo and Ruiz-Verdu (2009)	$-$
Fund turnover	Turn	Pastor, Stambaugh, and Taylor (2017)	$+$
R-squared	R-squared / R^2	Amihud and Goyenko (2013)	$-$
Return gap	RG	Kacperczyk, Sialm, and Zheng (2008)	$+$

Table 19: Mutual fund predictors used in the study. This table summarizes mutual fund predictors chosen to be replicated and used in this study. Column (2) shows a short abbreviation for a corresponding predictor that is used throughout this paper. Column (3) indicates the original paper, from which each predictor is taken. Column (4) contains the expected sign of the relationship between a given predictor and *higher* fund returns in the next month, based on the results from the original papers.

Panel A: Number of funds and observations

Year	Number of distinct funds	Number of fund-month observations
1985	411	4,515
1986	474	5,160
1987	551	6,021
1988	593	6,793
1989	625	7,166
1990	674	7,645
1991	733	8,312
1992	879	9,275
1993	1,020	11,041
1994	1,150	12,583
1995	1,266	13,904
1996	1,421	15,348
1997	1,562	17,340
1998	1,667	18,513
1999	1,794	20,116
2000	1,981	21,772
2001	2,053	23,194
2002	2,118	24,239
2003	2,157	24,786
2004	2,190	25,046
2005	2,204	25,027
2006	2,160	24,942
2007	2,074	24,043
2008	1,957	22,835
2009	1,833	21,066
2010	1,678	19,493
Total	2,815	420,175
Average per year	1,431	16,160

Panel B: Summary statistics

	Mean	Median	Standard deviation	25%	75%
Return (per month)	0.007	0.039	-0.02	0.011	0.055
TNA (total net assets, in millions $)	941.1	94.2	4 326	18.3	441.4
Age (in years)	12.2	7.8	13.5	3.6	15.2
Expense ratio (in %)	1.3	1.2	1.4	0.9	1.5
Turnover ratio (in %)	88.1	61	123	30	110
Proportion invested in stocks (in %)	94.2	95.4	4.4	92.2	97.4
Proportion invested in cash (in %)	4.6	3.6	4.3	1.6	6.3
Proportion invested in bonds (in %)	0.6	0	0	0	0.3
Proportion invested in other securities (in %)	0.5	0	2.5	0	0.4

Table 20: Summary statistics of the fund universe. This table provides summary statistics of mutual funds over a period between January 1985 - December 2010. The funds were selected according to the filtering procedure by Kacperczyk et al. (2008).

Panel A: Summary statistics of distinct predictor

	Number of funds	Number of fund-month observations	Mean	Standard deviation	25%	75%
AS	2,399	227,677	0.751	0.221	0.663	0.909
CA	2,697	318,690	-0.001	0.019	-0.01	0.008
CS	2,750	322,863	0.000	0.069	-0.035	0.028
CT	2,399	170,656	0.003	0.123	-0.003	0.073
Exp	2,815	229,129	0.013	0.006	0.0091	0.015
Turn	2,417	206,238	0.004	0.917	-0.707	0.691
R^2	2,781	355,254	0.902	0.088	0.875	0.961
RG	2,759	158,674	-0.001	0.003	-0.002	0.0003

Panel B: Correlation of predictors

	AS	CA	CS	CT	Exp	Turn	R^2	RG
AS	1.000							
CA	-0.002	1.000						
CS	0.003	0.041	1.000					
CT	-0.008	-0.019	-0.055	1.000				
Exp	0.168	-0.027	-0.009	0.016	1.000			
Turn	0.003	0.008	0.025	0.023	0.022	1.000		
R^2	-0.255	-0.005	-0.035	0.088	-0.196	-0.031	1.000	
RG	-0.016	-0.021	0.040	-0.066	-0.048	0.014	-0.018	1.000

Table 21: Statistics across distinct predictors. *Panel A* presents the summary statistics for eight mutual fund predictors used in the analysis. Predictors are constructed as follows: AS is active share is from *Cremers & Petaijisto (2009)*, CA is three-year Carhart alpha from *Carhart (1997)*, CS and CT are characteristic selectivity and characteristic timing from *Wermers (2000)*, Exp is expense ratio from *Gil-Bazo & Ruiz-Verdo (2009)*, Turn is fund turnover from *Pastor, Stambaugh, and Taylor (2014)*, R^2 is the R-squared from a regression on a multi-factor benchmark model from *Amihud & Goyenko (2013)*, RG is the return gap from *Kacperczyk, Sialm, and Zheng (2008)*. *Panel B* shows the pairwise Pearson product-moment correlation across pairs of fund predictors. The predictors are winsorized at 1% level for the whole sample period, and missing values are filled with cross-sectional means. The sample period is from January 1985 to December 2010, with a monthly frequency of observations.

Panel A: Raw Excess Returns

Portfolio	AS	CA	CS	CT	Exp	Turn	R^2	RG
1	0.0051	0.0044	0.0054	0.0049	0.0059	0.0046	0.0061	0.0060
2	0.0048	0.0051	0.0057	0.0063	0.0053	0.0048	0.0058	0.0064
3	0.0112	0.0049	0.0052	0.0114	0.0078	0.0050	0.0055	0.0065
4	0.0056	0.0052	0.0056	0.0093	0.0062	0.0070	0.0048	0.0099
5	0.0064	0.0061	0.0061	0.0049	0.0053	0.0057	0.0046	0.0067
5–1	0.0015***	0.0016***	0.0006	0.00064**	-0.0009***	0.0011***	-0.0015**	0.00072**
	(3.12)	(4.36)	(1.25)	(1.99)	(-4.06)	(4.88)	(-2.08)	(2.32)

Panel B: CAPM alphas

Portfolio	AS	CA	CS	CT	Exp	Turn	R^2	RG
1	0.0045*	0.0037	0.0046*	0.0046*	0.0053**	0.0039	0.0053**	0.0051*
	(1.82)	(1.30)	(1.74)	(1.76)	(2.14)	(1.63)	(2.11)	(1.96)
2	0.0043	0.0045*	0.0049**	0.0059*	0.0046*	0.0042*	0.0051*	0.0057*
	(1.47)	(1.71)	(1.98)	(1.88)	(1.79)	(1.69)	(1.87)	(1.72)
3	0.0079	0.0045	0.0046	0.0095	0.0073*	0.0049	0.0048*	0.0057*
	(0.89)	(1.59)	(1.64)	(1.62)	(1.94)	(1.15)	(1.77)	(1.72)
4	0.0049*	0.0046**	0.0049*	0.0085**	0.0057**	0.0063**	0.0041	0.0089***
	(1.94)	(1.80)	(1.93)	(2.41)	(2.03)	(2.30)	(1.50)	(2.91)
5	0.0055**	0.0054**	0.0053**	0.0054**	0.0042	0.0051**	0.0039	0.0055**
	(1.99)	(2.01)	(2.01)	(2.13)	(1.60)	(2.09)	(1.50)	(1.98)
5–1	0.0011*	0.0017***	0.0007	0.0007**	–0.0011***	0.0012***	–0.0013***	0.0006**
	(1.74)	(4.47)	(1.35)	(2.22)	(-2.37)	(4.84)	(-2.87)	(2.01)

Panel C: Fama–French alphas

Portfolio	AS	CA	CS	CT	Exp	Turn	R^2	RG
1	0.0048*	0.004	0.0048*	0.0049*	0.0056**	0.0042*	0.0055**	0.0053**
	(1.92)	(1.40)	(1.80)	(1.84)	(2.21)	(1.72)	(2.14)	(2.01)
2	0.0049*	0.0047*	0.0052**	0.0062*	0.0049*	0.0045*	0.0053*	0.0056
	(1.66)	(1.78)	(2.03)	(1.94)	(1.86)	(1.81)	(1.95)	(1.65)
3	0.0048	0.005*	0.0048*	0.0093	0.0076*	0.0050	0.0051*	0.0056
	(0.60)	(1.77)	(1.69)	(1.50)	(1.98)	(0.98)	(1.85)	(1.65)
4	0.0051**	0.0049*	0.0051**	0.0081**	0.0061**	0.0062**	0.0043	0.0085***
	(2.00)	(1.89)	(1.99)	(2.28)	(2.09)	(2.18)	(1.58)	(2.76)
5	0.0057**	0.0057**	0.0057**	0.0056**	0.0045*	0.0053**	0.0042	0.0057**
	(2.03)	(2.12)	(2.11)	(2.19)	(1.69)	(2.14)	(1.58)	(2.05)
5-1	0.0009	0.0017***	0.0007	0.0007**	-0.0011***	0.0013***	-0.0012***	0.00063*
	(1.41)	(4.53)	(1.57)	(2.28)	(-2.28)	(4.46)	(-2.07)	(1.72)

Panel D: Carhart alphas

Portfolio	AS	CA	CS	CT	Exp	Turn	R^2	RG
1	0.005**	0.005*	0.0052*	0.0052*	0.0059**	0.0045	0.0061**	0.0061**
	(1.98)	(1.72)	(1.89)	(1.94)	(2.32)	(1.80)	(2.34)	(2.27)
2	0.0051*	0.0054**	0.0054**	0.0068**	0.0054**	0.0048*	0.0059**	0.0057*
	(1.71)	(2.00)	(2.12)	(2.09)	(2.01)	(1.87)	(2.13)	(1.68)
3	0.0039	0.0055*	0.0054*	0.0098	0.0079**	0.0041	0.0056**	0.0057*
	(0.53)	(1.89)	(1.87)	(1.59)	(1.98)	(0.79)	(2.01)	(1.68)
4	0.0056**	0.0053**	0.0055**	0.0084**	0.0065**	0.0063**	0.0048*	0.0085***
	(2.14)	(2.02)	(2.11)	(2.34)	(2.19)	(2.19)	(1.70)	(2.75)
5	0.0064**	0.0061**	0.0063**	0.0062**	0.0049*	0.0057**	0.0045	*0.0068**
	(2.27)	(2.22)	(2.32)	(2.39)	(1.86)	(2.25)	(1.66)	(2.41)
5–1	0.0014*	0.0011***	0.00104**	0.0009***	–0.00096**	0.0012***	–0.0016**	0.00077
	(1.67)	(2.96)	(2.12)	(2.76)	(-1.94)	(4.75)	(-2.09)	(1.12)

Panel E: Fama–MacBeth regressions

Portfolio	AS	CA	CS	CT	Exp	Turn	R^2	RG
Estimate	0.011	0.057***	0.02	0.004	–0.108***	0.0006***	–0.0021	0.009
	(0.63)	(3.51)	(0.28)	(0.92)	(–3.07)	(6.59)	(–0.71)	(0.12)
Intercept	0.005*	0.0052**	0.0057**	0.0055**	0.007***	0.0051**	0.007**	0.0059**
	(1.94)	(2.00)	(2.29)	(2.22)	(2.84)	(2.13)	(2.65)	(2.30)
R^2	0.030	0.035	0.032	0.009	0.011	0.003	0.023	0.005

Table 22: Univariate test of each predictor. *Panel A* of this table presents average excess returns of portfolios sorted on each predictor. *Panels B–D* show alphas from the univariate regressions of monthly portfolios' returns or of a return spread on factors. Every month we sort funds into five equal-size quintiles based on a predictor in the previous month. The return spread is the difference in returns between the top and the bottom quintiles (*5-1* in the table). We regress next month's portfolios' return or return spread on factors. Alphas and their corresponding t-statistics are in brackets. Variables are winsorized at 1% level for the whole sample period and missing values are filled with the cross-sectional means. *Panel E* demonstrates the results from Fama–MacBeth regressions: each predictor is regressed on the next month's excess fund returns. AS is active share is from *Cremers & Petaijisto (2009)*, CA is three-year Carhart alpha from *Carhart (1997)*, CS and CT are characteristic selectivity and characteristic timing from *Wermers (2000)*, Exp is expense ratio from *Gil–Bazo & Ruiz-Verdo (2009)*, Turn is fund turnover from *Pastor, Stambaugh, and Taylor (2014)*, R^2 is the R–squared from a regression on a multi-factor benchmark model from *Amihud & Goyenko (2013)*, RG is return gap from *Kacperczyk, Sialm, and Zheng (2008)*. The sample period is from January 1985 to December 2010, with a monthly frequency of observations.

	Return	CAPM	Fama-French	Carhart
	(1)	(2)	(3)	(4)
AS	0.0018	0.0011	0.0007	0.0004
	(1.18)	(0.78)	(1.11)	(0.59)
CA	0.0531***	0.0475***	0.0426***	0.0401***
	(3.49)	(3.73)	(3.83)	(3.64)
CS	–0.0019	–0.0003	0.0051*	0.0021
	(–0.36)	(–0.08)	(1.86)	(0.77)
CT	0.0032	0.0027	0.0033	–0.0003
	(0.75)	(0.77)	(1.33)	(–0.12)
Exp	–0.1085***	–0.1692***	–0.1568***	–0.1111***
	(–4.47)	(–10.60)	(–10.03)	(–8.15)
Turn	0.0005***	0.0004***	0.0003***	0.0003***
	(5.97)	(5.00)	(4.48)	(5.52)
R^2	0.0025	–0.00009	0.0003	0.00141
	(0.91)	(–0.04)	(0.16)	(0.78)
RG	0.0541	–0.0027	–0.0260	0.0534
	(0.76)	(–0.03)	(–0.29)	(1.04)
constant	0.003	0.003	0.0028	0.003*
	(0.90)	(1.25)	(1.40)	(1.68)
R^2	0.12	0.26	0.39	0.35

Table 23: Fama–MacBeth multivariate regressions. The table shows the resulting estimates from the Fama-MacBeth regressions. Explanatory variables include all eight replicated predictors. The next month's excess return is the dependent variable. Each column indicates whether additional risk factors are included in the regressions. Column (1) specification does not include any risk factors and represents coefficients and the constant without controlling for any risk model.

	Time split		Investment style split			Size split		
	1985-1997	1998-2000	Growth	Value	Other	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AS	0.0026	0.0014	0.0014	0.0066**	0.0018*	0.007**	0.0018	0.0003
	(0.92)	(0.82)	(0.70)	(2.48)	(1.84)	(2.38)	(1.15)	(0.22)
CA	0.0864***	0.027	0.0537***	–0.011	0.0508***	0.044***	0.058***	0.051***
	(3.96)	(1.33)	(3.45)	(-0.69)	(2.87)	(3.01)	(3.75)	(2.81)
CS	0.0046	-0.0074	-0.0107	0.0022	-0.0033	-0.003	-0.0026	-0.0012
	(0.70)	(-0.95)	(-0.89)	(0.27)	(-0.48)	(-0.49)	(-1.14)	(-0.14)
CT	0.0073	0.000	0.0168	0.0017	0.0045	0.0017	-0.0016	0.014
	(1.29)	(0.02)	(1.51)	(1.56)	(0.68)	(0.25)	(-0.29)	(1.61)
Exp	-0.095**	-0.117***	-0.001	-0.116***	-0.152***	-0.12***	-0.071**	-0.096***
	(-2.27)	(-4.21)	(-0.05)	(-2.99)	(-4.79)	(-4.60)	(-2.08)	(-3.12)
Turn	0.0004***	0.0006***	0.0006***	0.0001	0.0004***	0.0006***	0.0005***	0.0004***
	(3.37)	(4.90)	(5.36)	(0.63)	(3.24)	(3.32)	(4.11)	(4.12)
R^2	0.0049	0.0002	0.0013	0.0001	0.0052	0.0045	-0.0014	0.0017
	(1.49)	(0.07)	(0.45)	(0.24)	(1.45)	(1.49)	(-0.49)	(0.47)
RG	0.099*	0.0166	-0.0276	0.1898	0.0149	0.18**	0.0105	-0.021
	(1.85)	(0.13)	(-0.28)	(1.61)	(0.26)	(2.55)	(0.15)	(-0.32)
Constant	0.002	0.003	0.0057*	0.0007	0.0011	-0.003	0.0058**	0.0064**
	(0.90)	(0.92)	(1.86)	(0.17)	(0.39)	(-0.96)	(1.97)	(2.07)
R^2	0.11	0.12	0.006	0.006	0.16	0.13	0.14	0.16

Table 24: Time and cross-sectional subsamples. The table shows slope estimates from Fama-MacBeth regressions that include all predictors as independent variables and the next month's excess return as a dependent variable. Values are coefficients for subsamples of size and style portfolios. Style portfolios are based on Lipper classification objective/Wiesenberger type/ Strategic insight objective from *CRSP Survivor-Bias-Free US Mutual Fund Database*. Values of *t*-statistic are in brackets.

Panel A: Portfolio sorting

Portfolio	Raw Return (1)	CAPM (2)	Fama-French (3)	Carhart (4)	2 months (5)
1	0.0038*	-0.0030***	-0.0029***	-0.0028***	0.0074
	(1.64)	(-4.72)	(-6.21)	(-5.86)	(1.61)
2	0.0047	-0.0019***	-0.0019***	-0.0018***	0.0093***
	(1.61)	(-4.12)	(-5.68)	(-5.58)	(2.08)
3	0.0058**	-0.00084*	-0.00081**	-0.00095***	0.0114***
	(1.98)	(-1.86)	(-2.76)	(-3.20)	(2.57)
4	0.0069***	0.00025	0.00028	0.00008	0.0136***
	(2.34)	(0.49)	(0.81)	(0.23)	(3.05)
5	0.0086***	0.00198***	0.002***	0.0016***	0.0171***
	(2.89)	(2.82)	(4.01)	(3.18)	(3.81)
5–1	0.0048***	0.0051***	0.005***	0.0045***	0.0097***
	(6.68)	(7.07)	(7.01)	(6.34)	(9.27)

Panel B: Fama-MacBeth regressions

	Raw Return (1)	CAPM (2)	Fama-French (3)	Carhart (4)
Coefficient	0.940***	0.789***	0.543***	0.515***
	(7.00)	(7.12)	(7.19)	(7.32)
Intercept	0.0011	-0.0027	-0.0017	-0.0014
	(0.36)	(-1.16)	(-1.09)	(-0.93)
R^2	0.039	0.190	0.350	0.382

Table 25: Combined predictor. The table shows the performance of the newly created "prediction" variable. We run Fama-MacBeth rolling estimation procedure with a fixed estimation window of 36 months, regressing next month's excess returns on eight predictors, and save the fitted values. We then sort funds monthly into five equal portfolios based on these predicted returns and regress the return spread between the top and the bottom quintiles on factors. *Panel A* shows average raw returns, alphas from regressing each portfolio on different factors. Column (5) shows average cumulative returns in the next two months after sorting. In *Panel B* we also test Fama-MacBeth regressions: next month's excess returns are a left-hand variable and predicted values are on the right–hand variable. Corresponding *t*-statistics of the estimations are in brackets. The sample period is between January 1986 and December 2010. All variables are winsorized at 1% level and missing values were filled by cross-sectional means.

Risk factors	Fama-MacBeth coefficients				
MKT	–0.0091	–0.0047	–0.0077	–0.012	-0.0097
	(–0.54)	(–0.28)	(–0.45)	(–0.72)	(–0.46)
SMB	0.0444*	0.0459*	0.0246	0.0515*	0.0437
	(1.70)	(1.76)	(0.87)	(1.97)	(1.50)
HML	0.0553**	0.0578**	0.0023	0.0722**	0.0548*
	(2.05)	(2.13)	(0.07)	(2.57)	(1.87)
UMD	0.073***	0.0750***	0.0889***	0.0736***	
	(4.52)	(4.62)	(4.99)	(4.15)	
LIQUI		–0.0141	–0.0104		
		(–1.30)	(–0.95)		
LTREV			0.0770**		
			(2.06)		
STREV			–0.0993***		
			(–3.94)		
BAB				–0.0481**	
				–2.03	
QMJ				–0.0020	
				(–0.05)	
constant	0.005***	0.004***	0.005***	0.004***	0.004***
	(7.07)	(5.19)	(6.15)	(6.52)	(5.87)
R^2	0.048	0.097	0.086	0.107	0.090

Table 26: Additional risk factors. Every month we sort funds into five equal-size quintiles based on the newly created ”prediction” variable. The return spread is the difference in returns between the top and the bottom quintiles (5-1). We regress return spread on combinations of different factors. Corresponding t-statistics of slope and alpha estimations are in brackets. Variables are winsorized at 1% level for the whole sample period and missing values are filled with the cross-sectional means. The sample period is from Jan 1985 to Dec 2010, with the monthly frequency of observations. The factors are: market (MKT), small-minus-big (SMB), high-minus-low (HML) from Fama and French (1993), monthly premium on winners minus losers (UMD) based on Carhart (1997), marketwide liquidity (LIQUI) introduced as a factor by Pastor and Stambaugh (2003), long-run reversal effect (LTREV) studied by De Bondt and Thaler (1985), factor that exploits the fact that stock returns exhibit reversal at short horizons of one month (STREV by Jegadeesh, 1990), betting-against-beta (BAB) found by Frazzini and Pedersen (2014), and quality-minus-junk (long high-quality stocks and shorts low-quality stocks) factor from Asness et al. (2013).

Panel A: Robustness across time subsamples

	Portfolio sorts		Fama–MacBeth	
	1985-1997	1998-2010	1985-1997	1998-2010
CAPM alpha	0.0054***	0.0048***	0.8797***	0.7228***
	(5.66)	(4.63)	(5.64)	(4.66)
FF alpha	0.0055***	0.0047***	0.7852***	0.3649***
	(5.58)	(4.54)	(6.32)	(4.00)
Carhart alpha	0.0052***	0.0044***	0.7565***	0.3366***
	(4.95)	(4.47)	(6.52)	(3.98)

Panel B: Robustness across fund investment styles

	Value	Growth	Value	Growth
CAPM alpha	0.0034***	0.0050***	0.3799***	0.8096***
	(4.27)	(6.31)	(2.77)	(6.20)
FF alpha	0.0033***	0.0050***	0.1376	0.5478***
	(4.20)	(6.30)	(1.18)	(6.48)
Carhart alpha	0.0031***	0.0044***	0.1909*	0.5125***
	(4.06)	(5.63)	(1.67)	(6.47)

Panel C: Robustness across estimation windows

	Portfolio sorts				Fama–MacBeth		
	36-month	48-month	60-month	expanding	36-month	48-month	60-month
CAPM alpha	0.0051***	0.0044***	0.0035***	0.0030***	0.7895***	0.7638***	0.6973***
	(7.07)	(5.93)	(4.72)	(4.74)	(7.12)	(6.18)	(5.49)
FF alpha	0.0050***	0.0044***	0.0034***	0.0030***	0.5437***	0.4896***	0.4663***
	(7.01)	(5.88)	(4.73)	(4.68)	(7.19)	(6.37)	(5.71)
Carhart alpha	0.0045***	0.0040***	0.0030***	0.0028***	0.5153***	0.4731***	0.4516***
	(6.34)	(5.37)	(4.18)	(4.36)	(7.32)	(6.39)	(5.61)

Panel D: Robustness across fund size

	Small	Medium	Large	Small	Medium	Large
CAPM alpha	0.0052***	0.0051***	0.0050***	0.9139***	0.6603***	0.6828***
	(7.72)	(6.54)	(6.31)	(6.53)	(5.00)	(5.59)
FF alpha	0.0051***	0.0051***	0.0050***	0.7189***	0.3954***	0.3763***
	(7.63)	(6.47)	(6.23)	(5.67)	(4.13)	(4.44)
Carhart alpha	0.0047***	0.0044***	0.0044***	0.6706***	0.3754***	0.3301***
	(7.02)	(5.79)	(5.64)	(5.51)	(4.35)	(4.27)

Table 27: Robustness tests of the combined predictor. The table shows alphas from portfolio sorts and slope coefficients from FMB regressions. Fama–MacBeth regressions include all predictors as independent variables and the next month's excess return as dependent variable. *Panel A* contains results for the whole period for all funds, but for different estimation windows for constructing the combined predictor. *Panel B* shows coefficients for time subsamples. *Panels C-D* include results for different size and style portfolios splits. Style portfolios are based on Lipper classification objective/Wiesenberger type/ Strategic insight objective from *CRSP Survivor-Bias-Free US Mutual Fund Database*. *t*-statistics are in brackets.

Panel A: How significant predictors explain alpha

	CAPM			Fama-French			Carhart		
	All	85-97	98-10	whole	85-97	98-10	All	85-97	98-10
long-short	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CA	0.438***	0.571***	0.342***	0.436***	0.569***	0.343***	0.437***	0.567***	0.341***
	(9.61)	(13.41)	(4.07)	(9.63)	(13.59)	(5.02)	(9.61)	(13.48)	(3.92)
Exp	0.095	0.067	0.158	0.094	0.069	0.156	0.093	0.064	0.160
	(1.46)	(1.35)	(1.20)	(1.49)	(1.38)	(1.15)	(1.46)	(1.26)	(1.18)
Turn	0.495***	0.043	0.575**	0.492***	0.057	0.804***	0.491***	0.059	0.803***
	(3.06)	(0.26)	(2.18)	(3.04)	(0.34)	(3.38)	(3.02)	(0.35)	(3.32)
constant	0.003***	0.002***	0.003***	0.003***	0.002***	0.003***	0.003***	0.002***	0.003***
	(4.71)	(3.78)	(3.19)	(4.67)	(3.40)	(3.17)	(4.62)	(3.75)	(3.07)

Panel B: How insignificant predictors explain alpha

	CAPM			Fama-French			Carhart		
	All	85-97	98-10	All	85-97	98-10	All	85-97	98-10
long-short	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R^2	-0.126	0.169	-0.224**	-0.127	0.181	-0.219**	-0.126	0.167	-0.224**
	(-1.54)	(1.45)	(-2.16)	(-1.63)	(1.51)	(-2.13)	(-1.63)	(1.33)	(-2.16)
CT	–0.104	0.076	–0.241**	–0.111	0.073	–0.249**	–0.112	0.071	–0.241**
	(–1.48)	(0.76)	(–2.49)	(–1.37)	(0.71)	(–2.35)	(–1.37)	(0.69)	(–2.54)
CS	0.031	0.070	0.083	0.029	0.076	0.091	0.029	0.071	0.091
	(0.53)	(0.82)	(1.01)	(0.51)	(0.88)	(1.12)	(0.51)	(0.81)	(1.10)
AS	0.004	–0.016	0.056	–0.050	–0.013	0.058	–0.051	–0.022	0.067
	(0.08)	(–0.22)	(0.68)	(–0.94)	(–0.18)	(0.72)	(–0.95)	(–0.29)	(0.82)
RG	0.167**	0.010	0.270**	0.175**	0.106	0.270**	0.175**	0.109	0.271**
	(2.15)	(1.08)	(2.28)	(2.31)	(1.12)	(2.31)	(2.31)	(1.14)	(2.32)
constant	0.005***	0.005***	0.004***	0.005***	0.004***	0.004***	0.005***	0.004***	0.004***
	(6.64)	(4.26)	(4.11)	(6.62)	(3.97)	(4.21)	(6.69)	(3.81)	(4.14)

Table 28: Performance of the trading strategy controlled for two combinations of predictors. This table contains results from multivariate regressions: the long-short portfolio is regressed on set of predictors. Regressions reported in *Panel A* contain only predictors that appeared to be significant in multivariate regressions of future month's returns. *Panel B*, respectively, contain all other predictors. All variables are contemporaneous. The sample period is from January 1985 to December 2010.

Appendix

	Mean	Median	Standard deviation
Small funds			
Number of distinct mutual funds	2,478		
Number of fund–month observations	138,069		
TNA (total net assets) (in millions $)	12.2	8.6	19.1
Expense ratio (in %)	1.7	1.5	1.9
Turnover ratio (in %)	101.7	69	158
Proportion invested in stocks (in %)	94.2	95.7	5.3
Proportion invested in cash (in %)	4.2	3.2	4.2
Proportion invested in bonds (in %)	0.44	0	1.5
Proportion invested in other securities (in %)	0.48	0	2.3
Middle-size funds			
Number of distinct mutual funds	1,937		
Number of fund–month observations	137,834		
TNA (total net assets) (in millions $)	115.9	97.1	71.3
Expense ratio (in %)	1.3	1.2	0.5
Turnover ratio (in %)	87.6	59	109
Proportion invested in stocks (in %)	93.5	95.1	5.6
Proportion invested in cash (in %)	4.7	3.6	4.3
Proportion invested in bonds (in %)	0.4	0	1.4
Proportion invested in other securities (in %)	0.4	0	2.0
Large funds			
Number of distinct mutual funds	1,136		
Number of fund–month observations	137,795		
TNA (total net assets) (in millions $)	2,825.5	2,131.5	7,384.1
Expense ratio (in %)	0.98	0.95	0.47
Turnover ratio (in %)	71.4	52	69.9
Proportion invested in stocks (in %)	92.3	93.7	6.1
Proportion invested in cash (in %)	5.5	4.5	4.4
Proportion invested in bonds (in %)	0.6	0.05	1.4
Proportion invested in other securities (in %)	0.5	0	3.3

Table 29: Summary statistics of fund sample to size. This table summarizes the characteristics of the mutual funds' sample over the period January 1985 to December 2010. Every month the sample was divided into three equal parts, based on the funds' total net assets (TNA). TNA represents the total of all investor dollars invested in all share classes of the fund.

	Portfolio sorts		
Small funds	Whole sample (Jan 1985-Dec 2010)	Earlier sample (Jan 1985-Dec 1997)	Later sample (Jan 1998-Dec 2010)
CAPM alpha	0.0052***	0.0056***	0.0048***
	(7.72)	(5.42)	(5.43)
Fama-French alpha	0.0051***	0.0057***	0.0047***
	(7.63)	(5.35)	(5.37)
Carhart alpha	0.0047***	0.0055***	0.0045***
	(7.02)	(4.82)	(5.32)
	Fama-MacBeth regressions		
”prediction” variable	1.01***	1.10***	0.94***
	(7.67)	(4.95)	(5.90)
intercept	0.0003	0.0011	-0.0003
	(0.10)	(0.30)	(-0.07)
	Portfolio sorts		
Middle–size funds	Whole sample	Earlier sample	Later sample
CAPM alpha	0.0051***	0.0055***	0.0048***
	(6.54)	(5.49)	(4.21)
Fama-French alpha	0.0051***	0.0056***	0.0047***
	(6.47)	(5.42)	(4.12)
Carhart alpha	0.0044***	0.0053***	0.0043***
	(5.79)	(4.81)	(4.04)
	Fama–MacBeth regressions		
”prediction” variable	0.9142***	1.037***	0.824***
	(6.09)	(5.63)	(3.69)
intercept	0.0014	0.0022	0.0008
	(0.46)	(0.57)	(0.18)
	Portfolio sorts		
Large funds	Whole sample	Earlier sample	Later sample
CAPM alpha	0.0050***	0.0054***	0.0048***
	(6.31)	(4.81)	(4.21)
Fama–French alpha	0.0050***	0.0055***	0.0045**
	(6.28)	(4.76)	(4.10)
Carhart alpha	0.0044***	0.0053***	0.0043**
	(5.64)	(4.24)	(3.99)
	Fama-MacBeth regressions		
”prediction” variable	0.926***	0.997***	0.871***
	(5.77)	(4.70)	(3.77)
intercept	0.0012	0.0018	0.0008
	(0.39)	(0.44)	(0.18)

Table 30: Detailed split of size portfolios. The table demonstrates the performance of the joint predictor for a split of three size portfolios into time subsamples: the whole sample period, as well as earlier and later periods (13 years each). Fund size is based on the average fund TNA.

EKATERINA SERIKOVA

+41-788-31-31-35 ekaterina.serikova@unisg.ch
Im Hölzli 6, 9000, St Gallen, Switzerland

EDUCATION

University of St. Gallen (HSG), Switzerland 2014-2019
Ph.D. Candidate, Finance
Thesis "Essays on market microstructure and predictability of mutual fund returns"
Supervisors: Prof. Dr. Paul Söderlind, Prof. Dr. Albert Menkveld.

Vrije Universiteit Amsterdam, Netherlands 01/2018-07/2018
Visiting scholar. Host: Prof. Dr. Albert Menkveld

Central European University, Hungary 2010-2012
MA in Economic policy on global markets distinction
Thesis "Is Moscow Stock Exchange sufficiently liquid? Evidence from cross-listing". Outstanding thesis award.

University of Maryland University College, USA (double-degree program) 2008-2010
BS in Management distinction

Irkutsk State University, Russia 2006-2010
Bachelor in Management distinction

ADDITIONAL EDUCATION

Gerzensee European Summer Symposium, Switzerland July 2019
One-week conference on asset pricing organized by the Centre for Economic Policy Research (CEPR). Organizing committee: Terrence Hendershott (University of California, Berkeley), Dmitry Livdan (University of California, Berkeley), Vikrant Vig (London Business School and CEPR).

Swiss Finance Institute (SFI) Lugano, Switzerland June 2017
Summer School on Market Microstructure

Istituto di Studi Economici e per l'Occupazione (ISEO), Italy June 2012
Summer School with Nobel Laureates in Economics and Finance

PRESENTATIONS AT CONFERENCES

Sydney Banking and Financial Stability Conference, Sydney	13-14/12/2019
10th Annual Financial Market Liquidity Conference, Budapest	14-15/11/2019
International Risk Management Conference, Milan	17-18/06/2019
The economics of central clearing workshop, Paris	22/05/2019

AWARDS

Swiss Government Excellence Scholarship	2014-2016
Outstanding Master Thesis Award, Central European University	2012
Full Scholarship, Central European University	2011-2012
Partial Scholarship, Central European University	2010

WORK EXPERIENCE

SIX Swiss Exchange, Zürich, Switzerland 01/2019-now
Quantitative Risk Management, part-time (35%)

University of St. Gallen (HSG), Switzerland 09/2016-now
TA to Prof. Söderlind

STOXX Ltd, Deutsche Börse Group, Germany 09/2015-12/2015
Product development intern

Anheuser-Busch InBev, Russia 06/2013-07/2014
Treasury & CaPex Controller

Anheuser-Busch InBev, Russia 07/2012-05/2013
Global management trainee

TECHNICAL STRENGTHS

Software	Python, MATLAB, Stata, EViews, R, MS Office
Databases	Bloomberg, Datastream, CRSP, Factset

LANGUAGES

English	fluent
German	upper intermediate (C1 Goethe certificate: August 2018)
Russian	native