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Essays on Intraday Trading Behavior and Price Patterns in Financial Markets

Dissertation

Essays on Intraday Trading Behavior and Price Patterns in Financial Markets

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Vorwort

Die vorliegende Arbeit ist während meiner Tätigkeit als wissenschaftlicher Mitarbeiter am Lehrstuhl für Bank- und Finanzwirtschaft der FernUniversität in Hagen entstanden. Im Sommer 2025 wurde sie von der Fakultät für Wirtschaftswissenschaft der FernUniversität in Hagen als Dissertationsschrift angenommen.

Eine Dissertation birgt Herausforderungen, die sich erst im Laufe ihrer Entstehung offenbaren. Als Doktorand lernt man, dass wissenschaftlicher Fortschritt Zeit braucht und sich Erfolge häufig erst nach zahlreichen Rückschlägen einstellen. Die Bewältigung dieser Herausforderungen fällt glücklicherweise leichter, wenn das Forschungsgebiet faszinierend ist und man mit Menschen zusammenarbeiten darf, die dieselbe Faszination und denselben Forschungsdrang teilen. Unter diesen Umständen kann selbst ein kleiner Erkenntnissgewinn viele Widrigkeiten aufwiegen. Ich möchte mich daher bei mehreren Menschen herzlich für ihren Beitrag zum Gelingen meiner Promotion bedanken.

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Hannover, im Oktober 2025 Sebastian Schlie

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Chapter 1

Introduction

Financial markets bring together a wide range of participants to fund investments and share risks, while also facilitating liquidity – the ability to enter and exit positions when needed – and price discovery – the timely formation of efficient prices that reflect available information (e.g., Foucault et al., 2023, Ch. 1). Most modern markets achieve this through electronic limit order books, where participants can express their interest to buy or sell a security by submitting orders specifying a price and a quantity (e.g., Hasbrouck, 2007, Ch. 2). While matching orders result in trades, unmatched orders remain in the book, providing liquidity to subsequently arriving participants seeking to trade immediately. This microstructure perspective on the trading mechanism highlights two key aspects: First, each infrequent trade involves both a buyer and a seller, with one acting as the active initiator, demanding immediacy, and the other as the passive counterparty, providing liquidity. Second, maintaining a liquid market requires certain participants – often called market makers – to continuously post buy and sell orders in the book, thereby offering immediacy to others. Improving our understanding of price dynamics, therefore, requires to better understand the behavior of both liquidity demanders and suppliers, whose interactions generate trades and determine prices. This behavior can be studied directly, through observable activities of specific groups of market participants, or indirectly, through the identification of systematic patterns in prices. Broadly defined, the study of trading behavior and price patterns in consideration of the trading mechanism and frictions is the domain of empirical market microstructure research and represents the topic of this thesis.

Records of order book activity generate high-frequency datasets, encompassing billions of trades, bids, and offers – often timestamped with nanosecond precision. These records are at the heart of this thesis. Their granularity enables the identification of activity originating from specific groups of market participants. Analyzing their behavior yields insights into their trading strategies, performance, and impact on price discovery and liquidity – core components of market quality. These insights are of interest to academics, market participants, and regulators alike. The first two essays of this thesis contribute to the literature on intraday trading behavior through the study of retail investors and short sellers. They are presented in Chapters 2 and 3.

In addition, high-frequency data provide insights into intraday dynamics of prices and liquidity that are inaccessible through aggregated, lower-frequency data. Intraday patterns are of broad interest, because every market participant – regardless of the investment horizon – has to engage with the market to enter or exit a position. Therefore, a better understanding of intraday patterns is not only of academic interest, but also of practical value for informing strategies that reduce transaction costs (Admati and Pfleiderer, 1988), conceal informed trading (Kyle, 1985), and realize trading gains from market inefficiencies (Fama, 1970) and frictions (Stoll, 2000). The last two essays of this thesis add to the literature on intraday price patterns through the analysis of price dependencies. They are presented in Chapters 4 and 5.

Overall, this thesis comprises four essays which focus on the microstructure of financial markets. Collectively, they enhance our understanding of market participants' intraday trading behavior, intraday price patterns, market characteristics, as well as the interplay of these topics.

In **Chapter 2**, co-authored with Rainer Baule and Bart Frijns, the trading behavior of retail investors is analyzed in terms of intraday feedback trading patterns. Feedback trading concerns the dynamic relation between trading activity and past returns. Negative feedback traders buy securities after prices have fallen and sell them after prices have risen, while positive feedback traders do the reverse (De Long et al., 1990). Importantly, equilibrium constraints imply that not all investors can follow the same feedback trading strategy. Previous empirical studies show that the group of retail investors tend to follow negative feedback trading strategies, while professional investors tend to follow positive feedback trading strategies based on recent returns (e.g., Sias, 2007; Ng and Wu, 2007; Barber et al., 2009b; Kelley and Tetlock, 2013; Barrot et al., 2016). However, the majority of the feedback trading literature focuses on responses to past returns for horizons from one day up to one year. In contrast, little is known about the feedback trading behavior of retail investors with respect to past intraday returns. Hindering factors include the reluctance of brokers to provide data on individual investors' trading accounts and the difficulty in disentangling exchange order flow with regard to its origin.

To circumvent these problems, we focus on the order flow in a unique market that is exclusively designed for retail investors — the European market for retail derivatives. This market has one major advantage over traditional equity markets: Retail trading activity can be identified directly, without the need for proxies, due to the market design. As the derivatives are listed on the European Warrant Exchange (EUWAX), transactions and quotes are available and provide an accurate view on retail trading activity. Within this market, we focus on leveraged retail derivatives, which are particularly appealing to investors seeking to speculate on small intraday price movements. These instruments are highly popular among retail traders and, therefore, offer an ideal opportunity to study intraday feedback trading behavior in this investor segment.

Based on exchange trades and high-frequency quotes in leveraged retail derivatives, we first provide evidence that retail investors actively and consciously respond to short-term intraday returns in a negative feedback, contrarian fashion. Second, we show that some retail investors also feedback trade on tick-by-tick returns. Third, we find that on average this behavior leads to significant losses on the day they open a position. These losses are primarily due to the bid-ask spread and to investors' timing inability, but not to market makers taking advantage of investors. Based on our results, we conclude that retail investors who use leveraged retail derivatives to feedback trade on intraday returns are noise traders who earn, on average, negative returns.

In **Chapter 3**, co-authored with Xiaozhou Zhou, we examine the role of short sales in U.S. off-exchange trading, focusing on their impact on liquidity and price discovery. In today's fragmented equity markets, investors can trade not only on traditional "lit" exchanges but also on numerous off-exchange "dark" venues. Notably, more than a third of the U.S. equity trading volume is now executed off-exchange through alternative trading systems and broker-dealer internalization (FINRA, 2024). Special regulations – such as Regulation ATS and SEC Rule

3a1-1 – allow off-exchange venues to selectively grant access, operate with reduced transparency regarding available counterparties, and execute trades at a finer price grid, thereby offering potential for price improvement. This regulatory framework creates a trade-off between traditional exchanges and off-exchange venues in terms of immediacy and trading costs, leading to a segmentation of order flow by its short-term informativeness (e.g., Hendershott and Mendelson, 2000; Zhu, 2014; Comerton-Forde and Putniņš, 2015; Menkveld et al., 2017; Boehmer et al., 2021). Relatively uninformed order flow migrates off-exchange, as traders direct orders there to minimize trading costs when immediacy is not crucial, and because uninformed, non-directed orders are more likely to be selected for internalization by broker-dealers. In contrast, informed order flow remains on-exchange, due to its demand for immediacy and lower likelihood of being internalized.

A puzzling, yet unexplained, feature of off-exchange trading is the substantial involvement of short selling: 44% of the off-exchange trading volume between 2019 and 2021 involved a short seller, according to data from the Financial Industry Regulatory Authority (FINRA). This prevalence is difficult to reconcile with the notion that off-exchange venues primarily attract uninformed order flow, given that short sellers are typically viewed as particularly well-informed market participants (e.g., Christophe et al., 2004; Boehmer et al., 2008; Diether et al., 2009; Karpoff and Lou, 2010; Engelberg et al., 2012).

To resolve this puzzle, we follow Comerton-Forde et al. (2016) and zoom in on the transaction level to show that short sales serve a dual role: seller-initiated short sales demand liquidity and contribute to price discovery, while buyer-initiated short sales provide liquidity to investors seeking immediate execution of buy orders. If off-exchange short sales are used primarily for liquidity provision – for example by market makers with depleted inventories – short sales could be both prevalent and uninformed. Liquidity provision thus offers a compelling explanation for the prevalence of short selling in off-exchange trading.

We provide the first transaction-level analysis of the dual role of short sales in off-exchange trading and empirically investigate the liquidity-provision explanation for the puzzle outlined above. Specifically, we address the following key questions: Do short sellers add or remove off-exchange liquidity? Under which market conditions do they trade? How informed are they? Do they exaggerate price declines or lean against overreactions? Do they contribute to deteriorating on-exchange liquidity?

We find that short sales are pivotal in providing off-exchange liquidity and improve price discovery. Short sellers represent the passive side in 55% of buyer-initiated volume and the active side in 34% of seller-initiated volume. Compared to long sellers, they provide liquidity at wider spreads and consume liquidity at narrower spreads. Seller-initiated short sales tend to be better informed than long sales but less informed than on-exchange sales. Consistent with both an inventory effect and trading against overreactions, short selling increases after positive returns over the past week. Finally, we show that short sellers' contribution to higher off-exchange trading activity raises on-exchange trading costs.

In **Chapter 4**, co-authored with Xiaozhou Zhou, we examine cross-sectional momentum in intraday returns across successive trading days in global stock markets and explore its relationship to market characteristics. The momentum effect describes the continuation of the direction of past stock returns. A trading strategy that buys stocks that have performed (relatively) well in the past and sells stocks that have performed (relatively) poorly in the past can exploit this effect and generates significantly positive returns (Jegadeesh and Titman, 1993). For formation and holding periods of a few months up to a year, this effect is extensively documented in the literature (e.g., Rouwenhorst, 1998; Griffin et al., 2003; Asness et al., 2013). However, little is known about whether momentum patterns are also present at a higher frequency. For U.S. stocks, Heston et al. (2010, 2011) are the first to show that a stock's half-hour return positively predicts its return in the same interval on successive days, particularly during the first and the last half-hour of a trading day. The same effect is documented for the Indian stock market (Murphy and Thirumalai, 2017) and we refer to it as interday cross-sectional momentum (ICSM).

The theory of slow-moving capital offers an explanation for the existence of ICSM (e.g., Mitchell et al., 2007; Duffie, 2010): due to transaction costs, informational frictions, institutional constraints, and behavioral biases, investment capital moves slowly and not instantaneously to new trading opportunities. Systematic price pressure – and therefore ICSM – can result from multiple sources, including institutional investors executing large orders piece-wise over multiple days (Murphy and Thirumalai, 2017), positive autocorrelation in the inflows and outflows of funds, and scheduled, repetitive trading activity of fund managers or investment advisors (Heston et al., 2010). However, based on the current state of the literature, it remains unclear whether ICSM holds across international markets and whether it persists over time. For other return patterns, a growing literature documents significant variability along these two dimensions (e.g., Hameed and Kusnadi, 2002; Jacobs and Müller, 2020; Rosa, 2022; Kaplanski, 2023).

We provide a global study on ICSM by extending the work of Heston et al. (2010, 2011) and Murphy and Thirumalai (2017) to more markets and a more recent sample period. We first show that ICSM is still present in the previously studied U.S. market, and that it also exists in the eight novel markets of our sample. We find that the pattern is strongest in the last half hour, but barely present during the remainder of the trading day. We moreover examine determinants of the strength of ICSM in the last half hour by proposing and testing hypotheses related to firm-level market characteristics and trading motives derived from the literature. We find that ICSM is stronger when volatility is low, and absolute overnight returns are small, while liquidity has no significant effect. Finally, we show that international investors can save transaction costs of economically significant size by strategically timing trades based on ICSM.

In **Chapter 5**, co-authored with Rainer Baule and Xiaozhou Zhou, we analyze intraday return autocorrelations across a fine grid of different horizons in the cross-section of the U.S. stock market and investigate their links to major sources of market frictions and systematic trading needs. In frictionless and weak-form efficient markets, return autocorrelations should be zero (Fama, 1970). In real-world markets, however, return autocorrelations often deviate moderately from zero. This stylized fact is well documented for intraday returns (e.g., Conrad et al., 2015;

Dong et al., 2017), as well as for returns over longer horizons (e.g., Jegadeesh and Titman, 1993; Avramov et al., 2006; Hendershott and Menkveld, 2014). The literature attributes these deviations to various sources of market frictions (Stoll, 2000; Duffie, 2010) and trading behavior that systematically depends on past returns (Sentana and Wadhwani, 1992; Baltussen et al., 2021; Barbon et al., 2021; Huang et al., 2023). Importantly, different reasons may generate opposing effects on return autocorrelation. For instance, liquidity-motivated trading of asynchronously arriving buyers and sellers with a risk-averse intermediary tends to induce negative return autocorrelation (e.g., Stoll, 1978; Ho and Stoll, 1981; Grossman and Miller, 1988; Hendershott and Menkveld, 2014), whereas informed trading in the presence of asymmetric information typically generates zero or positive return autocorrelation (e.g., Glosten and Milgrom, 1985; Sadka, 2006; Dong et al., 2017; Van Kervel and Menkveld, 2019). Given the presence of multiple and opposing forces, their relative importance could vary depending on the time horizon, in turn, altering return autocorrelations across frequencies.

Studies on stock-level intraday return autocorrelations typically analyze a single or a limited set of return horizons. As a consequence, little is known about how intraday return autocorrelations depend on the return horizon. We address this gap by constructing and analyzing a term structure of intraday return autocorrelations. While computationally challenging, this approach allows us to examine two key questions: At which horizons are patterns of return continuations and reversals most pronounced, and how do market characteristics shape the term structure of return autocorrelations?

Using high-frequency data on the cross-section of U.S. stocks, we construct the term structure of intraday return autocorrelations. While average return autocorrelations are mostly negative, we find that the degree of autocorrelation depends on the return horizon. On 15-minute horizons, return reversals are most pronounced. On sub-minute horizons, return continuations occur in relatively larger stocks, during periods of market stress, and in the first half hour of trading. Drawing on the literature, we derive and test hypotheses that link intraday return autocorrelations to specific sources of market frictions and trading needs that systematically depend on past returns. We find evidence that return autocorrelations depend on the ease with which intermediaries can control their inventories, the degree of informational asymmetry, and dynamic hedge adjustments of option market makers. Finally, despite of these distinct and robust patterns in the term structure of return autocorrelations, it is noteworthy that return autocorrelations deviate only modestly from zero. This means that, after all, deviations from weak-form efficiency are relatively minor.

The four essays in this thesis extend the literature in multiple directions and contribute to a more nuanced understanding of intraday trading behavior and price patterns in financial markets. The first essay characterizes the feedback trading behavior and the performance of short-term-oriented retail investors. The second essay demonstrates how off-exchange short sellers affect liquidity and price discovery in today's fragmented equity markets. The final two essays shift the focus to intraday price dynamics, offering extensive stock-level evidence on persistent intraday price patterns. Notably, the findings suggest that the strength of these price patterns is closely linked to systematic trading behavior and market frictions.

Chapter 2

Feedback Trading: The Intraday Case of Retail Derivatives

Co-authored with
Rainer Baule and Bart Frijns

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Abstract
We analyze retail order flow in terms of intraday feedback trading patterns. Using a unique data set of exchange trades and high-frequency quotes, we first provide evidence that retail investors actively and consciously respond to short-term intraday returns in a negative feedback, contrarian fashion. Second, we show that some retail investors also feedback trade on tick-by-tick returns. Third, we find that on average this behavior leads to significant losses on the day they open a position. These losses are primarily due to the bid-ask spread and to investors' timing inability, but not to market makers taking advantage of investors.

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Keywords: Feedback trading, retail investors, investor returns, retail derivatives, warrants, order flow, issuer pricing strategies, intraday

2.1 Introduction

The empirical literature shows that (misguided) beliefs in contrarianism or momentum are important drivers that make investors trade (Grinblatt and Keloharju, 2001).[1] This dynamic relation between trading activity and past returns is referred to as feedback trading. Negative feedback traders buy securities after prices have fallen and sell them after prices have risen, while positive feedback traders do the reverse (De Long et al., 1990). However, equilibrium constraints imply that not all investors can follow the same feedback trading strategy. Empirical studies show that the group of individual (retail) investors tend to follow negative feedback trading strategies, while professional investors tend to follow positive feedback trading strategies based on recent returns (e.g., Sias, 2007; Ng and Wu, 2007; Barber et al., 2009b; Kelley and Tetlock, 2013; Barrot et al., 2016).

The vast majority of the feedback trading literature focuses on responses to past returns for horizons from one day up to one year. In contrast, little is known about the feedback trading behavior of retail investors with respect to past intraday returns. Hindering factors include the reluctance of brokers to provide data on individual investors' trading accounts and the difficulty in disentangling order flow with regard to its origin. Often, small trades or broad exchange classifications are used as proxies for retail trades (e.g., Barber et al., 2009a; Lemmon and Ni, 2014). However, these proxies become increasingly unsuitable to identify retail trading activity, as the number of algorithmic traders who slice and dice orders into smaller pieces increases (O'Hara et al., 2014).

To circumvent these problems, we focus on the order flow in a unique market that is exclusively designed for retail investors — the European market for retail derivatives. This market has one major advantage over traditional equity markets with regard to analyzing retail trading activity: There is no need for a proxy to identify retail investors. As the derivatives are listed on the European Warrant Exchange (EUWAX), transactions and quotes are available and provide an accurate view on retail trading activity. Furthermore, retail derivatives are very popular among retail investors. According to the German Derivatives Association, the traded volume of leveraged retail derivatives amounted to 44 billion euros in 2022. A total of 63% of this volume is attributable to equity index derivatives. The German market index (Deutscher Aktienindex, DAX) is the most important underlying among these equity index derivatives, according to EUWAX.

We extend the literature by analyzing the trading patterns of investors in retail derivatives on an intraday basis. In particular, we analyze the trading activity in bank-issued warrants, which are securitized options specifically tailored to meet the needs of small investors. Their contract size is much smaller than that of regular options and they are traded like stocks (Schmitz and Weber, 2012). Due to their embedded leverage, they are attractive to investors who want to

[1] In addition to other motives for noise trades that are rooted in behavioral biases, there are also rational motives such as portfolio rebalancing or tax-loss selling.

speculate on small intraday price movements. They are therefore an ideal instrument to analyze intraday feedback trading of retail investors.

We hypothesize that retail investors use bank-issued warrants to speculate on price movements in the underlying. Schmitz and Weber (2012) document a consistent picture of negative feedback trading with respect to returns of the underlying over the last days: Following negative returns, retail investors expect future positive returns, causing them to buy calls and sell puts. Following positive returns, they tend to buy puts and sell calls. Our first research question is whether this pattern also holds for short-term intraday returns of the underlying.

To answer this question, we aggregate trading activity within 15-minute intervals during a trading day at the EUWAX, the world's largest exchange for bank-issued warrants. We analyze the trading activity in call and put warrants on the German DAX, EUWAX's most important underlying. Our data set reveals that the pattern of negative feedback trading is also present for short-term intraday returns. Investors respond to past return intervals of up to two hours.

Furthermore, we consider tick-by-tick returns in the warrants themselves. Issuers act as market makers for their warrants and quote prices throughout the trading hours. On average, they quote two to three price updates (ticks) per minute for a warrant. Analyzing the trading response to such ticks, we find some evidence for a reversal of the feedback trading direction on very high frequencies: While the majority of retail investors do not care about past returns in the subminute segment, some traders react positively to tick-by-tick returns of the warrant (not the underlying). That is, they tend to buy calls and puts after a positive price tick of the respective warrant. We interpret this finding as an indication of a small subgroup of retail investors that speculates on momentum in the tick-by-tick returns of warrants.

The second part of the paper deals with the returns related to the observed intraday feedback trading behavior. On average, retail investors experience a negative return on the day they open a position, which is consistent with the literature on stock trading (e.g., Barrot et al., 2016). Using a decomposition, we show that losses are primarily due to the bid-ask spread. Moreover, by comparing actual trades to a randomized control sample, we reveal that some investors use limit orders to enter trades skillfully but that, on average, they are also incapable of earning the bid-ask spread. The timing returns of investors who use market orders are indistinguishable at best and sometimes worse than those achieved by randomizing. Moreover, investors who positive feedback-trade in the direction of the last tick cannot enhance their intraday returns. We thus conclude that retail investors' feedback trading in warrants is noise trading.

Investors' returns are determined by the bid and ask prices quoted by issuers in their role as market makers. These prices do not necessarily reflect the fair value but rather the issuers' price-setting policy, which usually includes a dynamic mark-up (e.g., Stoimenov and Wilkens, 2005; Baule, 2011; Henderson and Pearson, 2011). There is evidence that market makers anticipate and exploit specific order flow patterns by increasing their prices when they expect an excess in net investor demand and decreasing them when they expect an excess in net investor supply (Baule, 2011; Baule et al., 2018). Despite the intensive trading activity in the overall market,

trade in a single warrant occurs rarely. This is because investors can choose from a large variety of warrants from different issuers on the same underlying and a fine grid of strike prices and maturities. Consequently, market makers could employ a strategic intraday quotation policy, responding to a trade event by adjusting the traded warrant's quoted price to position themselves for future intraday order flow in that particular warrant. There are two competing hypotheses: (i) An investor buy could indicate great attractiveness and lead to further buys by other investors; and (ii) an investor buy could be followed by a resale by the same investor if they are speculating on short-term (intraday) gains. According to (i), market makers should increase the warrant's mark-up, according to (ii), they should decrease it.

We analyze whether market makers affect investor returns by strategically adjusting their quoted prices in response to a trade. To this end, we analyze differences-in-differences between prices of traded and nontraded warrants with identical features before and after a trade. We find no evidence that issuers adjust their mark-ups in response to single trades. Thus, neither of the two hypotheses dominates the other, meaning that timing returns are a reflection of investors' (in)ability and not market-making strategies.

Our paper adds to the literature in several ways. First, we extend the literature on feedback trading with the first analysis on the intraday behavior of retail investors. We identify intraday price movements as distinct trade-motivating factors to which investors react with negative feedback trading for intervals covering the last two hours. A small subset of retail investors also consider price movements in time intervals of less than one minute and exhibit positive feedback trading on this time scale. On average, the intraday trading behavior leads to significant losses during the day on which a position is opened.

Second, this paper contributes to the literature on market-making strategies for exchange-traded structured products with the first analysis of strategic quotations in response to order flow. We demonstrate that investors' losses are primarily due to the bid-ask spread and not to strategic market-making in response to order flow. This is noteworthy, as existing studies show that issuers do exploit order flow patterns in other situations (Baule, 2011; Baule et al., 2018; Pelster and Schertler, 2019).

The remainder of this paper is organized as follows. Section 2.2 relates the paper to the existing literature on feedback trading, intraday trading, and market-making strategies. Section 2.3 introduces the data. Section 2.4 is dedicated to the analysis of feedback trading and Section 2.5 to investor returns. Section 2.6 concludes.

2.2 Relation to the Literature

2.2.1 Feedback Trading

The first strand of literature related to our paper provides empirical evidence for feedback trading from order flow and ownership data.[2] While there is extensive evidence for positive feedback trading by professional investors, the majority of findings for individual investors points towards negative feedback trading.[3] For recent returns, covering intervals up to six months in the past, this behavior is documented for the U.S. (Goetzmann and Massa, 2002; Griffin et al., 2003; Kaniel et al., 2008; Barber et al., 2009b; Kaniel et al., 2012; Kelley and Tetlock, 2013), Finland (Grinblatt and Keloharju, 2000, 2001), France (Barrot et al., 2016), Australia (Jackson, 2003; Colwell et al., 2008) and several emerging markets (Richards, 2005). For more distant returns, covering quarters $t-4$ through $t-10$, the feedback trading behavior tends to turn positive (Barber et al., 2009b). However, there are also studies where the findings are more nuanced. In China, Feng and Seasholes (2004) find no evidence of feedback trading, while Ng and Wu (2007) show that less wealthy individuals are negative feedback traders. In Germany, executed limit (market) orders are associated with negative (positive) feedback trading (Dorn et al., 2008). In Japan, the results seem to depend on the time period (Kamesaka et al., 2003; Kim and Nofsinger, 2007; Hood et al., 2013). Finally, in Thailand, there is no evidence of feedback trading (Phansatan et al., 2012).

With regard to trading in options, there is evidence from the Netherlands that retail investors tend to extrapolate the previous month's return into the next month (Bauer et al., 2009).[4] In the United States, aggregate daily and monthly trading activity in purchased and written options on individual stocks relates positively to past returns of the underlying for most horizons from one week up to two years (Lakonishok et al., 2007; Chen and Sabherwal, 2019). These effects are similar for public customers of discount brokers, including retail investors. Noteworthy are differences in terms of the underlying. Monthly demand for positive exposure to the underlying via options is positively related to past market returns only if the underlying is a stock and unrelated to past returns if the underlying is an index (Lemmon and Ni, 2014). Similarly, the daily aggregate open interest in U.S. index options is unrelated to the trailing 3-month return of the market index (Johnson et al., 2018).

[2] Feedback trading is also documented extensively from market prices (see, e.g., Tayeh and Kallinterakis (2022) for a recent overview), and from experiments (Bloomfield et al., 2009).

[3] Positive feedback trading is documented for institutional investors in general (e.g., Nofsinger and Sias, 1999; Sias, 2007; Choi and Skiba, 2015), and in particular for mutual fund managers (e.g. Boyer and Zheng, 2009) and foreign investors (e.g., Choe et al., 1999; Richards, 2005; Phansatan et al., 2012). However, there is also some contradictory evidence (e.g., Phansatan et al., 2012; Kremer and Nautz, 2013).

[4] To the best of our knowledge, Bauer et al. (2009) provide the only study on the relationship between trading activity in options and past returns that uses trades that can be clearly sourced to retail customers of a broker. Most of the remaining studies cited use open interest and trading volume of options listed on the Chicago Board Options Exchange (CBOE). Although the CBOE subdivided public customer orders into categories of origin until 2001, they switched to a volume-based classification scheme thereafter (Lemmon and Ni, 2014). For this reason, the origin of option trades cannot be determined with certainty.

Very few papers analyze feedback trading in bank-issued retail derivatives. For option-like warrants (Schmitz and Weber, 2012; Baule and Blonski, 2012) and knock-out warrants (Farkas and Váradi, 2021), there is evidence that individual investors follow negative feedback trading strategies with respect to recent inter-day returns of the underlyings. Consistent with stock trading behavior, the feedback turns positive for more distant returns and large trades (Schmitz and Weber, 2012; Baule and Blonski, 2012). Differences in whether the underlying is a stock or an index are minor (Schmitz and Weber, 2012). This paper extends the analysis of feedback trading towards the intraday case, covering the response to short-term and tick-by-tick returns.

2.2.2 Intraday Trading

The second strand of literature related to our paper covers intraday trading behavior. This literature focuses on day traders[5], while the relation to past intraday returns is only sparse. For institutional day traders, there is consistent evidence for positive feedback trading with respect to recent intraday returns in stocks from the United States (Griffin et al., 2003; Garvey and Murphy, 2005) and futures from Korea (Chou et al., 2015). In contrast, the majority of studies on the behavior of individual investors points towards negative feedback trading. There is corresponding evidence for stocks from the U.S. (Griffin et al., 2003), China (Seasholes and Wu, 2007) and Korea (Chung et al., 2009) as well as for futures from Korea (Eom, 2020) and Taiwan (Chou et al., 2015). However, some studies provide evidence that is inconsistent with this view. For futures in Taiwan, Cheng et al. (2016) find that most individual day traders follow positive feedback trading strategies. In addition, Harris and Schultz (1998) demonstrate that individual day traders, who use the small order execution system of the Nasdaq, tend to follow a momentum strategy. Although we do not focus exclusively on day traders, our study is related since we focus on intraday behavior and suspect that warrants, due to their high leverage, are also traded by day traders.

2.2.3 Market-Making Strategies

As bank-issued warrants belong to the retail market for exchange-traded structured products, our paper also relates to the literature on respective market-making strategies. The environment in this market is unique, as inventory costs and the presence of informed traders are insignificant (Baller et al., 2016). In addition, a product is only tradable with its market maker, and short-selling by investors is impossible. Consequently, market makers have almost exclusive price-setting power over their products.[6] In the empirical literature, several stylized characteristics of

[5] Day traders follow an active trading strategy in which they attempt to make intraday profits on small price changes (Barber and Odean, 2001). Typically, they close positions by the end of each trading day to avoid the risk associated with overnight price changes (Chung et al., 2009). We refer to an institutional (proprietary) day trader as an employee who day trades on behalf of a firm (Garvey and Murphy, 2005).

[6] In reality, limits to the price-setting power might arise from prices set by competing issuers for similar or identical products in combination with the investor's price sensitivity (Baule and Blonski, 2015).

prices in this market have been documented.[7] Many researchers find structured retail products overpriced relative to their components or a pricing model. In the case of bank-issued warrants, there is evidence of overpricing from Germany (Ruf, 2011; Baule et al., 2018), the Netherlands (ter Horst and Veld, 2008), Spain (Abad and Nieto, 2011) and Hong Kong (Li and Zhang, 2011). Examining the degree of overpricing more closely, the order flow hypothesis postulates that market makers anticipate systematic patterns in the order flow and adjust their quotes accordingly (Wilkens et al., 2003; Baule, 2011). While many studies find support for this hypothesis over longer time horizons, only very few test it in an intraday setting. For leverage certificates, Entrop et al. (2013) and Baller et al. (2016) find increased mark-ups towards the end of the day, though net investor supply dominates. They attribute this conflicting finding to an overnight jump risk of the underlying which dominates possible mark-downs from the order flow imbalance. In the case of warrants, which face no overnight jump risk, Baule et al. (2018) find decreasing mark-ups during the course of the day. They assume that issuers try to exploit an intraday order flow imbalance pattern. This paper provides evidence for its existence. Apart from strategies that anticipate order flow patterns, Pelster and Schertler (2019) analyze strategies that respond to past order flow. They find evidence that issuers engage in cross-pricing when supplementary products are sold to investors. We extend this path and provide the first intraday analysis on quotation strategies that respond to order flow on a trade-by-trade basis in the product to be priced.

2.3 Data and Descriptive Statistics

Bank-issued warrants are securitized options specifically tailored to meet the needs of retail investors. Their contract size is much smaller than that of regular options, with a typical cover ratio of 0.01 for DAX warrants (i.e., one warrant refers to 1% of the DAX level) and a lot size of one. Retail investors can only take long positions (although they can take a short exposure to the underlying through put warrants). As securities, warrants are traded like stocks. Since the maximum loss is limited to the investment amount, no margin account is required. Typically, the tick size is one cent.

We consider quoted prices and executed orders at the EUWAX in the year 2014 in call and put warrants from nine issuers with the DAX performance index as the underlying.[8] These issuers are: BNP Paribas, Citigroup, Commerzbank, Deutsche Bank, DZ Bank, Goldman Sachs, HSBC, UniCredit, and Vontobel. The intraday tick price quotations of the warrants as well as the DAX were obtained from LSEG Tick History. Warrant features were provided by Solvians IT Solutions GmbH. Data on the VDAX NEW were obtained from LSEG Datastream.

[7] A theoretical model of a profit-maximizing pricing strategy in the market environment of leveraged retail products is developed by Baller et al. (2016).

[8] We had to merge data from different sources, including academic research data offerings from EUWAX and Solvians IT Solutions. Unfortunately, both providers have since discontinued these special offers for academics, preventing us from using more recent data. However, since the market structure of EUWAX in 2014 remains unchanged until today, there is good reason to believe that the main conclusions are still valid.

	# Warrants traded		# Trades		Volume [Mio. euro]		# Ticks per minute	
Issuer	Call	Put	Buy	Sell	Buy	Sell	Call	Put
BNP Paribas	940	1,003	6,116	4,558	36.67	30.25	2.21	1.31
Citigroup	897	972	7,187	5,329	25.32	26.31	2.02	1.62
Commerzbank	1,324	1,509	12,405	9,958	45.17	47.00	2.67	1.99
DZ BANK	494	676	3,240	2,341	15.88	13.91	2.51	1.53
Deutsche Bank	1,366	1,777	17,911	12,753	104.42	95.41	1.76	1.57
Goldman Sachs	809	938	3,882	3,346	31.68	35.81	2.50	1.72
HSBC Trinkaus	113	138	710	445	2.62	2.38	1.86	1.29
UniCredit	572	646	2,656	2,280	9.92	9.67	2.03	1.82
Vontobel	948	1,158	6,782	5,104	30.86	32.36	1.93	1.61
Total	7,463	8,817	60,889	46,114	302.55	293.1	1.93	1.64

Table 2.1. ***Data Overview***. *The first two columns list the number of warrants which were traded on the exchange. The third and fourth columns list the number of exchange trades. Columns five to six list the total euro trading volume. The last two columns list the average number of ticks per minute within the investigation period. The data are separated by the issuer as well as the warrants' type or the investors' trade direction. The sample period covers the year 2014.*

Table 2.1 provides an overview of our trade and quote data. The original data set includes tick prices for approximately 41,000 warrants during our sample period. On average, there are 1.93 (1.64) price updates per minute for calls (puts). Of the 41,000 warrants, only about 16,000 were actually traded on the exchange.[9] The trading activity amounts to 107,003 trades with a total volume of almost 600 million euros. The order data provided by EUWAX directly classify trades into investor purchases (issuer sales) and investor sales (issuer repurchases). The number of investor purchases exceeds the number of investor sales by 32%, although the trading volume in euros is only slightly higher. As a possible explanation, some investors might hold warrants to maturity, buy warrants over time with several trades and sell them with a single trade, or execute sales over the counter via the issuers' trading platforms.

Table 2.2 provides an overview of the order characteristics. It shows that the median volume per trade is below 2,000 euros, although the volume is highly skewed. Investors prefer short-dated warrants, with 50% of the demanded warrants having a time to maturity of fewer than 34 days when they are bought. The median time to maturity is about nine days shorter when a warrant is sold; this difference can, however, deviate from the average holding period due to the reasons discussed above. Most of the trading activity is concentrated in warrants that are slightly out of the money, with a median moneyness of -1.7% for buys and -1.0% for sells. This behavior reflects a preference for leverage. Moreover, we report the time between an order entry or the last modification and its execution. Generally, orders are executed quickly regardless of their type, as 75% of the buys (sells) are filled within two minutes (seven minutes). As investors

[9] In order to satisfy different investor preferences for warrant features, banks typically issue a large number of warrants. Although all of these warrants are subsequently listed, not all of them are traded by investors.

predominantly use limit orders[10], the quick execution must be due to limits close to or at the market price. Overall, the behavior and preferences described above are similar for calls and puts.

Variable	Direction	Mean	5%	25%	50%	75%	95%
Volume	Buy	4,969	140	525	1,350	3,700	20,400
	Sell	6,356	116	636	1,771	4,806	24,768
Days to maturity	Buy	124	4	12	34	134	538
	Sell	102	3	10	25	104	453
Moneyness	Buy	−4.06	−19.18	−5.13	−1.67	−0.26	3.77
	Sell	−2.56	−15.67	−4.10	−1.03	0.43	5.26
Minutes to fill	Buy	176	0.01	0.01	0.08	1.80	212
	Sell	312	0.01	0.02	0.15	7.02	689
Variable	Direction	Limit	Market	Stop Loss	Stop Buy	Event-Driven	
Order types	Buy	73.84	24.33	–	1.61	0.22	
	Sell	59.33	23.14	14.72	–	2.81	

Table 2.2. ***Order Statistics***. *The table shows means and quantiles for the volume in euros, the days to maturity, the moneyness, measured for warrant i at time t as $\frac{S_t-K_i}{S_t}$ for calls and $\frac{K_i-S_t}{S_t}$ for puts, where S_t is the level of the DAX at time t and K_i is the strike price, and the minutes to fill for the transactions in our data set. Furthermore, the percentage proportion of order types is shown. The data are grouped by the trade direction (buy and sell).*

2.4 Feedback Trading

In this section, we examine whether and how retail investors respond to short-term intraday returns of the underlying and tick-by-tick returns of warrants themselves. The section is organized as follows: First, we examine the investors' response, as defined by different measures of intraday retail order flow, to returns of the underlying within the last two hours (Section 2.4.1). Second, we analyze the response to tick-by-tick returns of warrants,[11] with a usual reaction time of less than one minute (Section 2.4.2).

2.4.1 Short-Term Returns

2.4.1.1 Order Flow Measures and Descriptive Statistics

For the feedback trading analysis on short-term returns of the underlying, we aggregate information over 15-minute intervals in a trading day. This interval length is a compromise between keeping the information loss on the dynamics of the trading process low and avoiding too many

[10] Similar relations are reported by Baller et al. (2016) for transactions in leverage certificates. In contrast, a database of retail trades in U.S. common stocks, covering an estimated one-third of the retail market, used by Kelley and Tetlock (2013) contains significantly more market orders than limit orders.

[11] We refer to a *tick* as a price update in the issuer's quote (not a volume update).

zeros for intervals that are too small.[12] We measure order flow based on the number of orders executed. Weighting each order equally, regardless of its size, makes it robust against large-volume trades. We have also used other weighting schemes, in particular volume-weighted order flow measures, coming to very similar results.

As a first measure, we consider the number of orders executed within each 15-minute interval in a trading day (see Venezia and Shapira (2007) for a similar measure).[13] While EUWAX allows trading from 9:00 a.m. to 8:00 p.m. CET during our sample period, the DAX is only calculated from 9:00 a.m. to 5:30 p.m. CET during trading on XETRA. Since our feedback analysis requires lagged intraday returns of the DAX, we restrict our order flow sample to 15-minute intervals between 9:00 a.m. and 5:45 p.m. CET per day.[14] This gives us 35 intervals per 252 trading days in 2014 and a total of 8,820 observations. We define the buy and sell intensities in call and put warrants on day $t \in \{1, \ldots, 252\}$ within interval $i \in \{1, \ldots, 35\}$, $CALLBUY_{t,i}, CALLSELL_{t,i}, PUTBUY_{t,i}$, and $PUTSELL_{t,i}$, as the number of respective trades.

As a second measure, we compute the interval-wise order flow imbalance as the normalized difference in the buying and selling intensity (see, e.g., Venezia and Shapira (2007), Kelley and Tetlock (2013) and Barrot et al. (2016) for a similar measure). For each 15-minute interval, we divide the difference between sell and buy trades by the total number of trades:

$$IMB_{t,i}^{CALL} = \frac{CALLBUY_{t,i} - CALLSELL_{t,i}}{CALLBUY_{t,i} + CALLSELL_{t,i}}; \tag{2.1}$$

$$IMB_{t,i}^{PUT} = \frac{PUTBUY_{t,i} - PUTSELL_{t,i}}{PUTBUY_{t,i} + PUTSELL_{t,i}}. \tag{2.2}$$

If there is no trading within an interval, we set the imbalance measure equal to zero.

In addition, we calculate the overall and the purchase-based order flow imbalance in warrants as

$$IMB_{t,i} = \frac{(CALLBUY_{t,i} - CALLSELL_{t,i}) - (PUTBUY_{t,i} - PUTSELL_{t,i})}{CALLBUY_{t,i} + CALLSELL_{t,i} + PUTBUY_{t,i} + PUTSELL_{t,i}}; \tag{2.3}$$

$$IMB_{t,i}^{BUY} = \frac{CALLBUY_{t,i} - PUTBUY_{t,i}}{CALLBUY_{t,i} + PUTBUY_{t,i}}. \tag{2.4}$$

[12] Methodologically related studies on stock trades by Heinen and Rengifo (2007), Quoreshi (2008) and Jung et al. (2011) use 5-minute intervals. Since warrants are traded less frequently than stocks, our interval length of 15 minutes is slightly larger. However, our results are not driven by the particular choice of interval length. We rerun our analysis, outlined below, for 30-minute intervals and draw similar conclusions.

[13] In line with the literature, we allocate orders to an interval based on their time of execution. However, our results are almost unchanged when using the order entry time. This is because, for most orders, the time between entry and execution is well below 15 minutes (see, Table 2.2).

[14] To rule out any opening-effects on our results, we drop the first interval of each trading day and repeat our analysis. The results are very similar and do not alter our conclusions.

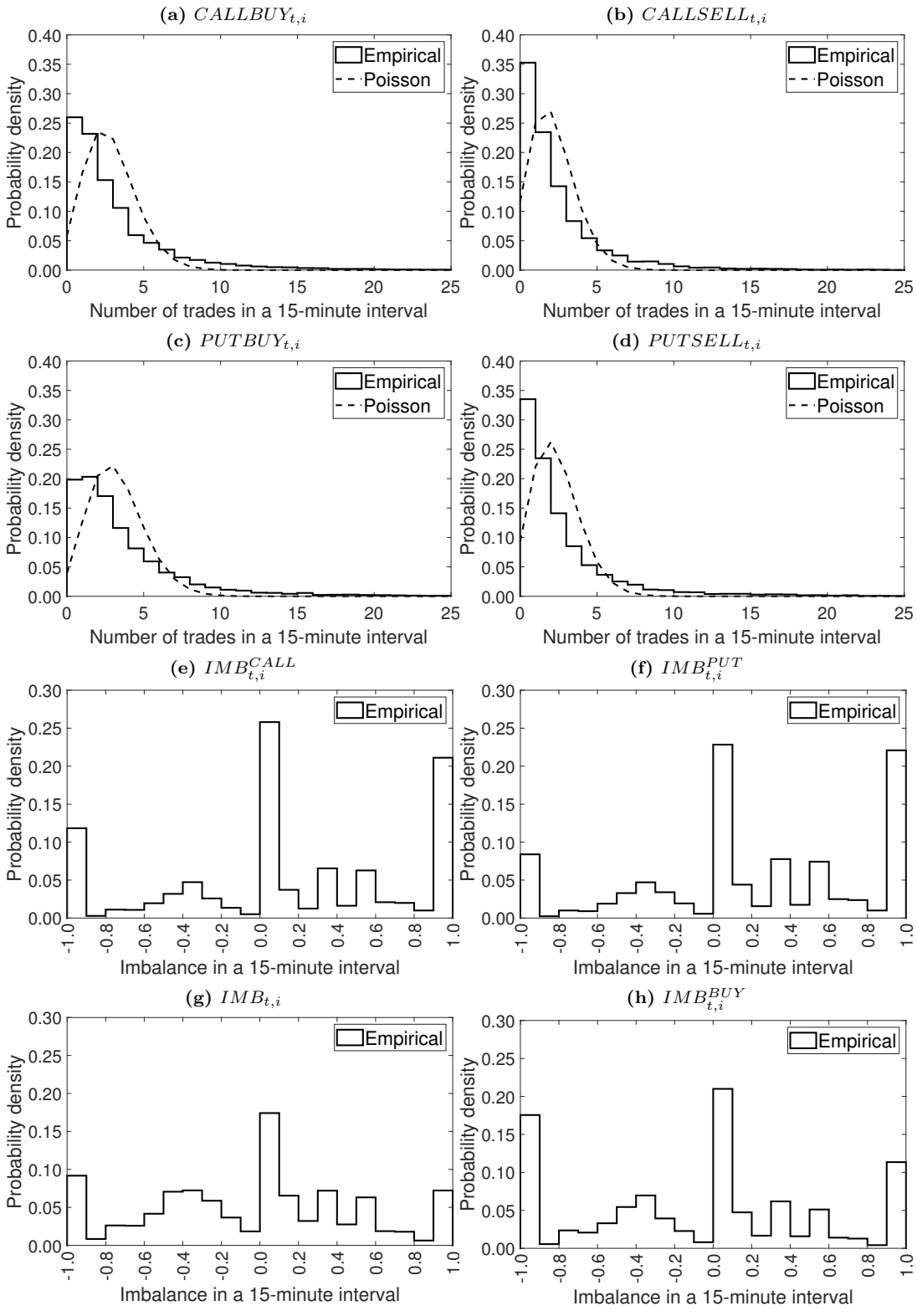


Figure 2.1. ***Histograms of Intensity and Imbalance of Order Flows.*** *Graphs (a) to (d) show the empirical and estimated unconditional Poisson density of the number of trades. Graphs (e) to (h) show the imbalance of the order flow.*

	$CALLBUY_{t,i}$	$CALLSELL_{t,i}$	$PUTBUY_{t,i}$	$PUTSELL_{t,i}$	$IMB^{CALL}_{t,i}$	$IMB^{PUT}_{t,i}$	$IMB_{t,i}$	$IMB^{BUY}_{t,i}$
Mean	2.85	2.15	3.25	2.38	0.13	0.20	−0.04	−0.09
Median	2.00	1.00	2.00	1.00	0.00	0.14	0.00	0.00
Std.	4.21	3.45	4.14	3.74	0.63	0.60	0.54	0.62
Skew	3.91	4.5	3.44	3.49	−0.22	−0.29	0.05	0.12
Min.	0	0	0	0	−1	−1	−1	-1
Max.	51	68	53	42	1	1	1	1
Q_{10}	12,511	8,991	9,656	9,768	1,520	1,552	2,931	2,143

Table 2.3. ***Descriptive Statistics of Order Flow Intensity and Imbalance.*** *The table shows descriptive statistics of the order flow per 15-minute interval. The Ljung-Box statistic Q_{10} assesses the null hypothesis that a series exhibits no autocorrelation for ten lags. For all measures, the null hypothesis is rejected as the critical value for $\alpha = 0.01$ is 23.21. The number of observations is T = 8,820.*

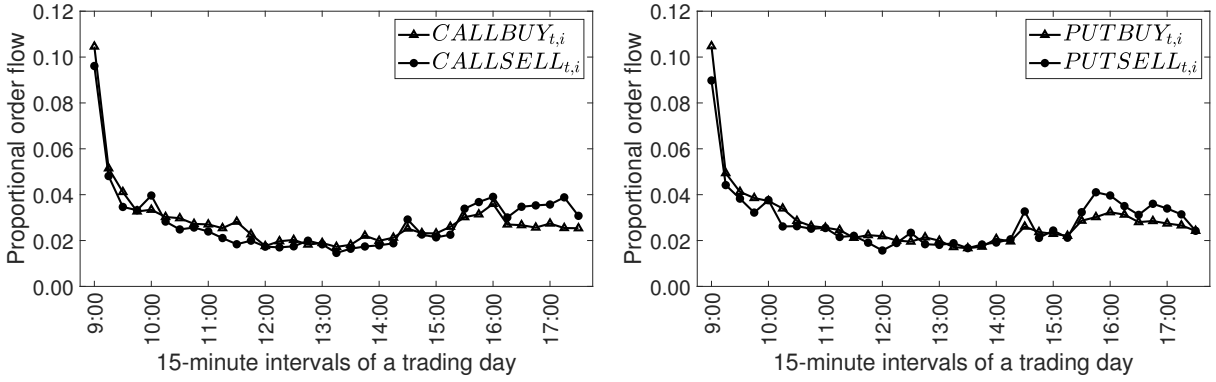
Table 2.3 provides descriptive statistics and Figure 2.1 shows histograms of the variables. The intensities are low nonnegative integers and highly autocorrelated. The imbalances in calls and puts are slightly positive, on average, but close to zero in aggregate. They are also significantly autocorrelated.[15]

The order flow exhibits a diurnal pattern. As shown in Panel (a) of Figure 2.2, the order flow intensities of buys and sells in calls and puts are highest in the morning, with the first 15-minute interval accounting for roughly 10% of the total number of daily trades. From then on, the intensity per 15-minute interval ranges between 2% and 5% of the total number of daily trades. After a low around midday, the intensity tends to increase again until the end of the day. This L-shape is similar for all four intensity measures. Such an activity peak in the morning is also reported for retail-oriented mini options in the United States and may be due to individual investors with full-time jobs who have little time to spare during working hours and place their orders before the market opens (Li et al., 2021). This order flow thus looks different from the distinct U-shape of trading activity in stocks (Admati and Pfleiderer, 1988).

With regard to the diurnal order flow imbalance, Panel (b) of Figure 2.2 shows that the number of calls bought on average exceeds the number of calls sold in most intervals of the day. Towards the end of the trading day, however, the imbalance decreases and turns negative for the interval 17:15–17:30. Although a gradual diurnal decrease in the order flow imbalance is also observed for puts, there is no interval with a negative imbalance. This pattern is likely caused by day traders closing their positions towards the end of the day (Baule et al., 2018).

[15] The count-based measures are highly correlated with their volume-based counterparts, which we have also calculated for robustness. The correlations are 0.87, 0.84, 0.80, and 0,83 for volume- and count-based order flow imbalances in calls, puts, overall, and purchase based respectively. Therefore, results are similar.

(a) *Diurnal proportional order flow intensity.*



(b) *Diurnal order flow imbalance.*

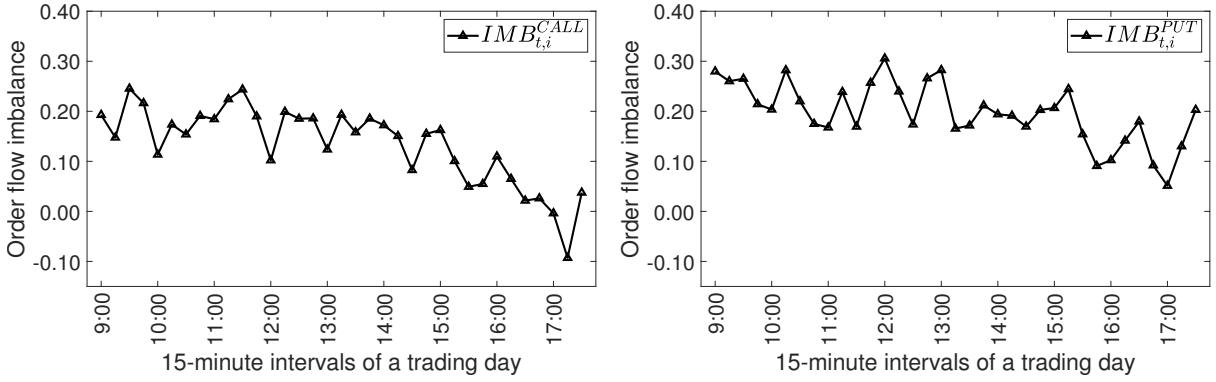


Figure 2.2. ***Diurnal Figures of Proportional Order Flow Intensity and Order Flow Imbalance.*** *Panel (a) shows the diurnal proportional number of trades, defined as the number of trades in a 15-minute interval divided by the total daily number of trades. The results are separated by the warrant's type and the trade direction. Panel (b) shows the diurnal imbalance in the number of buy and sell trades, calculated analogously.*

2.4.1.2 Feedback of Order Flow Intensity

In the following, we examine the response of the order flow intensities to short-term intraday returns of the underlying. We consider the intraday return of the DAX on day t within the 15-minute interval i, as defined above, denoted by $INTRA_{t,i}$. In our regression analysis for an order flow measure of interval i, we include up to eight lags of DAX returns, that is, two hours.[16] We also include recent interday returns of the underlying (Baule and Blonski, 2012; Schmitz and Weber, 2012). In particular, we consider three lags of daily returns, measured from close to close and denoted as $INTER_{t-k}$ for $k = 1, 2, 3$, as well as the overnight return $NIGHT_t$. Furthermore, we include squared returns $INTRA_{t,i}^2$, $INTER_t^2$, and $NIGHT_t^2$, as controls for non-linear responses.

Intraday trading activity has been found to increase near round numbers of the underlying (Niederhofer, 1965; Bhattacharya et al., 2012; Kuo et al., 2015; Chen, 2018). We introduce the

[16] During the first two hours of trading, we set $INTRA_{t,i-j} = 0$ if $i - j \leq 0$.

binary variable $ROUND_{t,i}$, which is 1 if the DAX passes a multiple of 100 within interval i and 0 otherwise. We also control for the impact of general market conditions on trading activity. For this purpose, we use the 1-day lagged implied DAX volatility $VOLA_{t-1}$, measured by the VDAX-NEW. To control for diurnal and weekly seasonal effects as well as monthly variability in trading activity (Chordia et al., 2001), we include a battery of respective dummy variables $\sum SEASONALS$.

For the regression model of the count data, we use a generalized linear autoregressive moving average model of order $p = 1$ and $q = 1$ (GLARMA(1,1)) with covariates, introduced by Davis et al. (2003, 2005). This model is particularly suitable for time series of low, nonnegative count data. It considers the order flow intensities $y_{t,i}$ as realizations of a Poisson process and models the log of the conditional mean of this process as the dependent variable of a linear regression:

$$y_{t,i}|\mathcal{F}_{t,i} \sim Po(\mu_{t,i}); \tag{2.5}$$

$$\begin{aligned}\log \mu_{t,i} = &\sum_{j=1}^{8} \beta_{1,j} INTRA_{t,i-j} + \beta_2 NIGHT_t + \sum_{k=1}^{3} \beta_{3,k} INTER_{t-k} \\ &+ \sum_{j=1}^{8} \beta_{4,j} INTRA^2_{t,i-j} + \beta_5 NIGHT^2_t + \sum_{k=1}^{3} \beta_{6,k} INTER^2_{t-k} \\ &+ \beta_7 ROUND_{t,i} + \beta_8 VOLA_{t-1} + \sum SEASONALS + z_{t,i}.\end{aligned} \tag{2.6}$$

Here, Po is the Poisson density. Furthermore, the model allows us to control for remaining serial correlation and persistence in order flow, which may result from positioning around news events (Barber and Odean, 2008; Riordan et al., 2013; Meyer et al., 2014), chart patterns (Grinblatt and Keloharju, 2001; Kavajecz and Odders-White, 2004; Bender et al., 2013) or herding in general (Dorn et al., 2008; Barber et al., 2009a). These effects are captured by the error term $z_{t,i}$, which is modeled as an autoregressive moving average process:

$$z_{t,i} = \phi_1 \, z_{t,i-1} + \theta_1 \, e_{t,i-1} \tag{2.7}$$

with

$$e_{t,i} = \frac{y_{t,i} - \mu_{t,i}}{\sqrt{\mu_{t,i}}}. \tag{2.8}$$

For $t \leq 0$, $e_{t,i} = z_{t,i} = 0$; and for $i - j \leq 0$, $e_{t,i-j} = e_{t-1,36-j}$ and $z_{t,i-j} = z_{t-1,36-j}$.

Fixed effects involve month, weekday, and 15-minute interval-of-day dummies. To address concerns about the impact of missing variables, we additionally consider a modified regression, where the fixed effects for weekdays and months are substituted with a dummy variable for each day of the year. Since this dummy controls for all effects measured on the daily frequency, we omit all other daily variables, in particular inter-day returns. Estimation is carried out using a maximum likelihood approach (Davis et al., 2005).

	$CALLBUY_{t,i}$		$CALLSELL_{t,i}$		$PUTBUY_{t,i}$		$PUTSELL_{t,i}$	
$INTRA_{t,i-1}$	−64.1***	−66.3***	48.7***	42.7***	30.6***	26.9***	−82.7***	−84.7***
$INTRA_{t,i-2}$	−43.4***	−51.1***	43.2***	40.9***	20.2***	19.5***	−68.7***	−76.4***
$INTRA_{t,i-3}$	−39.0***	−48.9***	18.5*	21.0*	11.4	13.7*	−68.7***	−75.2***
$INTRA_{t,i-4}$	−35.1***	−43.5***	18.3*	22.3**	16.6**	19.7**	−50.4***	−56.1***
$INTRA_{t,i-5}$	−33.8***	−41.4***	−1.8	2.4	−0.1	3.4	−58.8***	−64.4***
$INTRA_{t,i-6}$	−24.0**	−29.1***	7.0	9.4	0.1	2.1	−41.9***	−46.6***
$INTRA_{t,i-7}$	−23.1**	−26.5***	44.6***	43.0***	17.3**	18.2**	−22.3*	−28.0**
$INTRA_{t,i-8}$	−13.7	−14.4	9.1	8.5	−7.2	−5.4	−17.6	−19.5*
$NIGHT_t$	−11.50*		16.48***		−0.87		−27.39***	
$INTER_{t-1}$	0.73		3.35		1.80		−8.72***	
$INTER_{t-2}$	−0.33		1.82		1.49		−1.89	
$INTER_{t-3}$	−0.44		1.85		0.64		−0.57	
$INTRA^2_{t,i-1}$	616	441	6,213***	6,192***	8,524***	8,347***	649	−53
$INTRA^2_{t,i-2}$	3,529*	3,116*	5,246***	6,518***	4,598***	5,384***	-235	−710
$INTRA^2_{t,i-3}$	1,420	1,020	−969	448	1,609	2,281	-613	−983
$INTRA^2_{t,i-4}$	2,519	2,784	851	2,282	1,410	2,164*	1,599	1,108
$INTRA^2_{t,i-5}$	-910	−1,053	2,166	3,501**	−4,610***	−3,407*	152	−1,114
$INTRA^2_{t,i-6}$	395	56	−4,870*	−3,708	−748	176	2,632	1,146
$INTRA^2_{t,i-7}$	250	−195	−1,006	−400	−677	146	1,652	558
$INTRA^2_{t,i-8}$	4,166**	4,030**	−5,008*	−4,678*	−1,900	−1,224	1,023	445
$NIGHT^2_t$	1,479**		2,548***		2,388***		1,410**	
$INTER^2_{t-1}$	191		−138		−122		152	
$INTER^2_{t-2}$	−120		−146		−132		17	
$INTER^2_{t-3}$	−57		−242		−277**		57	
$ROUND_{t,i}$	0.224***	0.198***	0.273***	0.277***	0.182***	0.18***	0.297***	0.275***
$VOLA_{t-1}$	−0.006		0.089***		0.086***		0.019	
AR	0.901***	0.633***	0.875***	0.535***	0.914***	0.638***	0.785***	0.480***
MA	0.102***	0.083***	0.093***	0.079***	0.090***	0.080***	0.121***	0.107***
Interval	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day	No	Yes	No	Yes	No	Yes	No	Yes
Weekday	Yes	No	Yes	No	Yes	No	Yes	No
Month	Yes	No	Yes	No	Yes	No	Yes	No
T	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820
n	25,135	25,135	18,966	18,966	28,659	28,659	20,964	20,964
R^2	0.652	0.612	0.508	0.499	0.567	0.548	0.574	0.560

Table 2.4. ***Order Flow Intensity and Feedback Trading.*** *The table shows the estimation results for the GLARMA model (2.5). For each option type, the first column provides the results of the baseline regression, while the second replaces daily control variables with daily fixed effects. The final rows list the number of observations T, the number of trades n, and the adjusted R^2. Inference is based on robust standard errors. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).*

Table 2.4 presents the results of the time series regressions for the order flow intensities $CALLBUY_{t,i}, CALLSELL_{t,i}, PUTBUY_{t,i}$, and $PUTSELL_{t,i}$. The signs of the coefficients of the intraday returns are negative for calls bought and positive for calls sold. This indicates that the buying (selling) intensity of calls increases following negative (positive) intraday returns. Since the sensitivity of put prices towards price changes in the underlying is opposite to that of calls, we would expect opposite signs for the coefficients of puts. This is indeed the case. Thus we find consistent and significant negative feedback trading on intraday returns in all four categories. The investors' response tends to dwindle for more distant intraday returns and is strongest for buying calls and selling puts. In addition, for sales of calls and purchases of puts, the first two lags of squared intraday returns are significantly positive. For calls (puts), a one standard deviation shock of 0.14% to the intraday return translates via the coefficients of $INTRA_{t,i}$ and $INTRA^2_{t,i}$ to a decrease (increase) in the buying intensity of −8.7% (6.4%) and an increase (decrease) in the selling intensity of 7.4% (−9.7%) in the next interval. As illustrated in Figure 2.3 (a), the responses to this initial shock accumulate for calls (puts) to

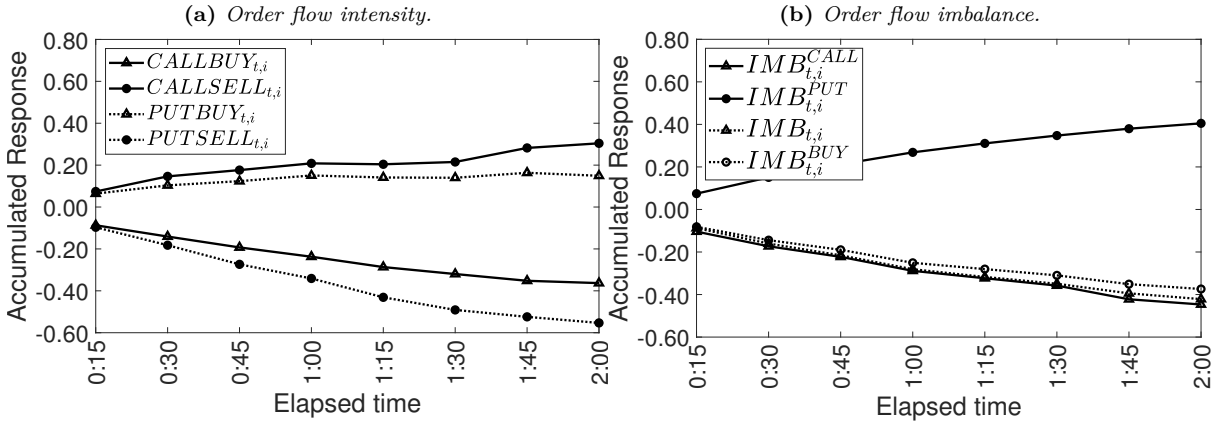


Figure 2.3. ***Accumulated Impulse Response Functions for an Intraday Return Shock.*** *The graphs show the accumulated responses of a one standard deviation impulse to the variable $INTRA_{t,i}$ (the 15-minute underlying return) on the future order flow intensity in percentage terms (a) and imbalance in absolute terms (b).*

a decrease (increase) in the buying intensity of −36.3% (14.9%) and an increase (decrease) in the selling intensity of 30.4% (−55.3%) over two hours. The results remain virtually unchanged when controlling for all effects on the daily frequency.

Investors also respond to past overnight returns (except for buying puts), showing the same negative feedback pattern. Furthermore, the significantly positive coefficients of squared overnight returns show that overnight price movements stimulate trading activity, regardless of the warrant type and trade direction. Surprisingly, the order flow intensities are almost unaffected by lagged inter-day returns. Only yesterday's return has a significant negative impact on the number of puts sold today.

It is possible that the results are influenced by the investors' preference for limit orders. Limit buy and sell orders that are not immediately marketable remain in the order book. These orders have buy (sell) limits below (above) the best ask (bid) quote. Therefore, declines (increases) in intraday prices could trigger these limit buy (sell) orders. Such trades would then be consistent with negative intraday feedback trading. The observed contrarian intraday order flow might thus be driven by limit orders instead of conscious responses to intraday returns.

To analyze the unbiased response to intraday returns observable at the time of order entry, we use the subsample of market orders only. Table 2.5 repeats the analysis of Table 2.4 for this subsample.[17] The results are fairly similar to the total sample, in particular, the strong evidence for negative feedback trading in the case of calls bought and puts sold. The effect for puts bought becomes somewhat weaker (no significance for the first two intraday lags), but the negative response remains significant in the majority of cases. We conclude that the observed negative feedback trading is not mainly driven by limit orders. Instead, individual investors consciously respond to intraday returns in a contrarian fashion.

[17] As an alternative, we repeat the analysis of Table 2.4 for the entire sample, but use the time of the order entry to allocate trades to an interval. This procedure is also robust against the choice of order type. The untabulated results are almost unchanged.

	$CALLBUY_{t,i}$		$CALLSELL_{t,i}$		$PUTBUY_{t,i}$		$PUTSELL_{t,i}$	
$INTRA_{t,i-1}$	−43.3***	−40.1***	31.5**	23.1	1.9	−1.2	−75.3***	−72.4***
$INTRA_{t,i-2}$	−34.4***	−31.5**	48.7***	41.4***	3.2	−1.7	−74.2***	−71.8***
$INTRA_{t,i-3}$	−44.2***	−41.5***	21.8	13.3	22.0**	17.7*	−56.1***	−52.5***
$INTRA_{t,i-4}$	−38.7***	−34.7***	27.3*	24.5*	23.3**	19.4*	−45.1***	−41.7***
$INTRA_{t,i-5}$	−50.7***	−44.7***	23.5	18.6	11.9	7.7	−75.8***	−73.2***
$INTRA_{t,i-6}$	−58.7***	−51.3***	41.0**	34.1*	9.2	6.6	−65.7***	−62.8***
$INTRA_{t,i-7}$	−48.8***	−43.9***	62.0***	57.2***	15.3	13.1	−28.8*	−27.3
$INTRA_{t,i-8}$	−24.4*	−15.8	22.6	22.6	−6.5	−6.0	−26.1	−23.6
$NIGHT_t$	5.29		13.47*		−9.40*		−24.72***	
$INTER_{t-1}$	2.68		8.59**		0.56		−8.04**	
$INTER_{t-2}$	−1.46		4.92		0.09		−5.42*	
$INTER_{t-3}$	-3.32		1.91		2.41		-2.06	
$INTRA^2_{t,i-1}$	8,009**	8,982***	13,529***	14,727***	9,175***	9,515***	6,080*	5,957*
$INTRA^2_{t,i-2}$	8,006***	8,610***	9,652***	10,813***	7,691***	8,023***	1,825	1,460
$INTRA^2_{t,i-3}$	2,620	2,685	2,820	3,584	5,063***	5,436***	1,552	1,566
$INTRA^2_{t,i-4}$	2,777	3,277	3,129	4,323	6,748***	6,997***	4,922***	4,674**
$INTRA^2_{t,i-5}$	1,750	2,263	846	2,579	−7,958**	−7,735**	−721	−1,262
$INTRA^2_{t,i-6}$	−5,989	−6,654	509	2,536	733	1,100	−1,418	−2,593
$INTRA^2_{t,i-7}$	1,410	1,332	−2,251	−528	155	402	3,951	3,884
$INTRA^2_{t,i-8}$	3,706	4,137	−2,583	−1,537	−407	−480	1,675	498
$NIGHT^2_t$	1,807**		2,937***		2,239***		1,412*	
$INTER^2_{t-1}$	106		−187		106		178	
$INTER^2_{t-2}$	−119		−238		−205		81	
$INTER^2_{t-3}$	−3		−268		−109		192	
$ROUND_{t,i}$	0.093*	0.048	0.089	0.09	0.092*	0.078*	0.141**	0.082
$VOLA_{t-1}$	0.038		0.069**		0.0730***		0.037	
AR	0.933***	0.385*	0.865***	0.440***	0.907***	0.498**	0.790***	0.451***
MA	0.095***	0.063***	0.114***	0.070***	0.085***	0.048***	0.150***	0.120***
Interval	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day	No	Yes	No	Yes	No	Yes	No	Yes
Weekday	Yes	No	Yes	No	Yes	No	Yes	No
Month	Yes	No	Yes	No	Yes	No	Yes	No
T	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820
n	5,539	5,539	3,721	3,721	7,417	7,417	5,226	5,226
R^2	0.417	0.417	0.267	0.327	0.351	0.366	0.402	0.421

Table 2.5. ***Order Flow Intensity and Feedback Trading (Market Orders).*** *The table shows the estimation results for the GLARMA model (2.5) for market orders only. For each option type, the first column provides the results of the baseline regression, while the second replaces daily control variables with daily fixed effects. The final rows list the number of observations T, the number of trades n, and the adjusted R^2. Inference is based on robust standard errors. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).*

2.4.1.3 Feedback of Order Flow Imbalance

Finding return-contrarian buy and sell intensities suggests a return-contrarian net positioning of individual investors. To analyze this net effect in more detail, we examine the response of order flow imbalances $IMB^{CALL}_{t,i}$, $IMB^{PUT}_{t,i}$, $IMB_{t,i}$, and $IMB^{BUY}_{t,i}$ to intraday returns. To this end, we use almost the same regression model as in (2.5), but regress directly on the imbalance as a metric variable instead of defining a Poisson process for the count data. As the imbalances respond to intraday returns in a way qualitatively similar to the intensities, we do not tabulate the results here.

However, we illustrate the accumulated impulse response function in Figure 2.3 (b). For calls (puts), a one standard deviation shock of 0.14% to the intraday return results, via the coefficients of $INTRA_{t,i}$ and $INTRA^2_{t,i}$, in a decrease (increase) in order flow imbalance of −0.104 (0.075) and a decrease in the overall (purchase-based) imbalance of −0.088 (−0.082). Over two hours,

the responses to the initial shock accumulate to a decrease (increase) in the order flow imbalance in calls (puts) by −0.447 (0.405) and the overall (purchase-based) imbalance by −0.422 (−0.374).

Overall, these results are consistent with those for order flow intensities but provide additional evidence that the net order flow is intraday return contrarian.

2.4.2 Tick-By-Tick Returns

2.4.2.1 Methodology

This subsection takes a closer look at the microstructure of trading activity. The sparse literature on traders who execute intraday strategies manually indicates that they closely monitor tick-by-tick returns to determine their entry and exit points (Harris and Schultz, 1998; Garvey and Murphy, 2005). Therefore, we examine whether and how individual investors respond to the last tick direction of the quoted warrant price when entering their orders.[18] In contrast to our analysis in the previous section, these incremental returns are not necessarily due to returns of the underlying (Bakshi et al., 2000). We focus on market orders since they reflect investors' unadulterated opinion at that moment about future prices (Dorn et al., 2008).

We restrict our sample to warrants that had at least two price changes within the 15 minutes before the order was placed. This ensures a lower bound of recent price fluctuations, which is attractive to active traders (Kyröläinen, 2008; Chung et al., 2009). For each order i, we denote the quoted price of the respective warrant at time t as $PRICE_{i,t}$. In the case of a buy (sell) order, we use ask (bid) prices. Let t_1^i be the time of the order execution, t_0^i the time of the order entry, t_{-1}^i and t_{-2}^i the times of the two most recent ticks in the warrant price with $t_{-2}^i < t_{-1}^i < t_0^i$ and $t_0^i - t_{-2}^i \leq 15$ minutes. Using the binary variables

$$BUY_i = \begin{cases} 1 & \text{if the order } i \text{ is an investor's buy order,} \\ 0 & \text{if the order } i \text{ is an investor's sell order,} \end{cases} \tag{2.9}$$

to distinguish trade directions and $UP_i = \mathbf{1}_{\{PRICE_{i,t_{-2}^i} < PRICE_{i,t_{-1}^i}\}}$ and $DOWN_i = \mathbf{1}_{\{PRICE_{i,t_{-2}^i} > PRICE_{i,t_{-1}^i}\}}$ to mark ticks with an increase or decrease in the warrant price from t_{-2}^i to t_{-1}^i, we determine the ratio of upticks to downticks before buy and sell orders, as

$$TICK^{\text{Buy}} = \frac{\sum_i UP_i \times \mathbf{1}_{\{BUY_i=1\}}}{\sum_i DOWN_i \times \mathbf{1}_{\{BUY_i=1\}}}, \tag{2.10}$$

$$TICK^{\text{Sell}} = \frac{\sum_i UP_i \times \mathbf{1}_{\{BUY_i=0\}}}{\sum_i DOWN_i \times \mathbf{1}_{\{BUY_i=0\}}}. \tag{2.11}$$

[18] We do not consider the last tick before the execution of an order. This is because the time between entry and execution could introduce a look-ahead bias since the investor cannot react to a tick in the future.

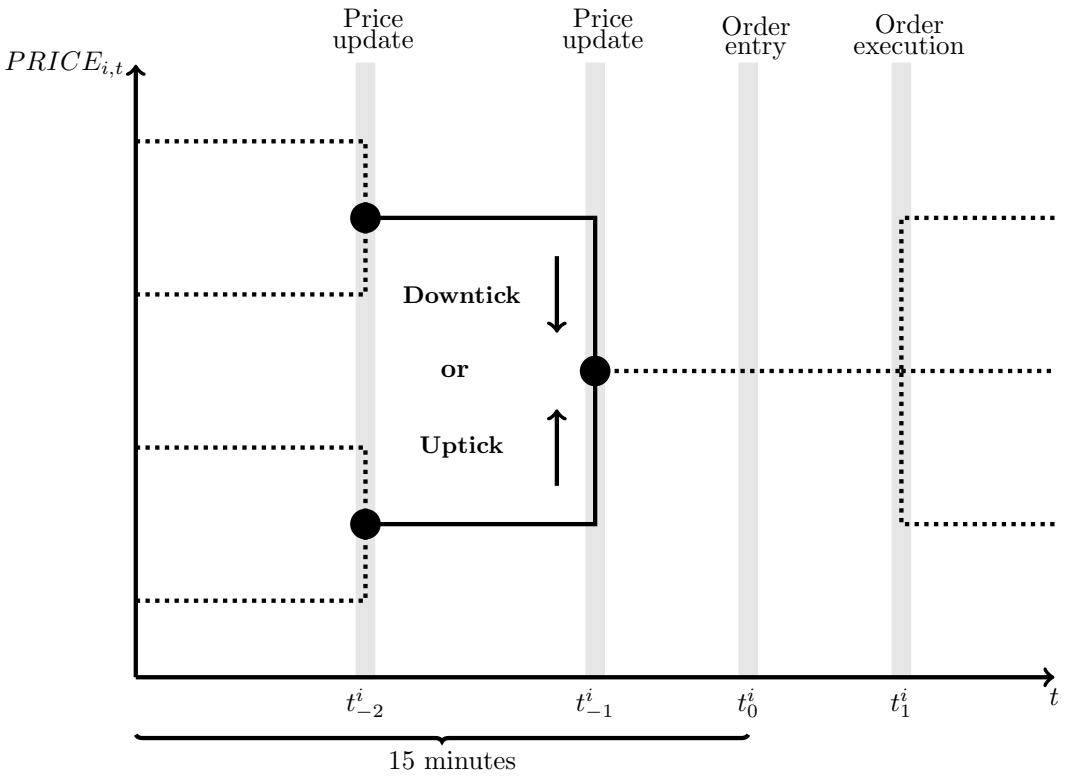


Figure 2.4. ***Illustration of Tick Price and Trade Direction Methodology.*** *The figure shows, for an order i, the price $PRICE_{i,t}$ of the respective warrant at time t. In the case of a buy (sell) order, we use ask (bid) price quotes. Dotted lines represent possible price paths. Bold circles represent the two most recent price changes before the order entry. The solid lines are the two possible price paths containing the tick on which we base our analysis. The points in time of the analyzed price updates, order entry, and order execution are highlighted in gray.*

The methodology is summarized in Figure 2.4 using a timeline of possible and analyzed price paths along with relevant events.

If investors do not react to previous ticks, we would expect the ratio of upticks to downticks prior to buy or sell orders to be equal to one.[19] Significant deviations from one would indicate conscious feedback trading on tick-by-tick returns.

2.4.2.2 Results

Table 2.6 shows the ratio of upticks to downticks before the entry of a market order (Panel A). The results are presented in aggregate and separated by the warrants' type and the trade direction.

We find slightly more buys after an uptick and more sells after a downtick, which is consistent with positive feedback trading. This pattern is consistent for calls and puts. The deviation from

[19] To be more precise, we would expect the ratio to equal the unconditional empirical ratio of upticks to downticks, which is 0.9989 in our entire sample, covering 4.1 billion ticks.

one is, however, small and amounts to only 6%–13%. For the total sample, it is nonetheless significant at the 1% level.

	Market orders					
	Call		Put		Total	
	Buy	Sell	Buy	Sell	Buy	Sell
Panel A: Full sample						
Up/Down	1.070	0.915	1.068	0.865***	1.069**	0.886***
# Obs.	2,703	1,856	3,477	2,482	6,180	4,338
Panel B: Time between tick and order entry $\geq$ 1-minute						
Up/Down	1.042	0.817	1.153	0.753***	1.105	0.779**
# Obs.	531	298	717	419	1,248	717
Panel C: Warrant price $\leq$ 0.5 euro						
Up/Down	1.173*	0.782**	1.147	0.830*	1.160**	0.808***
# Obs.	754	490	687	591	1,441	1,081
Panel D: Traded volume in the upper 20% quantile						
Up/Down	1.016	1.052	1.036	0.887	1.028	0.958
# Obs.	510	437	733	534	1,243	971
Panel E: Traded volume in the lower 20% quantile						
Up/Down	1.044	0.625***	0.990	0.828*	1.013	0.739***
# Obs.	464	351	595	510	1,059	861

Table 2.6. ***Tick Direction and Feedback Trading.*** *The table gives an overview of the ratio of upticks to downticks prior to the entry of a market order, separated by the warrants' type, the order type and the trade direction. Panel A considers all trades with at least two price updates within the last 15 minutes prior to the order entry. Panel B shows the ratio for orders with at least 1 minute between the last price update and the order entry. Panel C shows the ratio for orders where the warrants' ask price prior to the order entry was less or equal to 0.50 euros. Panel D (E) shows the ratio for orders with a traded volume in the upper (lower)* 20% *quantile. The number of observations is given in the second row of each Panel. Significant results of two-sided binomial tests for the null hypothesis, namely that up and down ticks are equally likely to occur before an order are indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).*

As the tilt is small, it could be the case that investors need some time to respond to a tick. We restrict the sample in Panel B to those orders where there is at least 1 minute between the last tick and the order entry. While the behavior observed in Panel A is confirmed, statistical significance does not increase.

Since tick-by-tick returns are more meaningful in percentage terms for warrants with a low price than for expensive ones, we suspect that the effect is more pronounced for low-priced warrants. In Panel C, we only consider warrants with an ask price of less than 0.50 euros before the order entry. Indeed, the deviations from one increase to 14%–21% at a high significance level, despite the smaller number of observations.

Separating trades with a traded volume in the upper and lower 20% quantile in Panels D and E shows that especially small traders respond to tick price changes when executing sales,

while larger traders do not. For large trades significance vanishes, while it increases at a high significance level for small sales.

In summary, we find that some retail investors use market orders to follow a momentum strategy (positive feedback trading) on tick-by-tick returns. This effect is more pronounced for low-priced warrants and small trades. According to these findings, there is a small subgroup of retail investors that act on the tick direction. Given negative feedback trading on lower frequencies (15 minutes to two hours), this could be interpreted as an attempt to time a reversal.

2.5 Investor Returns

In this section, we investigate how the observed feedback trading drives investment outcomes, that is, investor returns. The section is organized as follows: First, we separate components of investor returns and determine whether returns are attributable to timing and therefore associated with feedback trading. (Section 2.5.1). Second, we examine whether timing returns are only driven by investor behavior or whether they are influenced by market makers' strategic intraday quotation policies (Section 2.5.2).

2.5.1 Intraday Return Attribution

2.5.1.1 Methodology

As feedback trading is essentially a timing strategy, we are particularly interested in returns due to the ability to time entry points. Therefore, we decompose the intraday returns of investors who buy warrants into returns from this timing ability, (negative) returns from the bid-ask spread, and – in the case of market orders – returns from the order execution.[20]

For a given intraday holding period of τ minutes, we calculate the return for an investor buy trade i as

$$RETURN_{i,\tau} = \frac{PRICE^{Bid}_{i,t_1^i+\tau} - TRADE_i}{TRADE_i}, \tag{2.12}$$

where $TRADE_i$ is the transaction price and $PRICE^{Bid}_{i,t_1^i+\tau}$ is the quoted bid price τ minutes after the trade. We then decompose this return into three components: spread, timing, and execution.

As investors can only sell to the market maker at the quoted bid price, they lose the bid-ask spread when they wish to close the trade. This loss at the end of the holding period is the *spread component* computed as

$$RETURN^{Spread}_{i,\tau} = \frac{PRICE^{Bid}_{i,t_1^i+\tau} - PRICE^{Ask}_{i,t_1^i+\tau}}{TRADE_i}, \tag{2.13}$$

[20] We focus on buy trades, as our exchange data do not identify traders, making it difficult to match buys and sells and track inventory.

where $PRICE^{Ask}_{i,t^i_1+\tau}$ is the quoted ask price τ minutes after the trade.

With market orders, investors place an order based on the observed indicative quote. Thus the *timing component* is defined as

$$RETURN^{Timimg}_{i,\tau} = \frac{PRICE^{Ask}_{i,t^i_1+\tau} - PRICE^{Ask}_{i,t^i_{-1}}}{TRADE_i}, \tag{2.14}$$

where $PRICE^{Ask}_{i,t^i_{-1}}$ is the quoted ask price immediately before the entry of a market order.

However, the actual transaction price of an executed order can differ from the price quoted immediately before the execution. As quoted prices are indicative only, market makers are requested to submit a binding bid or ask after the arrival of a market order.[21] Acquiring knowledge of the investor's trade direction and volume, market makers might adjust their binding order. As such, a market order can be executed at a price better or worse than the last visible indicative quote on the basis of which the investor placed his order. We therefore define the *execution component* of the intraday return as

$$RETURN^{Execution}_{i,\tau} = \frac{PRICE^{Ask}_{i,t^i_{-1}} - TRADE_i}{TRADE_i}. \tag{2.15}$$

It is obvious that

$$RETURN_{i,\tau} = RETURN^{Spread}_{i,\tau} + RETURN^{Timing}_{i,\tau} + RETURN^{Execution}_{i,\tau}. \tag{2.16}$$

In contrast, investors who use limit orders do not trade directly on the basis of the quote $PRICE^{Ask}_{i,t^i_{-1}}$ – they know that their transaction price will be no more than the limit price. Therefore, we define the execution component as zero for these trades and calculate the timing component based on the transaction price:

$$RETURN^{Timing}_{i,\tau} = \frac{PRICE^{Ask}_{i,t^i_1+\tau} - TRADE_i}{TRADE_i}. \tag{2.17}$$

To determine whether feedback trading of retail investors reflects skill in intraday timing rather than noise trading, we compare the actual trading data with a randomized control sample. The control sample consists of trades in the same warrant and on the same trading day as in the original sample. Thus for each actual trade, we sample a randomized control trade for the same day.[22] For statistical inference, we resample the control data 10,000 times to get a bootstrapped distribution. In this way, we can reject the null hypothesis of no timing ability at level α if the actual average return lies beyond the respective quantile of the bootstrapped distribution.

[21] The principle that the transaction price for a market order is determined after an investor has entered into a buy or sell commitment is not unique to EUWAX. It is also applied on other exchanges in Germany that rely on indicative quotes, and when buying or redeeming mutual funds (see, e.g., Capponi et al. (2020)).

[22] Resampling returns from the same warrants as in the original data ensures that we generate returns that vary only due to timing and not to warrant features like moneyness or maturity.

2.5.1.2 Results

Table 2.7 shows weighted average returns (2.12) and their components (2.13), (2.14), (2.15), and (2.17) for holding periods of 1, 15, and 60 minutes. As weights, we use traded volume in euros. We indicate returns that are significantly different from zero with asterisks, and timing returns that deviate significantly on the lower (upper) side from bootstrapped resamples with minus (plus) signs.

Most of the returns are significantly negative. On average, investors who buy warrants lose money on the day they enter a trade. These losses tend to be larger for trades that are smaller (Panel A), where the warrants have a low price (Panel A), and where they are entered via market orders (Panel C). Furthermore, untabulated results show that returns remain negative until the end of the trading day.

The return decomposition shows that returns are primarily driven by losses due to the bid-ask spread. These losses amount to slightly more than 1% of the invested amount, on average. They are significantly larger for smaller trades (up to 7%), and warrants with a low price (6%).

The timing of entry points is poor in the short run (Panel A). However, for holding periods of more than 15 minutes, investors tend to earn slightly positive timing returns (less than 1%, on average). These timing returns are higher for investors who use limit orders and those who trade small amounts and warrants with a low price (Panels A & B). In these cases, these timing returns are almost instantaneously larger than expected from a random strategy according to the bootstrapped distribution. However, on average, they are insufficient to cover losses from the bid-ask spread. Therefore, significant timing returns could originate from market makers who are happy to fill limit orders inside the spread, if the spread is so large that they are confident of profiting from the trade anyway.[23] An alternative interpretation is that investors manage to buy low-priced warrants, which are usually very volatile due to high leverage, with limit orders at lower prices.

Users of market orders perform worse on average (Panel C). Market order users generate timing returns that are indistinguishable from zero and perform even significantly worse than if they submitted their orders randomly throughout the day. The execution returns resulting from differences with respect to the tick direction in a warrant's price before the entry of a market order are only minor. As such, investors who do positive feedback-trades on the last tick direction seem to trade on noise. Finally, although not significantly, market orders lead to slightly adverse execution prices, particularly for large trades. This indicates that some market makers could use their knowledge of the trade direction and size to fill market orders at adverse prices.

[23] Limit orders can receive price improvements compared to the current quote. When there is a limit order that could be matched with an indicative quote or lies within the bid-ask spread, market makers are requested to submit a binding bid or ask. By adjusting their binding order, they can (opportunistically) fill investors' orders that were previously inside the spread.

	Total			Spread			Timing			Execution
Panel	$t+1$	$t+15$	$t+60$	$t+1$	$t+15$	$t+60$	$t+1$	$t+15$	$t+60$	
A: Full sample	-1.19^{***}	-0.97^{***}	-0.88^{**}	-1.32^{***}	-1.40^{***}	-1.43^{***}	0.13_{++}	0.43^{**}_{+}	0.54^{*}_{+}	–
Calls	-1.29^{***}	-1.05^{***}	-1.15^{***}	-1.41^{***}	-1.49^{***}	-1.52^{***}	0.13_{+++}	0.44_{+}	0.37_{+}	–
Puts	-1.10^{***}	-0.89^{***}	-0.64	-1.23^{***}	-1.31^{***}	-1.34^{***}	0.14_{+}	0.42^{*}_{++}	0.70	–
Large volume	-0.85^{***}	-0.62^{***}	-0.58^{*}	-0.91^{***}	-0.97^{***}	-0.99^{***}	0.06	0.35^{*}_{+}	0.40	–
Small volume	-5.18^{***}	-4.71^{***}	-4.37^{***}	-6.51^{***}	-6.68^{***}	-6.90^{***}	1.33^{*}_{+++}	1.97^{**}_{+++}	2.53^{***}_{+++}	–
Low price	-4.98^{***}	-4.30^{***}	-3.84^{***}	-5.64^{***}	-6.09^{***}	-6.32^{***}	0.66_{+++}	1.79^{***}_{+}	2.48^{**}_{+}	–
B: Limit orders	-1.22^{***}	-0.92^{***}	-0.70^{*}	-1.40^{***}	-1.50^{***}	-1.53^{***}	0.18_{++}	0.59^{**}_{+}	0.83^{*}_{+}	–
Large volume	-0.85^{***}	-0.52^{***}	-0.33	-0.94^{***}	-1.02^{***}	-1.03^{***}	0.09_{+}	0.50^{**}_{+}	0.70^{*}	–
Small volume	-5.60^{***}	-4.97^{***}	-4.73^{***}	-7.18^{***}	-7.42^{***}	-7.69^{***}	1.58^{**}_{+++}	2.45^{***}_{+++}	2.96^{***}_{+++}	–
C: Market orders	-1.08^{***}	-1.11^{***}	-1.45^{***}	-1.04^{***}	-1.04^{***}	-1.07^{***}	0.05	0.01	-0.30_{-}	-0.08
Large volume	-0.87^{***}	-0.93^{***}	-1.42^{***}	-0.79^{***}	-0.79^{***}	-0.82^{***}	0.05	-0.01	-0.47_{-}	-0.13
Small volume	-4.02^{***}	-4.03^{***}	-3.37^{***}	-4.65^{*}	-4.63^{*}	-4.71^{*}	-0.08	-0.11	0.62	0.71
Down tick	-0.94^{***}	-0.99^{***}	-1.51^{**}	-0.95^{***}	-0.95^{***}	-0.94^{***}	0.07	0.02	-0.51_{-}	-0.06
Up tick	-1.14^{***}	-1.18^{***}	-1.35^{*}	-1.04^{***}	-1.04^{***}	-1.11^{***}	0.03	-0.01	-0.11	-0.13

Table 2.7. ***Return Decomposition.*** *The table shows volume-weighted averages of the returns (2.12) as well as the components of the returns (2.13), (2.14), (2.15), and (2.17) of investor buy trades for holding periods τ of 1, 15, and 60 minutes. The average returns are calculated for samples formed according to the warrants' type, the order size, the trade price, the order type, and the tick direction in the quoted price prior to the entry of a market order. Trades with a transaction volume in the upper (lower) 20% quantile are termed large (small). Trades with a transaction price of 0.50 euros or less are termed low-priced. The terms up and down indicate the tick direction prior to the entry of a market order. The returns are shown in percentage points. Mean returns that are significantly different from zero are indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). Mean timing returns that significantly deviate on the lower / upper side from bootstrapped resamples are indicated at the 5% level ($_{-/+}$), the 1% level ($_{--/++}$), and the 0.1% level ($_{---/+++}$).*

Overall, we find that retail investors who do feedback-trading on short-term returns of the underlying and use tick-by-tick returns of warrants are noise traders without sufficient timing ability to generate positive returns. Among different investors, those that trade small amounts, low-priced warrants and use market orders perform worst. On average, they experience a negative return on the day of a trade. This finding is consistent with short-term returns in stocks (Barrot et al., 2016) and longer term returns in retail derivatives (Entrop et al., 2016). Considering that retail investors may also pay commissions to their broker, their effective returns are likely to be even lower.

2.5.2 Strategic Quotation

2.5.2.1 Methodology

In the previous section, we showed that investor returns are determined by the bid and ask prices quoted by market makers. We now investigate whether market makers strategically alter these quotes in response to trades. If this is the case, then (poor) investor returns would not be due to investor behavior alone, but also to market makers exercising their price-setting power.

Usually the market maker for a warrant is the respective issuer and quotes prices with a mark-up on top of the fair value. There is evidence that market makers of retail derivatives increase their quoted prices when they expect an excess in net investor demand and decrease them when they expect an excess in net investor supply (Baule, 2011; Baule et al., 2018). This is reflected in the order flow hypothesis (Wilkens et al., 2003). As outlined in the introduction, there are two competing hypotheses that would both affect investors' timing returns: (i) An investor buy could indicate great attractiveness and lead further buys by other investors; and (ii) an investor buy could be followed by a re-sale by the same investor if they are speculating on short-term (intraday) gains. According to (i), the market maker should increase the warrant's markup, according to (ii), the market maker should decrease it.

To study if and how market makers use these hypothetical quotation strategies, we use a difference-in-differences (DD) approach. The DD approach is a popular method for estimating causal relationships and allows us to eliminate the effects of other factors, such as price changes in the warrants' underlying.[24]

We define an investor's trade as a "treatment" and use a matching procedure to create the control group. For each trade in a warrant, we look for an identical warrant (in terms of underlying, strike, and time to maturity) from a different issuer that was not traded within the investigation period (2014) and for which we observe at least one tick within 60 minutes before and after the treatment. If there is more than one match, we only add to our control group the

[24] Recent examples of applying DD in a similar context are Arnold et al. (2022), Pelster and Schertler (2019), and Pelster and Hofmann (2018).

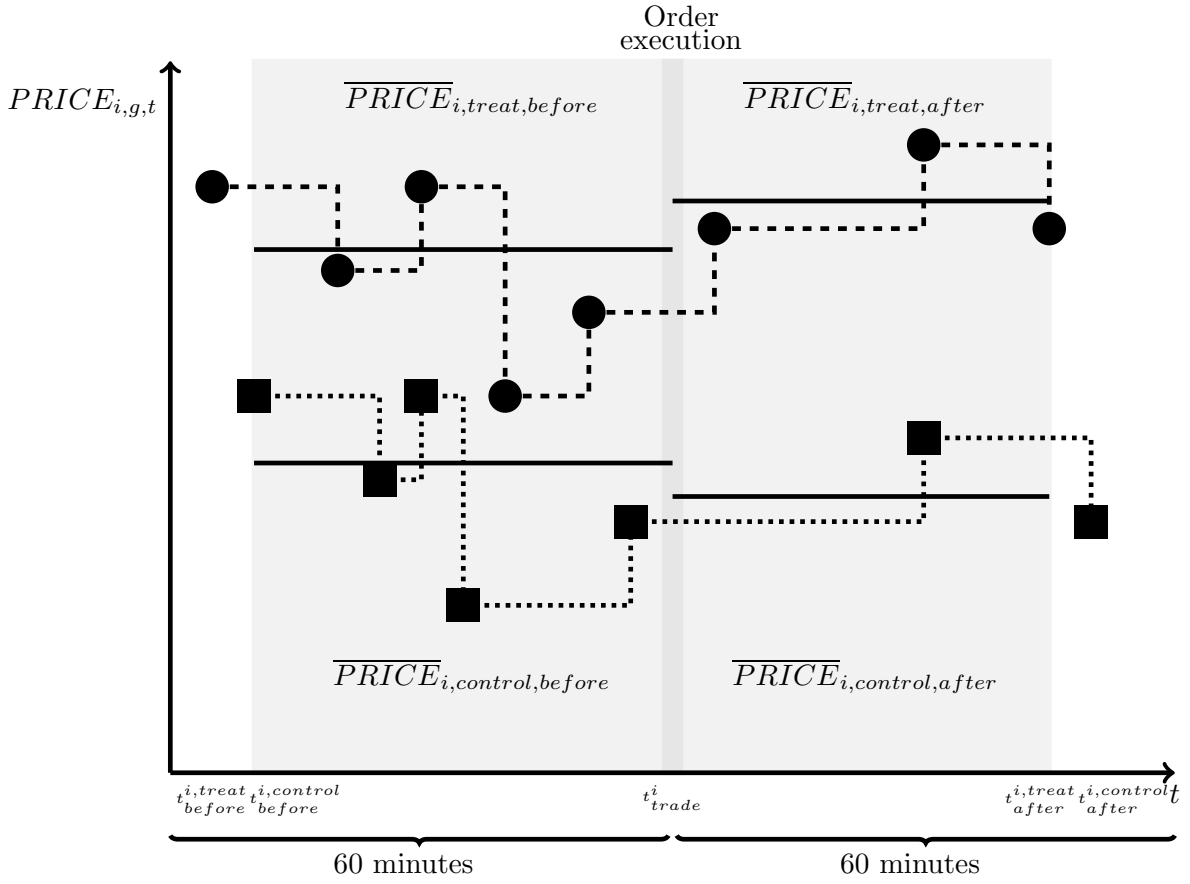


Figure 2.5. ***Illustration of Difference-in-Differences Methodology.*** *The figure summarizes the calculation of the time-weighted average prices $\overline{PRICE}_{i,g,p}$, represented by solid lines, used in the difference-in-differences analysis. For each trade i the averages are calculated as $\overline{PRICE}_{i,g,before} = \sum_{t=\underline{t}^i}^{t^i_{trade}} PRICE_{i,g,t}/(t^i_{trade} - \underline{t}^i)$ and $\overline{PRICE}_{i,g,after} = \sum_{t=t^i_{trade}}^{\overline{t}^i} PRICE_{i,g,t}/(\overline{t}^i - t^i_{trade})$, where time t is measured in millisecond increments, and $\underline{t}^i = \max\{t^{i,treat}_{before}, t^{i,control}_{before}\}$, $\overline{t}^i = \min\{t^{i,treat}_{after}, t^{i,control}_{after}\}$. The timestamp $t^{i,g}_{before}$ is the time of the first tick within 60 minutes before the trade and the timestamp $t^{i,g}_{after}$ is the time of the last tick within 60 minutes after the trade. The point in time of the order execution t_{trade} is highlighted in dark gray. The time window considered for calculating the time-weighted averages is shaded in light gray. For buy (sell) orders we use quoted ask (bid) prices. Dashed lines represent a possible price path of the treated warrant. Dotted lines represent a possible price path of the respective control warrant. Bold circles and rectangles represent observed price changes within 60 minutes before and after the trade. The time and price scales are for illustration only.*

warrant whose price is closest to the treated warrant.[25] If there is no match, we discard the trade from the treatment group.[26] This matching procedure ensures that common valuation effects, such as movements in the underlying, cancel out.

For each trade i, we compute time-weighted average prices of treated warrants and control warrants before and after the treatment. Averaging accounts for the effect that issuers do not

[25] For robustness, we have alternatively used the warrant with the highest number of ticks and rerun our analysis. The results are robust to this change in the matching procedure. If there are multiple treatments of a warrant on the same day, the same control warrant is matched throughout that day.

[26] Finally, we remove pairs from the top 10% quantiles of absolute and relative price differences between treatment and control warrant to eliminate possible mismatches and data errors.

update their quotes simultaneously. This leaves us with a total of four observations per trade i. To be more precise, for $g \in \{treat, control\}$ and $p \in \{before, after\}$, the price $\overline{PRICE}_{i,g,p}$ is the time-weighted average price within 60 minutes before and after the trade. The methodology is summarized in Figure 2.5.

For ease of notation, we introduce the binary variables $TREAT_{i,g} = \mathbf{1}_{\{g=treat\}}$ and $POST_{i,p} = \mathbf{1}_{\{p=after\}}$ to indicate to which group a specific price $\overline{PRICE}_{i,g,p}$ belongs. The baseline DD regression reads as follows:

$$\overline{PRICE}_{i,g,p} = \alpha_i + \beta_1 TREAT_{i,g} + \beta_2 POST_{i,p} + \beta_3 POST_{i,p} \times TREAT_{i,g} + \epsilon_{i,g,p}, \tag{2.18}$$

where α_i is a fixed effect for each trade covering all common pricing-specifics of each warrant pair at the time of trade. The coefficient of the variable $TREAT_{i,g}$ accounts for the mean difference in the average prices of treatment and control warrants. The coefficient of the variable $POST_{i,p}$ captures the mean change in average prices after a treatment. Since these variables cover all pricing-specific aspects, no further control variables are needed. The coefficient of the interaction term between $TREAT_{i,g}$ and $POST_{i,p}$ captures the additional mean change in the average prices of treated warrants after a treatment and thus represents possible effects of strategic quotation.

Pelster and Schertler (2019) have shown that issuers engage in cross-pricing when they have sold supplementary products. In particular, the magnitude of this effect depends on the trading volume. To analyze whether the degree of price adjustment in response to a trade similarly differs with trading volume, we indicate high-volume trades with the binary variable

$$HIGH_i = \begin{cases} 1 \text{ if the volume of trade } i \text{ is in the upper 20\% quantile,} \\ 0 \text{ if the volume of trade } i \text{ is not in the upper 20\% quantile,} \end{cases} \tag{2.19}$$

and include interaction terms with this variable in the DD regression.[27]

Above, we argued that there are two competing hypothetical quotation strategies. However, regardless of the strategy employed, it is unlikely that a market maker would react to a second trade in a particular warrant in the same way as to the first. The response to the first trade of the day in a warrant may therefore give a clearer picture of strategic quotation, while the responses to later trades of the day might be damped. To capture effects exclusive to the first trade per warrant and trading day, we introduce a further binary variable

$$FIRST_i = \begin{cases} 1 \text{ if the warrant is treated for the first time on the treatment day,} \\ 0 \text{ if the warrant was treated on the treatment day before.} \end{cases} \tag{2.20}$$

[27] The upper 20% quantile corresponds to a value of 5,400 euros. Since the variable itself is a linear combination of fixed effects, it is only included in interaction terms.

	$\overline{PRICE}_{i,g,p}$ [cents]					
	(1)		(2)		(3)	
	Buy	Sell	Buy	Sell	Buy	Sell
$TREAT_{i,g}$	−5.83***	−6.29***	−5.74***	−6.37***	−7.44***	−8.07***
	(0.15)	(0.18)	(0.17)	(0.21)	(0.26)	(0.27)
$TREAT_{i,g} \times HIGH_i$			−0.47	0.32		
			(0.38)	(0.40)		
$TREAT_{i,g} \times FIRST_i$					2.6***	3.4***
					(0.32)	(0.35)
$POST_{i,p}$	−2.33***	3.2***	−2.47***	2.63***	−3.01***	3.9***
	(0.17)	(0.25)	(0.18)	(0.28)	(0.30)	(0.34)
$POST_{i,p} \times HIGH_i$			0.73	2.27***		
			(0.50)	(0.65)		
$POST_{i,p} \times FIRST_i$					1.09**	−1.34**
					(0.37)	(0.5)
$POST_{i,p} \times TREAT_{i,g}$	0.03	0.06*	0.04*	0.08**	0.08*	0.00
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
$POST_{i,p} \times TREAT_{i,g} \times HIGH_i$			−0.05	−0.08		
			(0.05)	(0.06)		
$POST_{i,p} \times TREAT_{i,g} \times FIRST_i$					−0.07	0.12*
					(0.04)	(0.05)
FE per Trade	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	22,584	17,200	22,584	17,200	22,584	17,200
# Trades	5,646	4,300	5,646	4,300	5,646	4,300

Table 2.8. ***Strategic Quotation.*** *The table shows the estimation results for the difference-in-differences regressions of the time-weighted average prices, separated by buy and call trades. Fixed effects are included for each trade. The results are shown in euro cents. The final rows list the number of observations and the number of trades per regression. Inference is based on cluster-robust standard errors with clusters formed at the trade level. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).*

2.5.2.2 Results

Table 2.8 presents the results for the DD regression models. To capture nuances of strategic quotation, we run the regressions separately for purchases and sales. For the baseline regression (2.18) of buys and sells, we find that the coefficients of the interaction term are slightly positive and significantly different from zero. However, the size of the effect is economically insignificant, with a size of only 0.03 to 0.06 cents (where 1 cent is the minimum tick size). This observation still holds after separating high and low volume trades. Also the exclusive look at warrants that have been treated for the first time a day yields no considerably different results.

A reason for our lack of evidence on strategic quotation could be that not all issuers employ such strategies and that those who do might use opposing strategies. Consequently, it would be difficult to detect strategic quotation in the aggregate across all issuers. To address this cross-sectional issue, we re-run our regressions separately for each issuer. The results are similar to those shown for the aggregate and are therefore not tabulated here. As there is no evidence of economically significant strategic quotation, the returns according to (2.14) can be attributed solely to the investors' behavior.

The remaining variables in the regressions provide additional insights. The significantly negative coefficient of the variable $TREAT_{i,g}$ indicates, in all regressions, that treated warrants are on average cheaper than control warrants before the treatment. Put differently, at the time of trade there was at least one identical warrant offered by another issuer that was on average more expensive. This is consistent with the finding that retail investors' demand for warrants is price-sensitive (Baule and Blonski, 2015).[28] Finally, we find a statistically and economically significant pattern for the effect of the variable $POST_{i,p}$. For all regressions, the coefficient of this variable is negative for purchases and positive for sales. This indicates that, on average, the direction of retail investors' trades is contrary to the change in warrants' prices. As such, this pattern is consistent with negative feedback trading. However, as trades do not occur on average prices, no conclusions can be drawn about intraday timing ability.

Overall, our analysis in this section shows that retail investors who use warrants for feedback trading on recent intraday returns are noise traders who earn negative returns. These losses are primarily caused by the bid-ask spread, but are not due to market makers trying to take advantage of investors by responding to trades by strategically changing their quotes.

2.6 Conclusion

Although feedback trading is prevalent among professional and retail investors and across multiple time horizons, the existing literature documents little about its existence with regard to the intraday time scale. Using a unique data set of exchange trades and quotes for bank-issued warrants on the DAX, we provide new evidence on the intraday feedback trading behavior of retail investors.

We find that retail investors consciously respond to intraday returns of the underlying for up to two hours, showing a strong pattern of negative feedback trading. This behavior suggests that retail investors expect recent intraday returns to reverse. This is in line with the lower-frequency feedback trading literature. Moreover, there is a subgroup of investors who speculate on high-frequency momentum in the tick-by-tick returns of warrants. Although these investors appear more attentive, their returns are indistinguishable from returns of random order submissions.

Retail investors who use warrants to feedback trading on intraday returns are noise traders who earn, on average, negative returns. This is also consistent with the literature. We find that these losses are primarily caused by the bid-ask spread, but are not due to market makers trying to take advantage of investors by responding to trades by strategically changing their quotes. It is investors' behavior that determines returns. Among different investors, those that trade small amounts, low-priced warrants and market orders perform worst. Timing returns of investors who use market orders are at best indistinguishable and sometimes worse than those of random timing. Although some investors use limit orders skillfully to enter trades, on average they also fail to earn the bid-ask spread.

[28] An alternative interpretation is that investors prefer an issuer whose warrants are cheaper, although they do not compare prices.

Chapter 3

Shorting in the Dark: The Dual Role of Short Sales in Off-Exchange Trading

Co-authored with
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Abstract
Using transaction-level data, we examine the role of short sales in U.S. off-exchange trading for liquidity and price discovery. We find that short sales are pivotal in providing off-exchange liquidity and improve price discovery. Short sellers represent the passive side in 55% of buyer-initiated volume and the active side in 34% of seller-initiated volume. Compared to long sellers, short sellers provide liquidity at wider spreads and consume liquidity at narrower spreads. Seller-initiated short sales tend to be better informed than long sales but less informed than on-exchange sales. Consistent with both an inventory effect and trading against overreactions, short selling increases after positive returns over the past week. Finally, we show that short sellers' contribution to higher off-exchange trading activity raises on-exchange trading costs.

JEL Classification: D4, G14, G19
Keywords: short selling, off-exchange, broker-dealer, liquidity, price discovery

3.1 Introduction

In today's fragmented equity markets, investors can trade not only on traditional "lit" exchanges but also on numerous off-exchange "dark" venues. Notably, more than a third of the U.S. equity volume is now executed off-exchange through alternative trading systems and broker-dealer internalization (FINRA, 2024). Special regulations – such as Regulation ATS and SEC Rule 3a1-1 – allow off-exchange venues to selectively grant access, operate with reduced transparency regarding available counterparties, and execute trades at a finer price grid, thereby offering potential for price improvement. This regulatory framework creates a trade-off between traditional exchanges and off-exchange venues in terms of immediacy and trading costs, leading to a segmentation of order flow by its short-term informativeness (e.g., Hendershott and Mendelson, 2000; Zhu, 2014; Comerton-Forde and Putniņš, 2015; Menkveld et al., 2017; Boehmer et al., 2021). Relatively uninformed order flow migrates off-exchange, as traders direct orders there to minimize trading costs when immediacy is not crucial, and because uninformed, non-directed orders are more likely to be selected for internalization by broker-dealers. In contrast, informed order flow remains on-exchange, due to its demand for immediacy and lower likelihood of being internalized.

A puzzling, yet unexplained, feature of off-exchange trading is the substantial involvement of short selling: 44% of the off-exchange volume between 2019 and 2021 involved a short seller, according to data from the Financial Industry Regulatory Authority (FINRA). This prevalence is difficult to reconcile with the notion that off-exchange venues primarily attract uninformed order flow, given that short sellers are typically viewed as particularly well-informed market participants (e.g., Christophe et al., 2004; Boehmer et al., 2008; Diether et al., 2009; Karpoff and Lou, 2010; Engelberg et al., 2012).

To resolve this puzzle, we follow Comerton-Forde et al. (2016) and zoom in on the transaction level to show that short sales serve a dual role: Seller-initiated short sales demand liquidity and contribute to price discovery, while buyer-initiated short sales provide liquidity to investors seeking immediate execution of buy orders. If off-exchange short sales are used primarily for liquidity provision – such as by market makers with depleted inventories – short sales could be both prevalent and uninformed. Liquidity provision thus offers a compelling explanation for the prevalence of short selling in off-exchange trading.

In this paper, we provide the first transaction-level analysis of the dual role of short sales in off-exchange trading and empirically investigate the liquidity-provision explanation for the puzzle outlined above. Specifically, we address the following key questions: Do short sellers add or remove off-exchange liquidity? Under which market conditions do they trade? How informed are they? Do they exaggerate price declines or lean against overreactions? Do they contribute to deteriorating on-exchange liquidity? Our analysis draws on U.S. transaction-level stock data from FINRA, which enable us to accurately identify all short sales among off-exchange trades reported to the consolidated tape. Leveraging this granularity, we further classify off-exchange short sales as buyer- or seller-initiated. We apply the same classification to off-exchange long

sales, enabling us to construct a control group and detect unique behavioral patterns of short sales.

We start by examining the impact of short selling on off-exchange liquidity. Short sales supply liquidity to 55% of the buyer-initiated volume, and account for 34% of the liquidity-demanding sales, on average. These ratios are robust across the trading day, the sample period, and the firm size. They show that short sellers are net-positive providers of off-exchange liquidity and the primary source of liquidity for buyer-initiated trades, consistent with our expectations. Given that broker-dealers account for 69% of the off-exchange volume (FINRA, 2024, p. 38), this suggests that broker-dealers commonly use short sales to internalize customer buy orders when they have no positive inventory. This sheds novel light on the mechanism by which order flow is segmented away from exchanges. In addition, it shows that short sales are used quite differently off-exchange compared to on-exchange, where their impact on liquidity provision and demand is more balanced (Comerton-Forde et al., 2016).

We further analyze the prevailing market conditions and subsequent performance of off-exchange short sales. We focus on differences between short sales and long sales in the cases when they are liquidity-providing and liquidity-demanding. Short sellers provide liquidity at wider spreads but face increased adverse price movements compared to long sellers. Short sales that demand liquidity trade when spreads are unusually low and have a higher price impact compared to long sales. These behavioral differences hold across the trading day, the sample period, and differently sized stocks. Moreover, they cannot be attributed to differences in traded stocks, prevailing national best bid and offer (NBBO) spread, or trading volume. These findings support predictions of the competitive rational expectations model of Comerton-Forde et al. (2016), where market makers use short sales to provide liquidity and informed traders use short sales to demand liquidity.

Using a vector autoregression framework, our study also sheds light on the intraday informativeness of off-exchange short sales. Specifically, we measure the permanent price impact of the two types of short sales on stock prices and compare it to that of other sales. Following Hasbrouck (1991), we interpret the permanent price impact of an unanticipated order flow shock as a measure of the private information contained in the order flow. We find that seller-initiated short sales are informed on one-minute horizons, while buyer-initiated short sales are not. This pattern holds during both calm and tense market conditions, indicating that seller-initiated short sales contribute to intraday price discovery. In large and medium sized stocks, seller-initiated short sales are also significantly better informed than long sales when market conditions are normal, but indistinguishable when they are tense. In small stocks, long sellers are better informed throughout the sample period. Finally, consistent with the trade-off between off-exchange venues and traditional exchanges in terms of trading costs and execution certainty, we find that on-exchange order flow's informativeness dominates any of our off-exchange order flow partitions.

In addition, we examine whether off-exchange short sellers exaggerate price declines or lean against overreactions. To this end, we analyze how the daily short selling activity responds to

returns covering the previous night and week. We find that after positive returns both types of short selling increase. This finding aligns with the motive of trading against overreactions, and contradicts concerns that short sellers exaggerate price declines. In addition, we find that liquidity-providing short sales are more contrarian than any other sales type. This observation suggests an inventory effect. The rationale is that a surplus of buy orders, which translates into positive returns, can deplete market makers' inventory, prompting them to use short sales instead of long sales to fill further buy orders. This further strengthens the view that short sales are important for market makers' liquidity provision. Finally, previous returns are closely related to the Rule 201 of the U.S. Securities and Exchange Commission (SEC), which triggers restrictions on aggressive short selling when a stock's price declines by 10% in a single day. We find that when restrictions are active, short sellers reduce their demand for liquidity but increase their supply. This behavior suggests the effectiveness of the rule while also indicating efforts to bypass constraints.

Finally, we test the hypothesis that higher levels of off-exchange trading, actively driven by short sellers demanding off-exchange liquidity and passively enabled by their off-exchange liquidity provision, negatively impact exchange liquidity. This hypothesis is based on the theory of Zhu (2014), which predicts that when off-exchange venues attract relatively uninformed order flow, the concentration of informed traders increases on exchanges. This, in turn, elevates adverse selection risks, potentially causing market makers to quote wider on-exchange spreads. Our findings above demonstrate that while off-exchange trades do contain information, they are notably less informed than exchange trades. Moreover, the levels of off-exchange trading in our sample are above thresholds considered harmful in previous studies (Comerton-Forde and Putniņš, 2015). To empirically test this hypothesis, we employ a two-stage least squares panel regression framework, using instrumental variables to address potential endogeneity between exchange liquidity and off-exchange trading. Our results strongly support the hypothesis. We find that both types of off-exchange short selling cause the NBBO spread to widen significantly, with liquidity-providing short sales being most detrimental. These findings highlight a critical trade-off: Short sales' positive impact on off-exchange liquidity comes at the cost of deteriorating exchange liquidity.

Our study contributes to the literature in several ways. First, we extend the transaction-level short selling analysis of Comerton-Forde et al. (2016), which focuses only on traditional exchanges, to the increasingly important off-exchange venues. Our findings reveal substantial differences between off-exchange and on-exchange short selling in terms of their contributions to liquidity provision and price discovery. We find that the majority of off-exchange short sales are buyer-initiated and pivotal for off-exchange liquidity, consistent with a market making objective. Contrary, seller-initiated short sales make a small but significant contribution to price discovery on short intraday horizons.

Second, we add to the sparse literature on off-exchange short selling at intraday horizons, which does not distinguish between trade initiators. By disaggregating buyer- and seller-initiated short sales, we reveal a dominant liquidity-provision role, which helps reconcile the puzzle that off-exchange short selling is pervasive and yet short-term uninformed at the stock level, as

documented by Reed et al. (2020). In addition, our results suggest that the predictability of cross-sectional intraday returns from off-exchange short selling, as documented by Hu et al. (2021), may reflect compensation for liquidity provision.

Our results have important implications. Short sales are the most important source of liquidity for buyer-initiated off-exchange volume and increase the ability of investors to trade off-exchange. However, as the off-exchange order flow that short sellers provide liquidity to is significantly less informed than exchange order flow, off-exchange short sales contribute to order flow segmentation and deteriorating exchange liquidity, supporting the theory of Zhu (2014). This highlights an important liquidity trade-off and adds to the literature on liquidity in fragmented markets (e.g., O'Hara and Ye, 2011; Gresse, 2006; Comerton-Forde and Putniņš, 2015; Degryse et al., 2015; Comerton-Forde et al., 2018; Hu and Murphy, 2023). These insights are valuable not only to researchers and investors but also to regulators, who consider regulations on off-exchange trading and short selling.

The remainder of the paper is organized as follows: Section 3.2 introduces the market structure and our procedure to identify off-exchange short sales. Section 3.3 describes the data. Section 3.4 studies the behavior of off-exchange short sellers. Section 3.5 concludes.

3.2 Market Structure and Off-Exchange Short Sales

3.2.1 Market Structure

The U.S. equity market is highly fragmented in terms of trading venues. Investors today can trade on traditional exchanges, known as "lit" venues, as well as on a variety of off-exchange venues, commonly referred to as "dark" venues. The popularity of off-exchange venues has surged, now accounting for over one-third of the total trading volume.[1] Off-exchange venues are partially exempt from the SEC's Regulation National Market System (NMS), leading to significant differences in terms of access, transparency, and execution prices compared to traditional exchanges (see, Regulation ATS and SEC Rule 3a1-1).[2] First, off-exchange venues can restrict market participants from accessing their services and thereby control their trading population. Second, off-exchange venues lack pre-trade transparency, as their order books are typically not displayed, and therefore do not contribute to the national best bid and offer (NBBO). Post-trade transparency is also limited, with trades reported on a venue-anonymous

[1] Off-exchange venues accounted for 35% in 2019, 38% in 2020, 37% in 2021, 41% in 2022, and 43% in 2023 of the U.S. equity (dollar) volume (FINRA, 2023, 2024). Off-exchange trading accounts for similarly sizable levels of approximately 10% (dark pools only) in Canada (Foley and Putniņš, 2016), 40% in Europe (Gomber and Pierron, 2010), and 18% in Australia (Comerton-Forde and Putniņš, 2015).

[2] The SEC's Regulation NMS is fully implemented since 2007. It includes the following rules, among others. The "Order Protection Rule" mandates that trading venues implement procedures to prevent trades at prices inferior to protected quotations from other trading venues. The "Access Rule" fosters fair access to quotations, limits access fees, and prevents practices that lock or cross automated quotations. The "Sub-Penny Rule" prohibits the usage of orders in price increments smaller than a penny, except for shares priced below $1.

basis. Additionally, off-exchange venues are not required to disclose their market structure or matching procedures. Third, orders can execute at finer price increments, so-called subpennies.

Off-exchange venues can be classified into alternative trading systems (ATS) and broker-dealers (Non-ATS). There are 33 ATSs and 228 broker-dealers today (SEC, 2024, p. 370). An ATS is a multilateral trading platform where customers can interact with each other and with (multiple) liquidity providers. Examples include UBS ATS, Barclays ATS, and POSIT. Contrary, a broker-dealer offers unilateral trading, acting as the single counterparty that provides liquidity to customer orders. Broker-dealers offer trading platforms for end customers (e.g., Robinhood) or act as wholesalers who execute customer orders for other broker-dealers (e.g., Citadel). The order flow that broker-dealers execute includes a substantial share of marketable retail orders (Boehmer et al., 2021; Barber et al., 2024). Although the dataset used in our analysis does not differentiate between ATSs and broker-dealers, FINRA data show that broker-dealers account for an average daily market share of 69% of the off-exchange volume during our sample period (2019–2021), with similarly high levels afterwards (FINRA, 2023, p. 38). This means that market makers act as the passive counterparty in the majority of off-exchange trades. We investigate the composition of off-exchange traders further in the Appendix to Chapter 3.

Off-exchange venues can be attractive to investors because they offer potential price improvements relative to the best quotes on lit exchanges and conceal trading interests as order books are not displayed (Garvey et al., 2016). At the same time, however, customers have to bear an execution risk because the existence of counter parties cannot be observed ex ante (Næs and Ødegaard, 2006). In addition to orders that investors route to off-exchange venues deliberately, broker-dealers have an incentive to internalize non-directed customer orders, to save on fees paid to external trading venues or to earn payments for order flow by routing orders to other broker-dealers for execution (Zhu, 2014; Boehmer et al., 2021). There is growing empirical evidence showing that off-exchange order flow is less informed compared to on-exchange order flow (e.g., Comerton-Forde and Putniņš, 2015; Garvey et al., 2016; Hasbrouck, 2021). This phenomenon is driven by two main factors. First, informed traders tend to prioritize execution immediacy over opacity during periods of high information revelation (Menkveld et al., 2017). Second, the partial exemption from the requirement to grant access to all market participants allows ATSs and broker-dealers to filter out some informed orders based on their knowledge of the customer and the particular order. The literature provides respective evidence that off-exchange venues successfully "cream skim" uninformed order flow from exchanges, which can negatively affect the market quality (Comerton-Forde and Putniņš, 2015; Bolton et al., 2016; Hatheway et al., 2017). In this paper we shed light on the role that short sales play in this process.

3.2.2 Off-Exchange Short Sales

Each trade involves a seller and we adopt the seller's perspective to categorize off-exchange short sales as either seller-initiated or buyer-initiated. This distinction is critical because it shows that short selling includes both liquidity-demanding (seller-initiated) and liquidity-providing

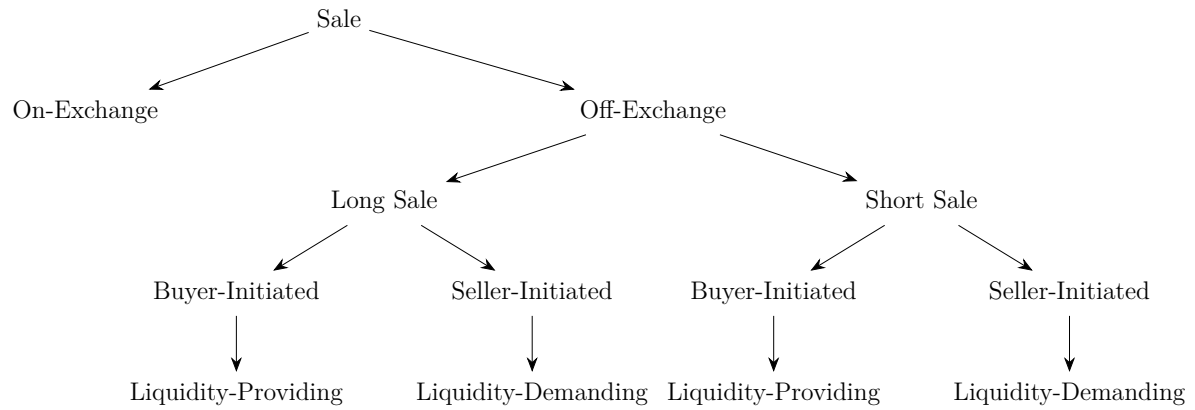

Figure 3.1. ***Classification of Sales****. The figure summarizes our methodology for classifying all publicly reported trades from the perspective of the seller. On-exchange ("lit") trading venues include NYSE exchanges, NASDAQ exchanges, and all regional exchanges. These venues display orders to the public and contribute to the NBBO. Off-exchange ("dark") trading venues are alternative trading systems (ATSs), and broker-dealers (Non-ATSs) for which trades are reported through a Financial Industry Regulatory Authority Trade Reporting Facility. The exchange code "D" for off-exchange trades in the TAQ data is used to separate on-exchange and off-exchange sales. The exact venue in which an off-exchange trade has occurred is not reported in public data. Off-exchange short sales are identified through a matching procedure of off-exchange trades in TAQ and transaction-level short sales reported by FINRA. Finally, all trades are signed into buyer-initiated or seller-initiated, using the algorithm of Lee and Ready (1991). The seller is the liquidity provider in a buyer-initiated sale and the liquidity demander in a seller-initiated sale.*

(buyer-initiated) activities. Microstructure theory and prior empirical evidence based on exchange trades suggest that these two types of short sales may originate from different types of traders (Comerton-Forde et al., 2016).[3] Seller-initiated short sales are liquidity-demanding and therefore associated with informed traders.[4] Contrary, buyer-initiated short sales are liquidity-providing and could be used by both market makers without private information and informed traders with slowly decaying information. To assess whether the behavior of these two types of short sales is special, we benchmark them to off-exchange long sales, categorized in the same manner. This categorization, summarized in Figure 3.1, forms the basis of our analysis and is elaborated upon below.

Orders executed both on-exchange and off-exchange are reported to the Trade and Quote (TAQ) consolidated tape. On-exchanges sales include an exchange code, publicly revealing their origin. In contrast, off-exchange sales are reported to the tape via a FINRA Trade Reporting Facility (TRF) under the generic exchange code "D", obscuring the specific venue. These TRF-sales cover ATSs and Non-ATSs, and have been used in prior off-exchange trading studies (e.g., O'Hara and Ye, 2011; Hatheway et al., 2017). Based on this, we use the exchange codes to clearly identify on- and off-exchange sales.

[3] Note that it if a trader employs multiple strategies, her short sales can be in both groups.

[4] Standard microstructure theory makes the simplifying assumption that all private information is held by some liquidity demanders who partially reveal them through their trades, while liquidity providers possess only public information (Glosten and Milgrom, 1985; Kyle, 1985). There is, however, empirical evidence that informed traders use limit orders, too (e.g., Bloomfield et al., 2005; Boulatov and George, 2013).

Additionally, SEC Rule 200 of Regulation SHO mandates that broker-dealers mark short sale orders at the time of placement. Although this marking is not disclosed in real time, FINRA publishes transaction-level data on off-exchange short sales with a time lag.[5] These data include the time, price, and volume of opening trades, allowing us to match them with TAQ records and identify whether the seller in an off-exchange transaction is a short or long seller. Finally, we use the Lee and Ready (1991) algorithm to sign all sales into buyer-initiated or seller-initiated.[6]

3.3 Data and Descriptive Statistics

We base our analysis on a stratified sample of 300 stocks over the 3-year period of January 2019 through December 2021. The sample thus includes both normal periods and the period of the COVID crash in February and March 2020. To select sample stocks, we sort all NYSE- and NASDAQ-listed stocks according to their market capitalization at the start of the sample period.[7] We then select the 100 largest stocks and randomly sample 20 stocks from each size decile of the remaining set. Similar stratified samples are commonly used in related microstructure studies (e.g., Comerton-Forde et al., 2016; Reed et al., 2020). For these stocks we retrieve all on- and off-exchange trades reported to the consolidated tape as well as the NBBO, both from the TAQ database.[8] We then match off-exchange trades with publicly available trade-level

[5] FINRA publishes transaction-level short-sale data free of charge on its website. In the middle of a month, a file containing data for the previous month is released. Similar data are sold for on-exchange short sales by the respective exchanges. Unfortunately, we do not have access to on-exchange short sales. Examples for the usage of on-exchange data are Comerton-Forde et al. (2016) and Goyal et al. (2024).

[6] Using order data that identify true trade initiators, Chakrabarty et al. (2012) show that the Lee-Ready algorithm correctly classifies most trades.

[7] For all stocks, we require that CRSP share codes are 10 or 11, that the respective identifiers are not duplicated and do not change during the sample period, that the market capitalization is at least $100m, and that the stock price is at least $1. The last two filters exclude thinly traded stocks and prevent possible tick-size effects of penny stocks. These filters are common in the literature.

[8] We apply a two-stage cleaning procedure for both trades and quotes to assure accuracy and consistency of the data. In the first stage, we clean the quote data: We retain only quotes with a correct timestamp and positive values for bid, ask, bid size, offer size and bid-ask spread. Moreover, we retain only quotes with bid (ask) prices that are at most 0.5% below (above) the daily low (high) of the quoted bid (ask) according to the daily CRSP files. In the second stage, we clean the trade data: We retain only trades with a correct timestamp, trade correction indicators 00 (correctly recorded trades) an 01 (late corrected trades, that reflect the actual trade price at the time), a positive trade price, and a positive volume. We remove trades reported under the conditions D, N, V, 7, which do not reflect the traders' directional preferences at the time of the transaction (e.g., distributions, and stock option contingent trades). Finally, we retain trades with prices that are at most 0.5% below (above) the daily low (high) of the quoted bid (ask) according to the daily CRSP files. We drop exchange holidays and days where the exchange closed early. We base our analysis on all non-auction trades during continuous trading. This procedure is motivated by commonly applied filters in the literature.

off-exchange short sales data from FINRA.[9] This provides us with a full view on off-exchange trading and short selling activity. In addition, we use firm-level market capitalization from the Center for Research in Security Prices (CRSP), short interest from FINRA, and instituional ownership from LSEG Refinitiv.

Table 3.1 presents descriptive statistics for the sales per stock-day in our stratified sample. Sales are broken down into on-exchange sales (4.77 billion trades), off-exchange long sales (0.97 billion trades), and off-exchange short sales (0.77 billion trades). The distributional statistics of the daily number and volume of sales reveal that off-exchange trading activity is prevalent and sizable (Panel A). On average per stock-day, there are 4,309 long sales over \$79 million (m) and 3,413 short sales over \$59m taking place off-exchange, compared to 21,161 sales over \$207m taking place on-exchange. In relative terms, off-exchange venues attract around 33% of the volume per stock-day on average.[10] A short sale is involved in about 44% of the off-exchange volume per stock-day. These proportions are quite stable across differently sized stocks (Panel B).[11] This demonstrates that short selling is common practice in off-exchange trading. The average off-exchange short (long) sale has a size of \$8,121 (\$9,571), and is larger than the average on-exchange trade with a size of \$5,288. Similar size-relations are reported in the literature (Hatheway et al., 2017).

We now examine intraday and monthly patterns of the traded volume. Figure 3.2 presents in Panel (a) the diurnal proportional distribution of on-exchange and off-exchange volumes. Both types exhibit a distorted U-shape, with a spike at the end of the trading hours. While off-exchange trading accounts for about 35% of the total trading volume in the first half hour, its share declines to 25% in the last half hour (Panel b). Among the off-exchange volume, the share of short sales is rather stable at about 44% and increases to 51% at the end of the day (Panel c). Finally, Panel (d) shows that short sellers are consistently involved in 42% to 47% of the monthly off-exchange volume in our sample period. We conclude that short sellers maintain a steady and sizable role in off-exchange trading.

[9] To match off-exchange short sales from FINRA to off-exchange trades in TAQ (assigned the venue code "D"), we proceed similar to Comerton-Forde et al. (2016). We merge by symbol, date, price, size, and time. To start, we look for exact matches down to the second. As FINRA short sale data are only timestamped to the second, we then allow for small discrepancies in the timestamps. We first allow matches where timestamps differ by one second and then by two seconds. We are able to match 99.79% of the short sales (99.67% are exact matches). We discard the unmatched short sales. Following the literature (see, e.g., Reed et al., 2020; Goyal et al., 2024), we also drop short sales from bona-fide market making activity that are exempt from the SEC Rule 201 according to the SEC Regulation SHO and its amendments (SEC, 2008). These short sales constitute about 1% of all short sales in our sample. Focusing on non-exempt short sales that are subject to the SEC Rule 201 is important to unambiguously analyze the regulatory effect in Section 3.4.4

[10] We calculate the percentage off-exchange market share per stock-day and average subsequently. This is most representative of the off-exchange market shares in the cross-section. Calculating first the respective average volumes across stock-days and subsequently the percentage share would only be representative of the highest-volume stock-days, leading to a market share of 40%.

[11] Similar short selling proportions are reported for regular exchanges with 40% for 2008 (Comerton-Forde et al., 2016) and 45% for 2014 to 2018 (Goyal et al., 2024). For ATSs the short selling share is 37% for 2012 to 2014 (Reed et al., 2020).

		Daily Number of Sales [#]			Daily Volume of Sales [$ Mio.]			Daily Volume Share [%]		Volume per Sale [$]		
		On	Off		On	Off				On	Off	
		All	Longs	Shorts	All	Longs	Shorts	Off/(On+Off)	Shorts/Off	All	Longs	Shorts
Panel A: Pooled												
	Mean	21,161	4,309	3,413	206.66	79.22	58.73	32.99	44.40	5,288	9,571	8,121
	25%	2,738	289	318	4.20	0.91	0.79	26.54	33.02	1,454	2,746	2,245
	50%	8,048	1,027	1,038	26.69	6.18	5.35	31.98	43.77	3,568	6,824	5,663
	75%	24,562	3,879	3,064	180.84	49.04	33.21	38.30	55.16	7,064	12,911	10,851
Panel B: By Size												
Small	Mean	3,371	552	531	4.87	1.70	1.30	34.56	45.16	1,293	3,012	2,229
	25%	860	90	90	0.73	0.16	0.13	25.74	32.15	634	1,276	1,039
	50%	1,924	217	228	2.14	0.50	0.40	33.22	45.44	1,040	2,069	1,674
	75%	4,139	549	563	5.00	1.34	1.11	42.05	57.70	1,664	3,434	2,717
Medium	Mean	10,010	1,300	1,280	41.18	10.94	9.13	30.54	47.27	4,150	8,445	6,856
	25%	4,068	390	448	11.03	2.08	1.94	24.97	35.40	2,255	4,069	3,390
	50%	6,961	791	836	24.95	5.37	4.73	29.88	47.14	3,495	6,631	5,575
	75%	11,964	1,534	1,528	53.15	12.84	10.74	35.30	58.90	5,165	10,476	8,640
Large	Mean	50,102	11,073	8,429	573.95	225.03	165.77	33.86	40.76	10,431	17,272	15,291
	25%	20,801	3,200	2,454	171.79	44.48	29.68	28.74	32.10	6,130	10,166	8,766
	50%	34,131	5,918	4,318	285.57	82.79	53.25	33.09	40.15	8,628	14,080	12,270
	75%	57,103	10,895	8,344	494.41	157.93	102.62	38.25	49.24	12,521	20,395	17,747

Table 3.1. ***Descriptive Statistics.*** *The table provides descriptive statistics for the number and volume of daily sales, the daily percentage volume share, as well the volume per sale. Buyer- and seller-initiated sales are included. The sales are split into on-exchange sales (On, All), off-exchange long sales (Off, Longs), and off-exchange short sales (Off, Shorts). For each variable and category, the mean and quartiles* $(25\%, 50\%, 75\%)$ *are reported. The daily number and volume are calculated by summing up the number and volume of sales per stock-day. Subsequently, the mean and quartiles are calculated. The daily volume shares are calculated per stock-day as the percentage proportion of off-exchange volume over total volume (Off/(On+Off)) and off-exchange short volume over off-exchange volume (Shorts/Off). Subsequently, the mean and quartiles are calculated. The volume per trade is calculated by averaging the volume of sales per stock-day and subsequently calculating the mean and quartiles over the stock-day observations. The size groups are formed according to market capitalization at the start of each year (Panel B). The sample compromises* 4.77 *billion on-exchange sales,* 0.97 *billion off-exchange long sales and* 0.77 *billion off-exchange short sales. The sample period is 2019 to 2021.*

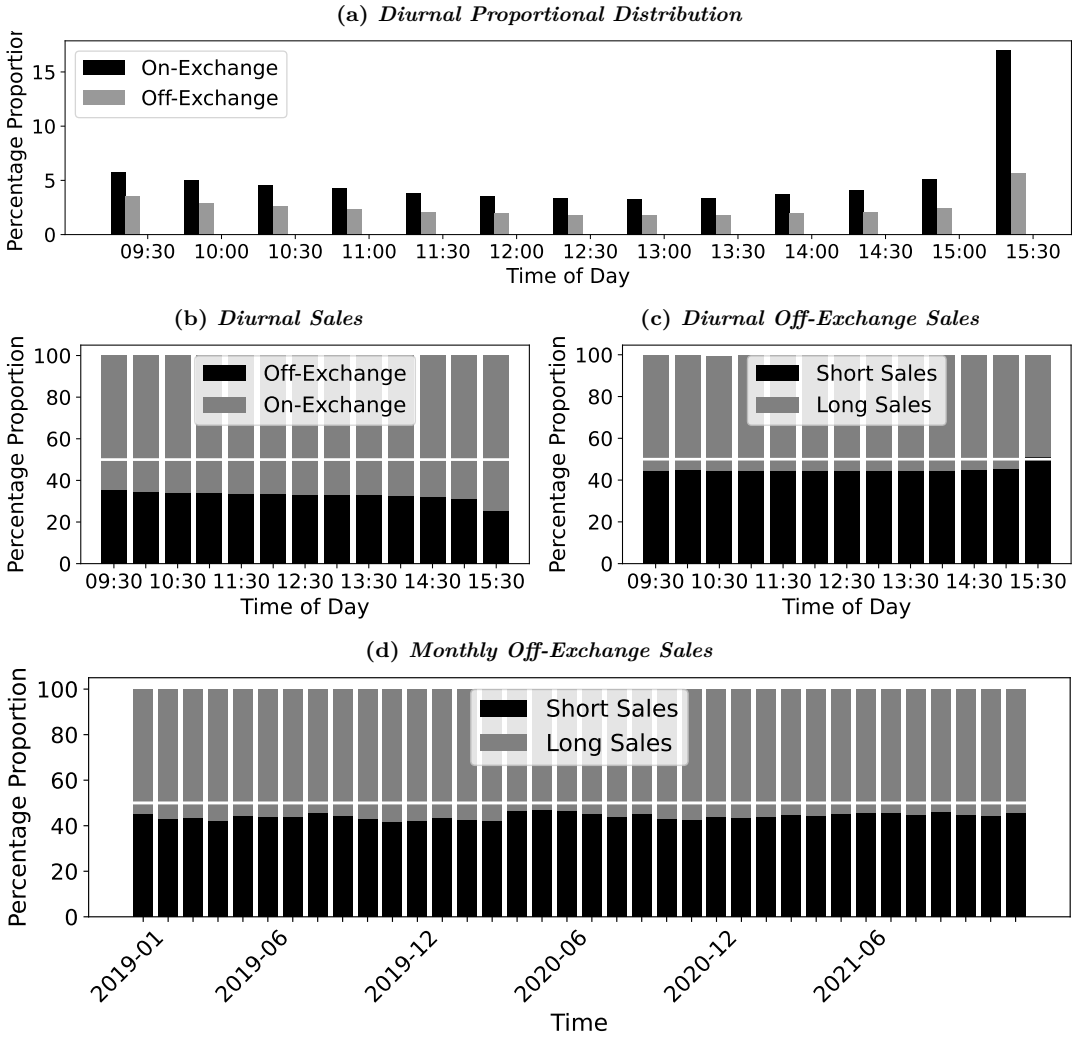

Figure 3.2. ***Proportional Distribution and Composition of Trading Volume.*** *The figure shows in Panel (a) the diurnal proportional distribution of on- and off-exchange trading volume, defined as the respective trading volume in a 30-minute interval during regular trading divided by the total daily volume of all trades (on-exchange and off-exchange). The diurnal distributions are calculated for each stock-day and subsequently averaged. Opening (closing) auctions, which account for* 1.4% *(12.0%) of the total daily volume, are not included. The Panels (b) and (c) show the composition all sales and off-exchange sales for each 30-minute intervals of the trading day. The Panel (d) shows the composition of monthly off-exchange trading volume. The compositions are calculated for each stock-day and subsequently averaged. White horizontal lines indicate 50%. The sample period is 2019 to 2021.*

3.4 Empirical Analysis

3.4.1 Impact on Off-Exchange Liquidity

3.4.1.1 Aggressiveness

We start by examining the aggressiveness of off-exchange sales relative to on-exchange sales, as well as comparing off-exchange short sales to long sales. From a seller's perspective, a liquidity-demanding sale is more aggressive than a liquidity-providing sale as it prioritizes immediacy over achieving a higher execution price. Moreover, a liquidity-demanding sale becomes increasingly aggressive the further below the mid-quote it executes. Conversely, a liquidity-providing sale is less aggressive the further above the mid-quote it is triggered by another trader's marketable buy order. To quantify the aggressiveness of different types of sales, we calculate the distributions of trade prices relative to the prevailing NBBO quotes for each stock-day and subsequently average them.[12]

Table 3.2 shows the aggressiveness of different types of sales. Panel A reports the results for the full sample. Both on-exchange and off-exchange sales are fairly symmetrically distributed around the mid quote. The key difference is that off-exchange sales are more concentrated within the bid-ask spread. To be precise, 65% (32.88% + 32.43%) of the off-exchange trades occur within the bid-ask spread, compared to only 46% (22.80% + 23.21%) of the on-exchange trades.[13] The majority of on-exchange trades thus occurs either at the bid or at the ask. This pattern is fairly stable for differently sized stocks (Panel B). The literature suggests two major reasons why off-exchange sellers tend to provide liquidity more aggressively and receive better prices when they demand liquidity. First, the off-exchange market design offers price improvements at the cost of execution certainty (e.g., Menkveld et al., 2017). Second, off-exchange order flow tends to be less informed since access restrictions to off-exchange venues and broker-dealers' discretion to decide which non-directed orders they internalize tend to filter out informed traders (Boni et al., 2013; Boehmer et al., 2021). Liquidity providers can therefore undercut the exchange spread and charge a smaller liquidity premium to impatient buyers and sellers (e.g., Comerton-Forde and Putniņš, 2015; Aramian and Nordén, 2024). Turning to the price distributions of off-exchange short sales and long sales, we find that the majority of short sales is liquidity-providing (62% = 2.94% + 18.84% + 40.19%) while the majority of long sales is liquidity-demanding (61% = 41.15% + 16.41% + 3.16%). The difference in the aggressiveness between the two types of sales is statistically significant at the 0.1% level and holds across all size groups. The difference in the aggressiveness is moreover dominated by non-midpoint sales,

[12] The results are qualitatively similar when we calculate the trade price distributions based on all trades immediately instead of averaging the stock-day distributions.

[13] On-exchange trades can occur within the bid-ask spread when incoming orders are matched with hidden limit-orders that are placed within the spread. The small percentage of trades reported outside of the NBBO are likely to result from exceptions to the Order Protection Rule of the Regulation NMS ("intermarket sweep" exception and "one-second window" exception) and delays in the trade-reporting process.

		Proportional Distribution of Sales [%]				
		On-Exchange	Off-Exchange			
		All	All	Longs	Shorts	Diff.
Panel A: Pooled						
	Buyer-Initiated					
	Above Ask	0.85	2.78	2.67	2.94	0.27***
	At Ask	26.02	14.51	10.60	18.84	8.24***
	Below Ask	22.80	32.88	26.01	40.19	14.18***
	...And Above Mid	16.23	19.57	12.24	27.47	15.23***
	Seller-Initiated					
	Above Bid	23.21	32.43	41.15	23.25	−17.90***
	...And Below Mid	16.53	18.84	25.95	11.57	−14.38***
	At Bid	26.26	14.56	16.41	12.38	−4.03***
	Below Bid	0.88	2.83	3.16	2.40	−0.76***
Panel B: By Size						
Small	Buyer-Initiated					
	Above Ask	0.80	2.19	2.23	2.21	−0.02
	At Ask	25.89	16.20	11.05	21.64	10.59***
	Below Ask	22.73	31.41	25.01	37.97	12.96***
	Seller-Initiated					
	Above Bid	23.44	31.54	40.46	22.62	−17.84***
	At Bid	26.32	16.44	18.94	13.54	−5.40***
	Below Bid	0.82	2.20	2.31	2.02	−0.29***
Medium	Buyer-Initiated					
	Above Ask	0.79	3.05	2.86	3.24	0.38***
	At Ask	23.95	14.26	10.47	18.10	7.63***
	Below Ask	25.11	32.69	26.26	38.66	12.40***
	Seller-Initiated					
	Above Bid	25.40	32.60	40.85	24.87	−15.98***
	At Bid	23.97	14.28	16.08	12.46	−3.62***
	Below Bid	0.81	3.12	3.48	2.67	−0.81***
Large	Buyer-Initiated					
	Above Ask	0.96	3.11	2.93	3.37	0.44***
	At Ask	28.23	13.05	10.28	16.77	6.49***
	Below Ask	20.56	34.54	26.77	43.94	17.17***
	Seller-Initiated					
	Above Bid	20.80	33.17	42.13	22.26	−19.87***
	At Bid	28.49	12.95	14.22	11.14	−3.08***
	Below Bid	1.00	3.19	3.67	2.52	−1.15***

Table 3.2. ***Trade Aggressiveness.*** *The table shows in Panel A the proportional distribution of sales relative to the prevailing NBBO quotes. The distributions are calculated for each stock-day and subsequently averaged. From the perspective of the seller, the categories are sorted from least aggressive (buyer-initiated and above ask) to most aggressive (seller-initiated and below bid). Sales are sorted into buyer-initiated or seller-initiated based on the Lee-Ready algorithm. The column one (two to four) shows the distribution of trades that were executed on-exchange (off-exchange). Off-exchange trades are show in aggregate and separated into long sales and short sales. The column five shows differences between short sales and long sales. In Panel B, the results are replicated for each of three size groups formed according to market capitalization (Small, Medium, Large). Differences that are statistically significant are indicated at the 0.1% level (***). The sample period is 2019 to 2021.*

showing that the result is robust to possible signing inaccuracies in mid-point sales. We thus conclude that off-exchange short sales are less aggressive than long sales.

3.4.1.2 Net Liquidity Effects

The distribution of trade prices suggests that short sellers could be net-providers of liquidity while long sellers could be net-demanders of liquidity in off-exchange venues. We now test this formally based on the traded volume. We therefore define the daily net liquidity effect of short sales as the difference between liquidity-providing and liquidity-demanding trading volume, scaled by the sum of both types of trading volume:

$$netliq_{i,t}^{\text{D, Shorts}} = \frac{v_{i,t}^{D,BIS} - v_{i,t}^{D,SIS}}{v_{i,t}^{D,BIS} + v_{i,t}^{D,SIS}}, \tag{3.1}$$

where $v_{i,t}^{D,BIS}$ denotes the off-exchange short-sale volume that is initiated by buyers in stock i on day t and $v_{i,t}^{D,SIS}$ is the seller-initiated short-sale volume. We calculate the net liquidity effect of short sales according to formula (3.1) for each stock-day and analogously for long sales.

Table 3.3 reports in Panel A the average net liquidity effect as well as the percentage of stock-days with a positive net liquidity effect for short sales and long sales. Short sellers are indeed net-providers of liquidity who supply 23.5% points more liquidity than they demand, on average. Their liquidity supply is net-positive on 87.8% of the stock-days in our sample. This pattern holds across differently sized stocks and is statistically significant. Contrary, long sellers are net-demanders of liquidity who demand 21.5% points more liquidity than they supply, on average. Again, this effect is statistically highly significant. There are only 14.3% of stock-days in our sample where long sellers supply more liquidity than they demand. This emphasizes that short sales are less aggressive and tilt towards providing liquidity compared to long sales in off-exchange markets.

The net-positive liquidity supply of short sellers raises the question of how important short sellers' provision and demand of liquidity is relative to the aggregate liquidity that is provided and demanded through off-exchange sales. To quantify this, we calculate the percentage proportion of liquidity-providing short sales over all liquidity-providing sales, and an analogous measure for liquidity-demanding short sales as

$$\begin{aligned} proliq_{i,t}^{\text{D, Shorts}} &= \frac{v_{i,t}^{D,BIS}}{v_{i,t}^{D,BIS} + v_{i,t}^{D,BIL}}, \\ demliq_{i,t}^{\text{D, Shorts}} &= \frac{v_{i,t}^{D,SIS}}{v_{i,t}^{D,SIS} + v_{i,t}^{D,SIL}}. \end{aligned} \tag{3.2}$$

Table 3.3 reports in Panel B the average share of short sales among liquidity-providing sales and liquidity-demanding sales, as well as the percentage of stock-days where this share exceeds 50%. We find that short sales account for 55.2% of all liquidity-providing sales, on average. They provide more than half of the liquidity on 60.3% of the stock-days in our sample. This proportion is significantly different from 50% at 0.1% level and holds across differently sized

Panel A			
		Net Liquidity Effect [%]	
	Size	Short Sales	Long Sales
Mean	Pooled	23.5^{***}	-21.5^{***}
	Small	28.1^{***}	-26.4^{***}
	Medium	19.2^{***}	-18.9^{***}
	Large	23.2^{***}	-19.3^{***}
> 0	Pooled	87.8	14.3
	Small	84.5	17.8
	Medium	84.2	17.5
	Large	94.7	7.8
Panel B			
		Share of Shorts [%]	
	Size	Buyer-Initiated Sales	Seller-Initiated Sales
Mean	Pooled	55.2^{***}	34.3^{***}
	Small	58.4^{***}	33.0^{***}
	Medium	56.3^{***}	38.7^{***}
	Large	50.8^{***}	31.2^{***}
> 50	Pooled	60.3	16.4
	Small	66.2	18.1
	Medium	64.1	25.3
	Large	50.6	5.9

Table 3.3. ***Provision and Demand of Liquidity in Off-Exchange Markets.*** *The table shows in Panel A the net liquidity effect of short sales and long sales that were executed off-exchange. The effect is defined as the difference between buyer-initiated (liquidity-providing) and seller-initiated (liquidity-demanding) trading volume, scaled by the sum of the trading volume. The effect is computed separately for short sales and long sales on each stock-day. The mean (Mean) and the percentage proportion of positive stock-days (> 0) are reported. Panel B shows the percentage proportion of short sales in buyer-initiated sales and seller-initiated sales. The shares are computed for each stock-day. The mean (Mean) and the percentage proportion of stock-days with shares of more than 50% (> 50) are reported. All results are shown for the full sample (Pooled) and for each of three size groups formed according to market capitalization (Small, Medium, Large). Means that are significantly different from zero (Panel A) or from 50% (Panel B) are indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is 2019 to 2021.*

stocks. It suggests that a substantial share of these short sales originates from broker-dealers that internalize customer orders, as broker-dealers had an average daily off-exchange market share of 69% within our sample period (FINRA, 2023, p. 38). This suggests that internalization and therefore order flow segmentation relies heavily on the ability to sell short. Among the liquidity-demanding sales, short sales have a share of 34.3%, on average. Short sellers are the dominant liquidity-demanders on only 16.4% of stock-days. These patterns hold on average for each month and half-hour of a trading day, as shown in Figure 3.3. The diurnal compositions of liquidity-demanding and liquidity-supplying sales indicate only minor seasonalities. Short sales have a slightly higher share in liquidity-providing sales in the first and the last half hour (Panel A). Additionally, the share of short sales among liquidity-demanding sales increases gradually

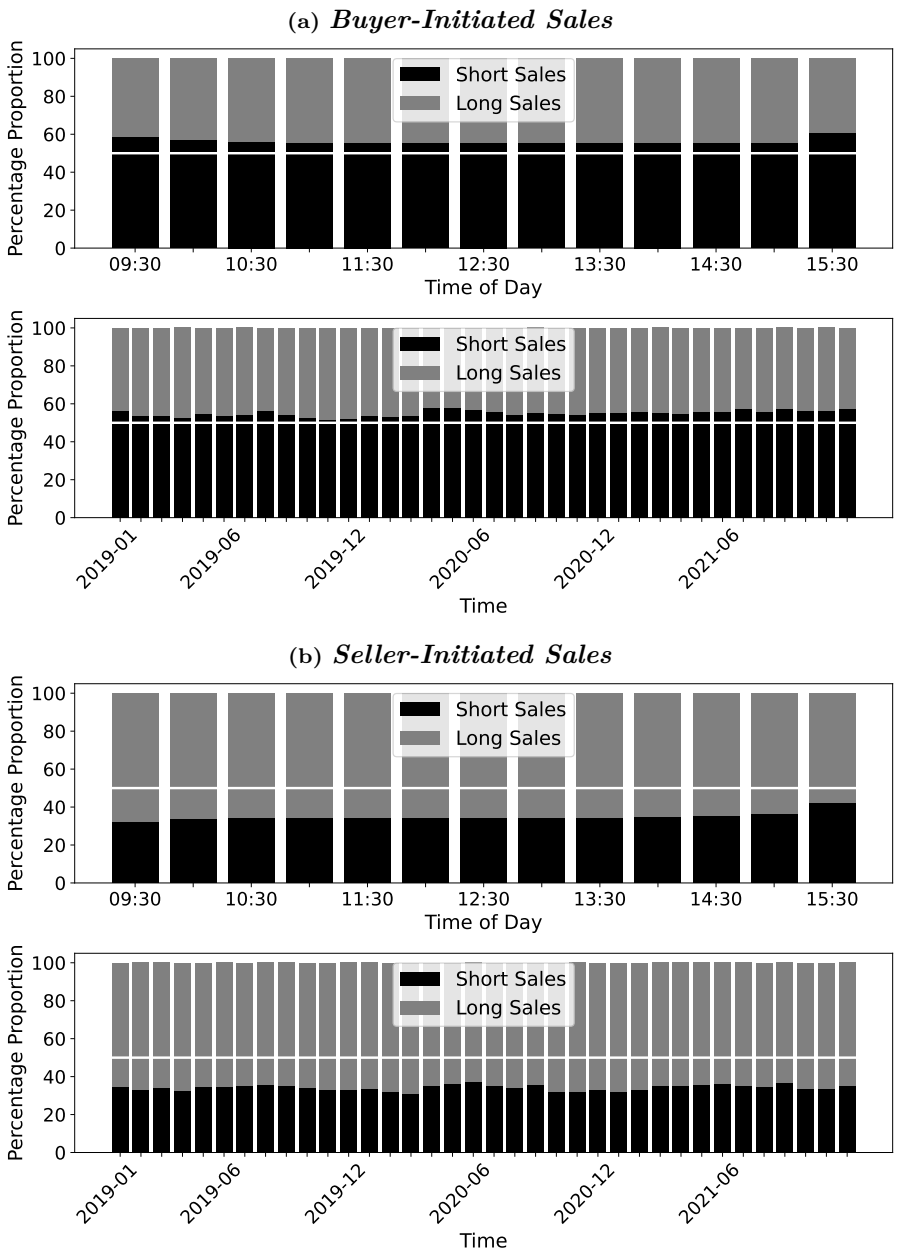

Figure 3.3. ***Provision and Demand of Liquidity through Off-Exchange Sales.*** *The figure shows in Panel (a) the composition of buyer-initiated (liquidity-providing) sales for 30-minute intervals of the trading day and for each month during the sample period. The Panel (b) shows the composition of seller-initiated (liquidity-demanding) sales for 30-minute intervals of the trading day and for each month during the sample period. The compositions are calculated based on off-exchange trading volume for each stock-day and subsequently averaged. White lines indicate 50%. The sample period is 2019 to 2021.*

from 32% to 42% over the course of the day (Panel B). It is also noteworthy that the average participation rate of short sales does not change substantially during the crash period.[14]

[14] The dollar amount of off-exchange short sales increases substantially during the crash (2020-02/03). It is only the percentage share that remains rather stable. There is, however, a slight decline in the share of shorts in liquidity-demanding sales. This could be related to temporary short selling restrictions induced through the SEC Rule 201, which we investigate in Section 3.4.4.

In summary, we show that off-exchange short sales are less aggressive and tilt towards providing liquidity compared to off-exchange long sales. This makes short sales the most important source of liquidity for marketable buy orders. These patterns prevail under both normal and tense market conditions. The evidence suggests that broker-dealers internalize customer buy orders, even when they have no positive inventory, using short sales. This adds to the understanding of how order flow is segmented away from exchanges. In addition, it shows that short sales are used off-exchange very differently than on-exchange, where their effect on liquidity provision and demand is rather balanced (Comerton-Forde et al., 2016).

3.4.2 Spreads and Price Impact

3.4.2.1 Baseline Analysis

The model of Comerton-Forde et al. (2016) predicts that short sellers provide liquidity at wider spreads and demand liquidity at narrower spreads compared to long sellers. We summarize the intuition underlying these theoretical results and extend their empirical testing from on-exchange trading to off-exchange trading, where access is restricted, and order flow is less informed. Moreover, we analyze the subsequent performance of sales.

The sequential trade model assumes that market makers use short sales when they have no positive inventory, and that informed traders, upon receiving a negative signal about a stock's value, use short sales after depleting their long positions to zero. When the proportion of informed traders is high, market makers set a relatively wide spread. In this environment, a positive signal to informed traders leads to a surge in buy orders, which market makers accommodate through short sales as their inventory turns negative. Conversely, a negative signal results in fewer buyer-initiated trades. When the proportion of informed traders and spreads are both low, buyer-initiated short sales and long sales are more balanced. Consequently, a disproportionately large number of buyer-initiated short sales occurs at relatively wide spreads. Short sellers thus provide liquidity at wider spreads than long sellers.

If informed traders receive a negative signal, their initial inventory determines their selling sequence. Informed traders with zero or negative inventory use seller-initiated short sales immediately. However, informed traders with positive inventory will initially use long sales until their inventory is zero, switching to short sales thereafter. As a result, seller-initiated short sales are more likely to occur after an extended period of informed selling. Over time, this sequence of trades gradually reveals the informed traders' information to the market maker, reducing information asymmetry and narrowing spreads. Consequently, a disproportionately large number of seller-initiated short sales occurs at relatively narrow spreads. Short sellers thus demand liquidity at lower spreads than long sellers.

We follow Comerton-Forde et al. (2016) and measure the immediately prevailing market condition of a sale by its effective spread, and the subsequent market condition or performance of a sale by its price impact and its realized spread. From the perspective of a liquidity provider,

the realized spread is a measure of revenue that nets out losses to better-informed traders, as measured by the price impact. From the perspective of a liquidity demander, the realized spread measures the trading costs, net of the permanent price impact of a trade. Formally, we define the three measures of market conditions as follows. The effective half-spread of sale ψ in stock i on day t is defined as the absolute distance of the transaction price $p_{i,t,\psi}$ from the prevailing NBBO mid-quote $m_{i,t,\psi}$, in basis points, denoted by the variable $s^{effective}_{i,t,\psi}$. We decompose this effective spread into two components: Price impact and realized spread. The price impact measures the change in the mid-quote prevailing the trade and the mid-quote 60 seconds later $m^{+60s}_{i,t,\psi}$. The realized spread measures the distance of the transaction price $p_{i,t,\psi}$ from the mid-quote 60 seconds later.[15] This leads to:

$$s^{effective}_{i,t,\psi} = \underbrace{\frac{(p_{i,t,\psi} - m_{i,t,\psi}) \cdot q_{i,t,\psi}}{m_{i,t,\psi}}}_{\text{Effective Spread}} = \underbrace{\frac{(m^{+60s}_{i,t,\psi} - m_{i,t,\psi}) \cdot q_{i,t,\psi}}{m_{i,t,\psi}}}_{\text{Price Impact}} + \underbrace{\frac{(p_{i,t,\psi} - m^{+60s}_{i,t,\psi}) \cdot q_{i,t,\psi}}{m_{i,t,\psi}}}_{\text{Realized Spread}}, \tag{3.3}$$

where $q_{i,t,\psi}$ is 1 (-1) if trade $\langle i,t,\psi \rangle$ is buyer (seller) initiated.

To start, we perform a baseline analysis on the stock-day level to detect behavioral differences between short sellers and long sellers in off-exchange venues. For each stock-day, we calculate volume-weighed averages for the three measures for each type of sale according to Figure 3.1.[16] Subsequently we calculate means and differences in means between short sales and long sales in the cases when they provide liquidity and when they demand liquidity.

Panel A of Table 3.4 shows the averages of effective spreads, price impacts, and realized spreads for off-exchange long and short sales. Among the buyer-initiated (liquidity-providing) sales, short sales occur at spreads that are 2.83 bps higher than those of long sales. Contrary, among the seller-initiated (liquidity-demanding) sales, short sales occur at effective spreads that are 1.27 bps lower than those of long sales. Both differences are statistically significant and, as shown in Panel B, persist across three size groups formed by market capitalization. These results support the predictions of the theoretical model.

Spreads are typically wider, when there is increased adverse selection. Liquidity-providing short sellers could therefore face higher adverse price movements than respective long sellers, which could diminish their return to providing liquidity. This is in fact the case, as we find significantly higher adverse price impacts for short sales (2.27 bps) than for long sales (1.44 bps). Still, short sellers retain a significantly higher realized spread (5.59 bps) than long sellers (3.63 bps). Panel B reveals, however, that this pattern only holds for small and medium sized stocks. In large stocks, the realized spread is slightly but significantly lower by 0.10 bps for liquidity-providing short sales compared to long sales. Thus, on average, liquidity-providing short sellers earn more among our small- and medium-sized sample stocks, but less in our

[15] The horizon of 60 seconds is often chosen in the literature (e.g., Comerton-Forde et al., 2016). It should be long enough such that prices can adjust to the permanent price impact of a trade. Moreover, it can be thought of as the horizon on which market makers can unwind their inventory.

[16] We present the results based on volume-weighted averages because they are most representative of the total trading activity, but come to the same conclusions when we use simple averages.

		Off-Exchange Sales					
		Buyer-Initiated			Seller-Initiated		
		Shorts	Longs	Diff.	Shorts	Longs	Diff.
Panel A: Pooled							
	Effective Spread	7.79	4.96	2.83***	6.11	7.38	−1.27***
		(0.609)	(0.372)	(0.251)	(0.468)	(0.586)	(0.127)
	Price Impact	2.27	1.44	0.83***	1.51	1.21	0.30***
		(0.126)	(0.084)	(0.060)	(0.102)	(0.087)	(0.040)
	Realized Spread	5.59	3.63	1.96***	4.68	6.29	−1.61***
		(0.507)	(0.307)	(0.215)	(0.387)	(0.510)	(0.139)
Panel B: By Size							
Small	Effective Spread	17.41	10.80	6.61***	13.40	16.59	−3.20***
		(1.354)	(0.835)	(0.565)	(1.051)	(1.310)	(0.286)
	Price Impact	4.57	2.99	1.58***	3.16	2.62	0.54***
		(0.202)	(0.133)	(0.136)	(0.196)	(0.168)	(0.108)
	Realized Spread	12.89	7.86	5.03***	10.30	14.05	−3.75***
		(1.216)	(0.753)	(0.507)	(0.920)	(1.174)	(0.305)
Medium	Effective Spread	4.67	2.98	1.69***	3.79	4.30	−0.51***
		(0.274)	(0.146)	(0.152)	(0.204)	(0.254)	(0.062)
	Price Impact	1.76	1.07	0.69***	1.12	0.84	0.28***
		(0.097)	(0.056)	(0.055)	(0.075)	(0.066)	(0.035)
	Realized Spread	2.98	2.00	0.97***	2.75	3.56	−0.81***
		(0.194)	(0.100)	(0.121)	(0.144)	(0.200)	(0.076)
Large	Effective Spread	1.40	1.17	0.24***	1.21	1.35	−0.14***
		(0.081)	(0.047)	(0.043)	(0.058)	(0.069)	(0.018)
	Price Impact	0.52	0.27	0.25***	0.26	0.19	0.08***
		(0.034)	(0.020)	(0.021)	(0.031)	(0.024)	(0.015)
	Realized Spread	0.97	1.08	−0.10**	1.04	1.33	−0.28***
		(0.054)	(0.040)	(0.032)	(0.040)	(0.055)	(0.029)

Table 3.4. ***Spreads and Price Impact.*** *The table shows in Panel A the means of effective half spreads, one-minute midpoint price impact, and one-minute realized spreads, all in basis points. Off-exchange trades are grouped into buyer-initiated (liquidity-providing) and seller-initiated (liquidity-demanding). Within both groups, sales are then split into short sales and long sales. Means of the four variables for each type of trade and differences in means between short sales and long sales are calculated as follows: First, volume-weighted means are computed for each stock-day. Second, differences in stock-day means are calculated. Third, stock-day means and differences in stock-day means are averaged. Prior to averaging on the stock-day level, and effective spreads are winsorized at the 99th percentile, and price impacts and realized spreads are winsorized at the 1st and 99th percentile. Due to winsorization, the mean price impact and the mean realized spread do not add up exactly to the mean effective spread. In Panel B, the results are replicated for each of three size groups formed according to market capitalization (Small, Medium, Large). Robust standard errors clustered by date and firm are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is 2019 to 2021.*

large sample stocks, compared to long sellers. This means that the additional risk of providing liquidity under tenser market conditions is not always compensated. Still, liquidity providers realize the majority of the effective spread across all size groups. Off-exchange liquidity provision therefore seems generally well compensated, in line with catering to relatively uninformed order

flow.[17] For liquidity-demanding sales, we find that the price impact of short sales (1.51 bps) is significantly higher than that of long sales (1.21 bps). Panel B shows that this holds for all size groups. This supports the view that aggressive short sales are, on average, slightly better informed than long sales, as they are less likely to occur for liquidity reasons.

How persistent are these behavioral differences over time? To investigate the diurnal persistence, we calculate means of the effective spreads, price impacts, and realized spreads for each type of off-exchange sale in 30-minute intervals throughout the trading day. Figure 3.4 shows that the behavioral differences between short sellers and long sellers persist over the whole trading day, on average. In addition, we investigate whether the differences persist during periods of both normal and tense market conditions. For each month, we test whether the average daily difference between short and long sales is statistically significant from zero across the three measures. The results are reported in the last three rows of Figure 3.4. We find that differences in effective spreads and realized spreads are statistically significant throughout the sample period for both types of sales. Moreover, during the crash period, the differences are substantially more pronounced. In terms of the price impact, we find that liquidity-providing short sellers are consistently subject to more adverse price movements than long sellers, particularly during the crash period. However, the price impact of liquidity-demanding short sales was weaker and indistinguishable from that of long sales during the crash period, but significantly positive during most of the no-crash period. This demonstrates that off-exchange short sellers did not contribute extraordinarily to price declines during the crash in 2020, confirming prior evidence on the role of short sellers at the start of the global financial crisis in 2008 (Aromi and Caglio, 2008; Comerton-Forde et al., 2016).[18]

[17] Unfortunately, we cannot say anything definite about the net profitability since we have no information on rebates or payments for order flow.

[18] We also investigate the time persistence separately for each of three size groups formed according to market capitalization. For all size groups. the behavioral differences are qualitatively similar to those shown in Figure 3.4. Only in the case of large stocks are differences in realized spreads between liquidity-providing short sales and long sales insignificant or slightly negative. This aligns with the respective result in Panel B of Table 3.4.

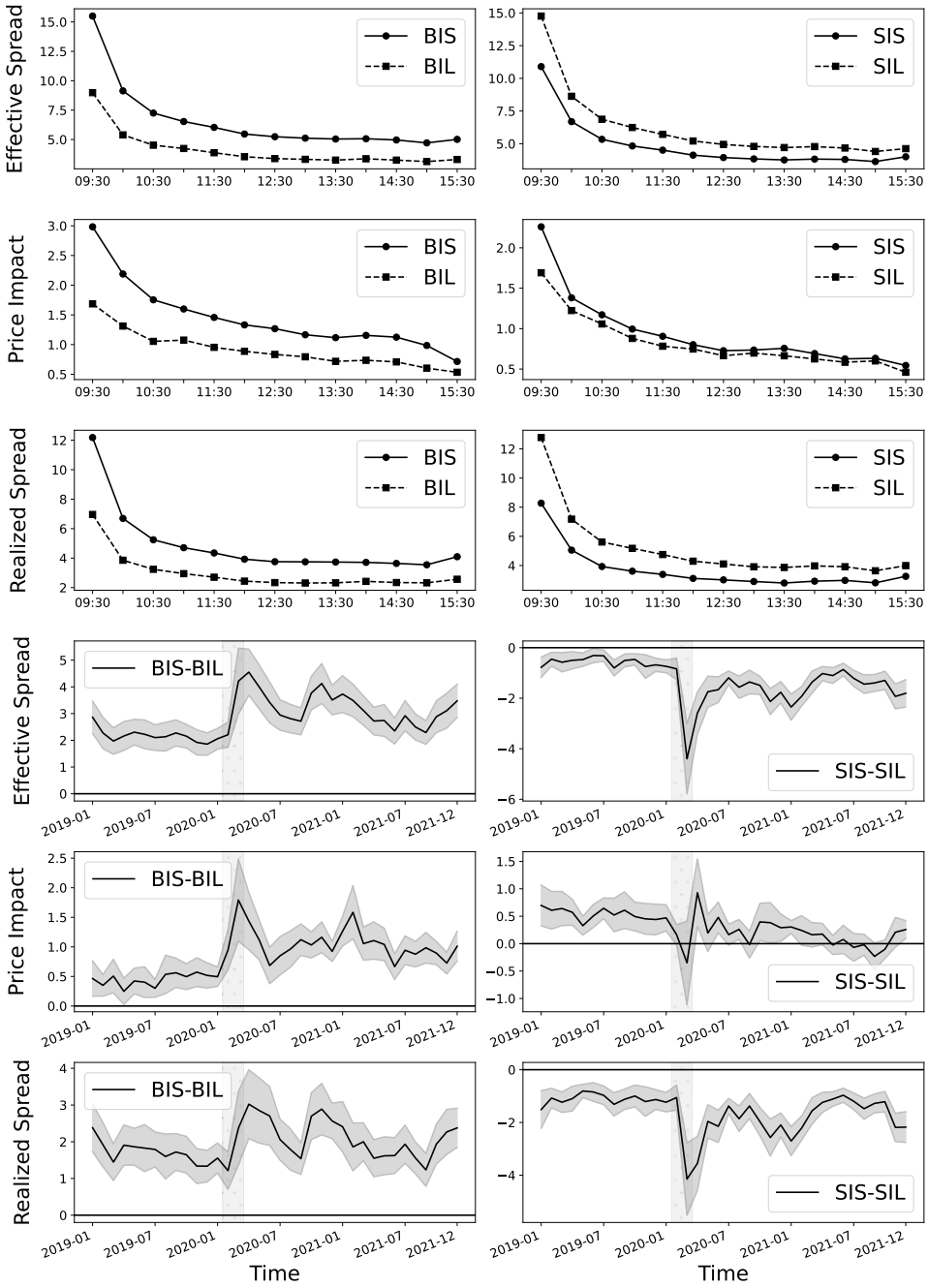

Figure 3.4. ***Spreads and Price Impact over Time.*** *The figure shows means of effective half spreads, one-minute midpoint price impacts, and one-minute realized spreads, all in basis points for off-exchange trades (rows one to three). Trades are grouped into buyer-initiated short sales (BIS), buyer-initiated long sales (BIL), seller-initiated short sales (SIS), and seller-initiated long sales (SIL). For each 30-minute interval of a trading day, means of the three variables are calculated as follows: First, volume-weighted means are computed for each stock-day-interval. Second, stock-day-interval means are grouped by interval and averaged. Rows four to five show mean differences between short sales and long sales. Monthly differences in means are calculated as follows: First, volume-weighted means are computed for each stock-day. Second, differences in stock-day means are calculated. Third, differences in stock-day means are averaged for each month. Effective spreads are winsorized at the 99th percentile, and price impacts and realized spreads are winsorized at the 1st and 99th percentile. 95% confidence intervals are based on robust standard errors clustered by date and firm. The period of the COVID crash (2020-02/03) is shaded in light gray.*

3.4.2.2 Trade-Level Robustness

We now move to the trade-level to verify that the behavioral differences between short and long sellers are not driven by differences in stocks, quoted spreads, and traded volume. To do so, we use trade-level panel regressions for each market condition, e.g. for effective spreads:

$$\begin{aligned} s^{effective}_{i,t,\psi} = \beta_1 \mathbf{1}^{SIS}_{i,t,\psi} + \beta_2 \mathbf{1}^{BIS-SIS}_{i,t,\psi} + \beta_3 \mathbf{1}^{BIL-BIS}_{i,t,\psi} + \beta_4 \mathbf{1}^{SIL-SIS}_{i,t,\psi} \\ + \beta_4 s^{quoted}_{i,t,\psi} + \beta_5 v_{i,t,\psi} + \beta_6 v^2_{i,t,\psi} + \mathrm{FE}_i + \epsilon_{i,t,\psi}, \end{aligned} \tag{3.4}$$

where $s^{quoted}_{i,t,\psi}$ is the quoted half-spread, defined as $(a_{i,t,\psi} - b_{i,t,\psi})/(2 \times m_{i,t,\psi})$, where $a_{i,t,\psi}$ and $b_{i,t,\psi}$ are the best ask and the best bid immediately prevailing the trade, $v_{i,t,\psi}$ and $v^2_{i,t,\psi}$ denoted dollar volume and the squared dollar volume per trade, and FE_i is a stock fixed-effect.[19] Following Comerton-Forde et al. (2016), the remaining binary variables are constructed in a way that differences between sales of our interest are immediately readable from the coefficients. With the binary variable $\mathbf{1}_{\{\#\}}$ that takes the value of one if the condition # is met and zero else, we define the following variables:[20]

$$\begin{aligned} \mathbf{1}^{SIS}_{i,t,\psi} &= \mathbf{1}_{\{g=\langle D \rangle\}}, \\ \mathbf{1}^{BIS-SIS}_{i,t,\psi} &= \mathbf{1}_{\{g=\langle D,BI \rangle\}}, \\ \mathbf{1}^{BIL-BIS}_{i,t,\psi} &= \mathbf{1}_{\{g=\langle D,BIL \rangle\}}, \\ \mathbf{1}^{SIL-SIS}_{i,t,\psi} &= \mathbf{1}_{\{g=\langle D,SIL \rangle\}}, \end{aligned} \tag{3.5}$$

where $g_{i,t,\psi}$ indicates whether the sale $\langle i,t,\psi \rangle$ is an off-exchange sale (D), a buyer-initiated sale (BI), a buyer-initiated long sale (BIL), or a seller-initiated long sale (SIL). In this configuration, the coefficient of $\mathbf{1}^{SIS}_{i,t,\psi}$ captures the average effective spread of seller-initiated short sales, the coefficient of $\mathbf{1}^{BIS-SIS}_{i,t,\psi}$ captures the difference between the effective spreads of buyer-initiated short sales and seller-initiated short sales, the coefficient of $\mathbf{1}^{BIL-BIS}_{i,t,\psi}$ captures the difference between the effective spreads of buyer-initiated long sales and buyer-initiated short sales, and the coefficient of $\mathbf{1}^{SIL-SIS}_{i,t,\psi}$ captures the difference between effective spreads of seller-initiated long sales and seller-initiated short sales. We estimate the model (3.4) for a randomly drawn sample representing 5% (86.8 million) of all off-exchange trades in our sample.

[19] The results are qualitatively similar when we add a time fixed effect.
[20] To improve readability, we suppress the trade identifying index (i,t,ψ) in the variable $g_{i,t,\psi}$.

	Effective Spreads [bps]				Price Impacts [bps]				Realized Spreads [bps]			
Variable	Pooled	Small	Medium	Large	Pooled	Small	Medium	Large	Pooled	Small	Medium	Large
$\mathbf{1}_{i,t,\psi}^{\{SIS\}}$	0.03^{*}	0.14	0.23^{***}	0.06^{**}	-0.08^{*}	0.32	-0.17^{*}	-0.10^{*}	0.15^{***}	-0.15	0.40^{***}	0.15^{***}
	(2.01)	(1.41)	(4.77)	(2.88)	(-2.21)	(1.79)	(-2.36)	(-2.29)	(4.57)	(-0.85)	(6.74)	(4.14)
$\mathbf{1}_{i,t,\psi}^{\{BIS-SIS\}}$	0.24^{***}	1.18^{***}	0.41^{***}	0.16^{***}	0.22^{***}	0.96^{***}	0.30^{***}	0.15^{**}	-0.01	0.15	0.06	-0.03
	(10.80)	(12.30)	(9.26)	(10.02)	(4.08)	(4.58)	(4.53)	(2.58)	(-0.20)	(0.64)	(0.76)	(-0.49)
$\mathbf{1}_{i,t,\psi}^{\{BIL-BIS\}}$	-0.21^{***}	-1.67^{***}	-0.58^{***}	-0.09^{**}	-0.18^{***}	-0.89^{***}	-0.31^{***}	-0.12^{***}	0.07^{*}	-0.67^{***}	-0.18^{**}	0.13^{***}
	(-5.26)	(-8.18)	(-7.86)	(-3.00)	(-8.85)	(-7.04)	(-6.98)	(-8.17)	(2.07)	(-3.73)	(-2.79)	(4.33)
$\mathbf{1}_{i,t,\psi}^{\{SIL-SIS\}}$	0.17^{***}	0.74^{***}	0.23^{***}	0.13^{***}	-0.05^{**}	-0.17	-0.08^{*}	-0.05^{**}	0.24^{***}	0.89^{***}	0.31^{***}	0.20^{***}
	(6.55)	(9.05)	(5.93)	(4.31)	(-2.82)	(-1.33)	(-2.06)	(-2.67)	(7.64)	(5.68)	(5.49)	(5.94)
$s_{i,t,\psi}^{\text{quoted}}$	0.55^{***}	0.57^{***}	0.52^{***}	0.52^{***}	0.14^{***}	0.13^{***}	0.16^{***}	0.14^{***}	0.44^{***}	0.46^{***}	0.39^{***}	0.44^{***}
	(133.53)	(113.04)	(86.59)	(47.81)	(19.65)	(12.24)	(12.48)	(16.30)	(68.06)	(50.38)	(43.86)	(50.42)
$v_{i,t,\psi}$	-0.33^{***}	0.38	-0.97^{***}	-0.31^{**}	0.70^{***}	7.20^{***}	2.72^{***}	0.57^{***}	-1.08^{***}	-6.90^{***}	-3.55^{***}	-0.94^{***}
	(-3.59)	(0.53)	(-5.58)	(-3.27)	(6.91)	(5.95)	(10.45)	(7.01)	(-8.63)	(-5.58)	(-9.94)	(-7.20)
$v_{i,t,\psi}^2$	1.13^{***}	-3.53	3.00^{***}	1.08^{***}	-2.97^{***}	-39.28^{***}	-13.31^{***}	-2.34^{***}	4.31^{***}	36.94^{***}	15.94^{***}	3.65^{***}
	(3.62)	(-1.09)	(4.49)	(3.38)	(-6.18)	(-6.74)	(-10.79)	(-6.17)	(8.74)	(6.89)	(10.65)	(7.56)
FE_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	28.96	36.30	29.29	16.09	0.08	0.12	0.27	0.03	0.77	1.38	1.44	0.26
# Obs. [Mio.]	86.8	4.1	9.7	73.1	86.8	4.1	9.7	73.1	86.8	4.1	9.7	73.1

Table 3.5. ***Determinants of Spreads and Price Impact.*** *The table shows the results for the trade-level panel regression according to (3.4). The first row indicates whether the dependent variable is the effective spread, price impact or realized spread. The independent variables are reported in the first column (Variable). Separate regressions are estimated for all sample stocks (Pooled), as well as for each of three size groups formed according to market capitalization (Small, Medium, Large). All regressions include a firm fixed-effects. The coefficient for $v_{i,t,\psi}$ is multiplied by 10^4. Inference is based on robust standard errors clustered by date and firm. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The adjusted R^2 excludes the explanatory power of the fixed effects. The sample consists of 5% of all trades, randomly sampled from each stock-day. The sample period is 2019 to 2021.*

Table 3.5 presents the regression results based on equation (3.4) for effective spreads, price impacts and realized spreads. The results are shown for all stocks (Pooled) and for three groups formed according to market capitalization. In terms of the effective spread, we find that liquidity-providing shorts are executed at wider spreads than longs, as indicated by the significantly negative coefficients of the variable $\mathbf{1}_{i,t,\psi}^{BIL-BIS}$. Moreover, compared to longs, shorts trade at narrower spreads when they demand liquidity and at wider spreads when they provide liquidity, as indicated by the significantly positive coefficient of the variable $\mathbf{1}_{i,t,\psi}^{SIL-SIS}$ and the significantly negative coefficient of the variable $\mathbf{1}_{i,t,\psi}^{BIL-BIS}$, respectively. These differences hold across all groups and confirm our previous results in Section 3.4.2.1. Similarly, the previous results on the differences in the price impacts are also confirmed on the trade level. Finally, the trade-level results confirm that liquidity-demanding short sales average lower realized spreads than long sales. For liquidity-providing shorts, the higher realized spreads are only confirmed for small and medium sized firms, while they are significantly lower for large firms. The control variables reveal that the quoted spread has a positive effect on all variables and that trade volume exerts a non-linear effect.

Overall, our results indicate that off-exchange short sellers, compared to long sellers, charge higher liquidity premiums when providing liquidity and pay narrower spreads when consuming it. This behavior aligns with theory and mirrors that of on-exchange short sellers (Comerton-Forde et al., 2016), despite the unique features of off-exchange venues. Moreover, off-exchange liquidity provision seems well compensated.

3.4.3 Informativeness

3.4.3.1 Methodology

Informed traders can trade on their private information that are not yet reflected in the displayed exchange quotes either by demanding liquidity with market orders or by providing liquidity with limit orders. This process partially reveals private information and incorporates them into public quotes and thus the NBBO. In contrast to that, changes in the opaque off-exchange order books do not contribute to the NBBO. This prevents off-exchange activity from directly altering the NBBO and contributing to price discovery. However, as the occurrence of off-exchange trades is publicly revealed via the consolidated tape, market participants can respond to this information with trades and quote revisions on exchanges. Respective activity increases are documented (Ernst et al., 2021) and explain how off-exchange trading can indirectly contribute to price discovery (e.g., Comerton-Forde and Putniņš, 2015; Menkveld et al., 2017; Hasbrouck, 2021). Quote revisions (returns), however, not only reflect private information but also transitory effects, for example due to inventory-control considerations of market makers (Hasbrouck, 1988; Hendershott and Menkveld, 2014). While transitory price effects should dissipate over time, the information effect is permanent.

To isolate the private information contained in the order flow, we follow Comerton-Forde and Putniņš (2015) and Comerton-Forde et al. (2016) by adapting a version of the Hasbrouck (1991)

vector autoregression framework to our order flow types. This framework captures the joint evolution of order flow and quote revisions, while accounting for the persistence and cross-correlation of order flow and autocorrelation in quote revisions (e.g., Biais et al., 1995; Menkveld et al., 2017). We partition off-exchange sales (D) according to Figure 3.1 into four types as before. Furthermore, we partition on-exchange sales (E) into buyer-initiated (BI) and seller-initiated (SI). For these six types of trades, we aggregate the traded dollar volume across 5-second clock-time intervals throughout the trading day, using the variable v_t.[21] We then log-transform the volume $\tilde{v}_t = \log(v_t)$ to account for a nonlinear effect of trade volume on returns. Moreover, the variable r_t measures the log NBBO-midquote return in interval t. This leads to the following system:

$$\mathbf{B}_0 \mathbf{y}_t = \mu + \sum_{j=1}^{p} \mathbf{B}_j \mathbf{y}_{t-j} + \epsilon_t, \tag{3.6}$$

where

$$\mathbf{y}_t = \left[r_t, \tilde{v}_t^{D,BIL}, \tilde{v}_t^{D,SIL}, \tilde{v}_t^{D,BIS}, \tilde{v}_t^{D,SIS}, \tilde{v}_t^{E,BI}, \tilde{v}_t^{E,SI} \right]', \tag{3.7}$$

$\mu \in \mathbb{R}^7$ is a vector that contains constants, $\mathbf{B}_j \in \mathbb{R}^{7\times 7}$ are matrices that contain the autoregression coefficients for the lags $j = 0, 1, \ldots, p$, and vector $\epsilon_t \in \mathbb{R}^7$ contains the errors. The coefficients of the matrix $\mathbf{B}_0$ are restricted, such that they form the identity matrix and the first row $\mathbf{b}_{0,1}$ is

$$\mathbf{b}_{0,1} = \left[1, -\beta_0^{D,BIL}, -\beta_0^{D,SIL}, -\beta_0^{D,BIS}, -\beta_0^{D,SIS}, -\beta_0^{E,BI}, -\beta_0^{E,SI} \right]. \tag{3.8}$$

This specification allows for a contemporaneous effect of the order flow on the return. We set the number of lags to $p = 12$, i.e. one minute. We estimate the system for the intraday observations of each stock-month separately. Based on the estimated coefficients, we calculate the permanent price impact per order flow type as the cumulative response of returns over $s = 60$ intervals (5 minutes), to separate order flow shocks. For comparability, the magnitude of each order flow shock is set equal to (the logarithm of) \$10,000. Following Hasbrouck (1991), we interpret the permanent price impact of an unanticipated order flow shock as a measure of the private information contained in the order flow.

3.4.3.2 Results

Figure 3.5 illustrates the emergence of the permanent price impact for off-exchange short sales and long sales. In Panel (a), permanent price impacts are averaged within groups of small,

[21] The choice of the interval length balances the trade-off between capturing more dynamics of the trading process with a smaller interval length which requires more parameters to capture the permanent price impact and the preference for a parsimonious model. To improve readability, we suppress the index i for individual stocks in the variables.

medium, and large stocks across the sample period, excluding the crash (2020-02/03). We find that seller-initiated off-exchange short sales are informed (negative permanent price impact), while buyer-initiated off-exchange short sales are not (positive permanent price impact).[22] The same pattern holds for off-exchange long sales. This demonstrates that traders with short-term information prefer to demand liquidity, on average. Moreover, Panel (b) shows that liquidity demanders are also better informed during the crash period, compared to liquidity providers. Overall, these findings indicate that off-exchange short sales carry relevant information on the intraday horizon, even after controlling for the information content of on-exchange sales. The short-term uninformedness of liquidity-providing short sales strengthens the view that they are primarily used for market making. In the following, we closely examine the permanent price impacts, focusing on the five-minute cumulative return responses after the order flow shocks.

Table 3.6 reports distributional statistics for the permanent price impacts of the off-exchange and on-exchange order flow. It moreover shows whether informational differences between short sales and long sales are statistically significant, according to cluster-robust paired t-tests. All results are presented across two dimensions: Time (no-crash period, crash period), and stock size (small, medium, large). During the no-crash period, buyer-initiated short sales face significantly higher adverse price impacts compared to long sales in all stock size groups, supporting the liquidity-provision hypothesis as their primary driver. Contrary, seller-initiated short sales in large and medium stocks have significantly higher price impacts compared to long sales. These short sales are the most informed off-exchange sales. In small stocks, however, long sales are significantly better informed. This suggests that there is some heterogeneity across firm size in terms of private information that off-exchange short sellers posses. We also find that the price impacts of on-exchange sales are substantially larger than those of off-exchange sales in all cases. This shows that the on-exchange order flow is the major driver of price discovery, consistent with the literature (e.g., Comerton-Forde and Putniņš, 2015; Hasbrouck, 2021).

During the crash, the price impact of all order flow types increases substantially, with on-exchange order flow remaining the most informed. While liquidity-demanding off-exchange short sales are less informed than long sales in small stocks, as before, they also lose their informational advantage over long sales in medium and large stocks during the crash period. This suggests that, during the crash period, informed liquidity-demanding off-exchange sellers consist disproportionately more of long sellers than short sellers.[23]

[22] It is possible that buyer-initiated (liquidity-providing) short sellers hold informational advantages over longer time horizons or relative to other stocks (Hu et al., 2021; Goyal et al., 2024).

[23] In untabulated robustness checks, we confirm that our conclusions hold when we vary the number of lags, alter the time horizon of the cumulative return responses, and omit the log-transformation of trade volume.

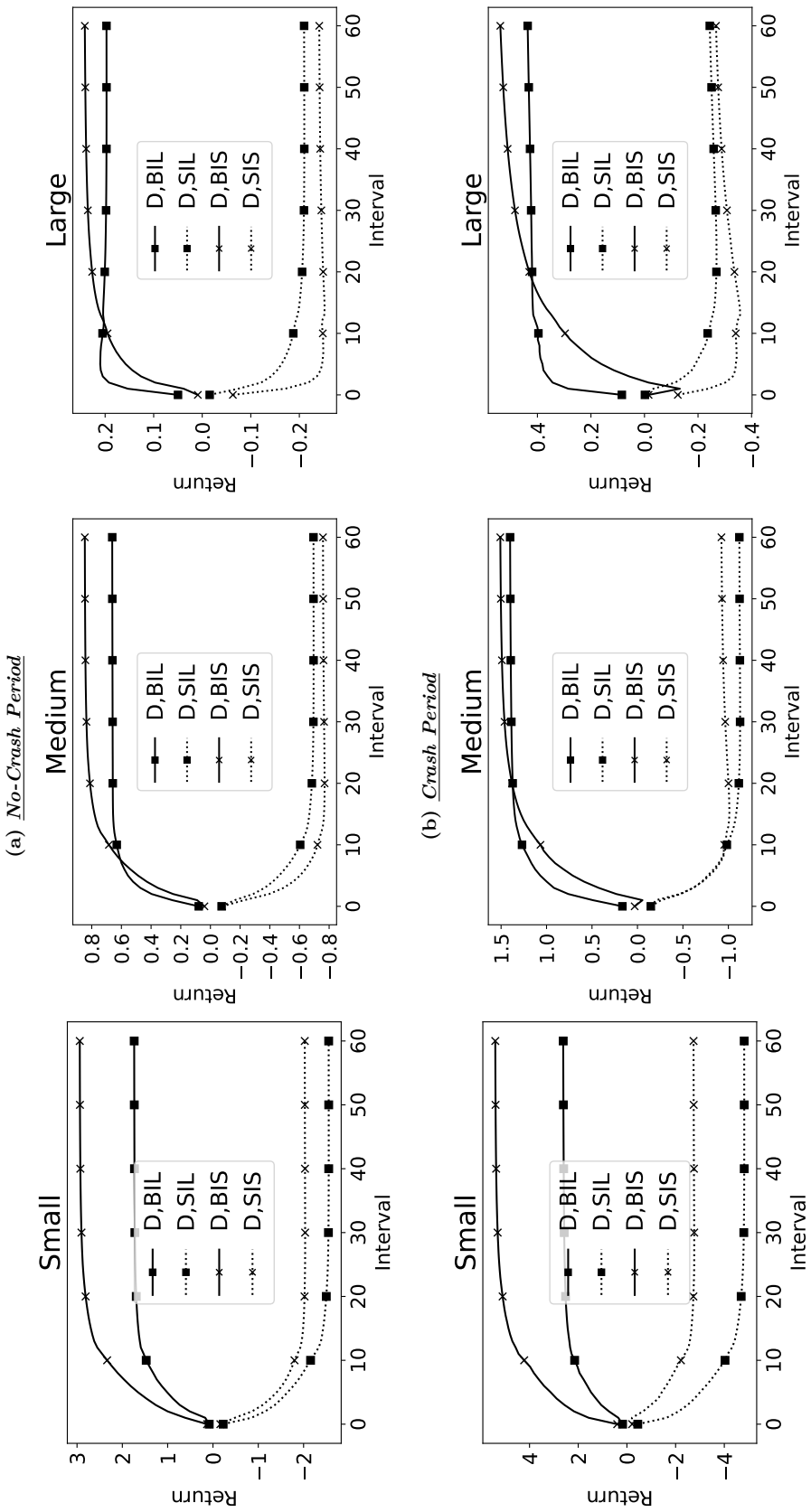

Figure 3.5. ***Cumulative Response of Return to Off-Exchange Volume Shocks.*** *The figure shows equally weighted cumulative impulse response functions of mid-quote log returns (in basis points), to separate shocks in buyer-initiated off-exchange long-sale volume (D,BIL), seller-initiated off-exchange long-sale volume (D,SIL), buyer-initiated off-exchange short-sale volume (D,BIS), and seller-initiated off-exchange short-sale volume (D,SIS). The model is given by (3.6). Intervals are of 5-second length. The magnitude of each shock is set equal to $10,000. Responses are calculated based on VAR coefficients, separately estimated for each stock-month. Responses are subsequently averaged for different periods and size groups. Panel (a) shows the no-crash period and Panel (b) shows the crash period (2020-02/03). The sample period is 2019 through 2021.*

		Informativeness [bps per $10,000]											
		No-Crash Period						Crash Period					
		Buyer-Initiated			Seller-Initiated			Buyer-Initiated			Seller-Initiated		
		Off		On	Off		On	Off		On	Off		On
		Shorts	Longs	All	Shorts	Longs	All	Shorts	Longs	All	Shorts	Longs	All
Small	Mean	2.94***	1.74***	8.82***	−2.03***	−2.55***	−8.74***	5.41***	2.62*	13.84***	−2.74***	−4.82***	−13.46***
	Diff.		1.20***			0.53***			2.79***			2.08**	
	Std.	3.05	2.89	5.58	3.66	2.60	5.44	6.12	4.71	8.56	4.82	5.63	8.39
	25%	1.14	0.60	4.98	−2.87	−3.43	−11.00	1.73	0.76	6.61	−4.06	−5.92	−18.32
	50%	2.14	1.38	7.34	−1.47	−1.89	−7.27	3.50	2.35	12.57	−1.71	−3.32	−12.35
	75%	3.83	2.40	10.90	−0.54	−0.93	−4.92	6.71	3.94	19.26	−0.20	−1.48	−6.61
Medium	Mean	0.85***	0.66***	3.15***	−0.76***	−0.69***	−3.13***	1.51**	1.40**	6.04**	−0.92***	−1.12***	−5.85**
	Diff.		0.18***			−0.06**			0.11***			0.20	
	Std.	0.71	0.57	1.58	0.68	0.64	1.54	1.39	1.22	3.66	1.33	1.24	3.32
	25%	0.36	0.30	2.00	−1.04	−0.97	−3.93	0.51	0.52	2.93	−1.46	−1.76	−7.97
	50%	0.69	0.54	2.81	−0.60	−0.55	−2.79	1.13	1.06	5.43	−0.73	−0.75	−5.26
	75%	1.17	0.90	3.94	−0.31	−0.27	−1.98	2.19	1.89	8.60	−0.20	−0.27	−2.97
Large	Mean	0.24***	0.20***	1.31***	−0.24***	−0.21***	−1.32***	0.54*	0.44**	3.63*	−0.27***	−0.24***	−3.62*
	Diff.		0.04*			−0.03*			0.10			−0.02	
	Std.	0.44	0.23	0.72	0.19	0.27	0.73	0.81	0.39	3.05	0.36	0.53	2.84
	25%	0.09	0.09	0.92	−0.33	−0.27	−1.55	0.09	0.18	1.33	−0.43	−0.32	−4.95
	50%	0.18	0.17	1.18	−0.21	−0.17	−1.20	0.34	0.35	3.39	−0.25	−0.14	−3.03
	75%	0.30	0.27	1.53	−0.12	−0.10	−0.92	0.71	0.64	5.08	−0.09	−0.01	−1.50

Table 3.6. ***Informativeness.*** *The table shows means, differences in means, standard deviations, and quartiles (25%, 50%, 75%) for the informativeness of different types of off-exchange trades. Informativeness is the permanent price impact in basis points per $10,000 trade innovation, calculated from the cumulative impulse response function. The VAR model is separately estimated for each stock-month. For cumulative responses 5 minutes after the shock, means and differences in means are calculated for the period 2020-02/03 (Crash Period) and the remainder of the sample (No-Crash Period) as follows: First, differences in stock-months are calculated. Second, informativeness per stock-month and differences are averaged. The size groups are formed according to market capitalization. Inference is based on robust standard errors clustered by firm and time. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is 2019 to 2021.*

Our results show that buyer-initiated short sales are uninformed on short intraday horizons, consistent with a liquidity-provision role. However, seller-initiated short sales contain private information that are not included in exchange order flow, albeit with lower informational content, and thus contribute to price discovery. As off-exchange short sales predominantly provide liquidity, our results can explain why the aggregate off-exchange short selling flow is uninformed on short intraday horizons at the stock level, as documented by Reed et al. (2020). In addition, our results support and complement on-exchange short selling flow evidence (Comerton-Forde et al., 2016).

3.4.4 Previous Returns and Short Selling Restrictions

3.4.4.1 Methodology

Short selling contributes to liquidity and price discovery, but there are concerns about its potential to exaggerate price declines and destabilize markets (e.g., ESMA, 2022). While the previous empirical evidence based on aggregate on-exchange short selling flows indicates contrarian behavior, meaning that short selling increases (decreases) after positive (negative) returns over daily, weekly and monthly intervals (Diether et al., 2009; Engelberg et al., 2012), the evidence on disaggregated on-exchange short selling flows reveals a nuance: Only short sellers who provide liquidity are contrarians, while those who demand liquidity exhibit a slight tendency towards momentum trading over one-day horizons (Comerton-Forde et al., 2016). The disaggregated evidence is, however, from a period when no regulatory circuit-breakers were in place to restrict short selling during price declines. Importantly, such circuit-breakers have been reintroduced in the U.S. in 2010, and the relation between disaggregated off-exchange short selling flows and previous returns has not yet been examined. Our study attempts to fill this gap.

Short sellers' ability to respond to previous returns is restricted by the SEC Rule 201.[24] The rule imposes a temporary restriction on short selling once a stock's price declines by 10% in a single trading day. This restriction prevents short sales at or below the national best bid, although short selling above the best bid remains allowed. Once activated, the restriction stays in place until the end of the following day. The rule aims to curb aggressive short selling, while providing investors an opportunity to sell long positions. As liquidity-providing short sales remain allowed, short sellers may adapt by shifting to these sales during periods of restriction. Such behavior would be in line with the evidence that short sellers seek to circumvent restrictions, for example by switching to other instruments (e.g., Karmaziene and Sokolovski, 2022; Switzer, 2023).

We now examine how liquidity-providing and liquidity-demanding off-exchange short sales respond to returns during the previous night and the previous week, as well as short selling restrictions. In addition, we examine whether the behavior changes during the crash period.

[24] The Rule 10a-1 of the Securities Exchange Act of 1934 governed short selling restrictions during price declines until it was lifted in 2007. In 2010, Rule 201 reintroduced a modified restriction.

We define short selling activity as the percentage of the off-exchange short selling volume relative to the total (off- and on-exchange) trading volume for stock i, on day t. We calculate this activity measure separately for liquidity-providing short sales (D, BIS), and liquidity-demanding short sales (D, SIS) as

$$\begin{aligned} pv_{i,t}^{D,BIS} &= \frac{v_{i,t}^{D,BIS}}{v_{i,t}^{Total}}, \\ pv_{i,t}^{D,SIS} &= \frac{v_{i,t}^{D,SIS}}{v_{i,t}^{Total}}, \end{aligned} \tag{3.9}$$

where $v_{i,t}^{Total}$ is the total dollar volume. This widely used metric (e.g., Diether et al., 2009; Engelberg et al., 2012) allows us to standardize short selling activity across different levels of trading volume. We moreover measure imbalances between the two short sale types as well as between short sales and corresponding long sales using the variables

$$\begin{aligned} pv_{i,t}^{D,BIS-SIS} &= \frac{v_{i,t}^{D,BIS} - v_{i,t}^{D,SIS}}{v_{i,t}^{Total}}, \\ pv_{i,t}^{D,BIS-BIL} &= \frac{v_{i,t}^{D,BIS} - v_{i,t}^{D,BIL}}{v_{i,t}^{Total}}, \\ pv_{i,t}^{D,SIS-SIL} &= \frac{v_{i,t}^{D,SIS} - v_{i,t}^{D,SIL}}{v_{i,t}^{Total}}. \end{aligned} \tag{3.10}$$

Then, we estimate the following panel regression for each short-selling measure $j \in \mathcal{J}$:

$$\begin{aligned} pv_{i,t}^{j} = {} & \beta_1 r_{i,t}^{ON} + \beta_2 r_{i,t-1} + \beta_3 r_{i,t-5\to t-2} \\ & + \beta_4 \mathbf{1}_{i,t}^{Crash} \times r_{i,t}^{ON} + \beta_5 \mathbf{1}_{i,t}^{Crash} \times r_{i,t-1} + \beta_6 \mathbf{1}_{i,t}^{Crash} \times r_{i,t-5\to t-2} \\ & + \beta_7 rule_{i,t} + \sum_k \gamma_k X_{i,t-1}^{k} + FE_i + FE_t + \epsilon_{i,t}, \end{aligned} \tag{3.11}$$

where, $r_{i,t}^{ON}$ denotes the overnight return, $r_{i,t-1}$ yesterday's return, $r_{i,m\to n}$ the cumulative return from day m to day n, $rule_{i,t}$ is the percentage time of the day that the SEC Rule 201 is active, and $\mathbf{1}_{i,t}^{Crash}$ is one during the crash period (2020-02/03) and zero else. In this setting, the coefficients of the interaction terms capture the differences between the crash period and the normal period. $X_{i,t-1}^{k}$ represents control variables motivated from the literature that account for other factors influencing short selling and off-exchange activity (e.g., He and Lepone, 2014; Comerton-Forde and Putniņš, 2015; Reed et al., 2020). Specifically, these are $pv_{i,t-1}^{j}$ (the lagged percentage trading activity of type j), $Volatility_{i,t-5\to t-1}$ (the lagged volatility as measured by the stock's 5-day high-low price range divided by the average midquote), $\log s_{i,t-1}^{quoted}$ (the lagged logarithm of the displayed NBBO spread in basispoints), $SI_{i,t-1}$ (the prevailing percentage of short interest), $IO_{i,t-1}$ (the prevailing percentage of institutional ownership), and $\log MarketCap_{i,t-1}$ (the

lagged logarithm of market capitalization). Finally, we add time-fixed and stock-fixed effects to control for omitted variables and any systematic heterogeneity over time.

3.4.4.2 Results

Table 3.7 reports the results for the regressions based on the Equation (3.11). Liquidity-providing short selling increases significantly when the overnight return and returns over the previous five trading days are positive. Similarly, though lower in magnitude, liquidity-demanding short selling increases significantly after positive overnight returns and returns on the previous day. Returns from more distant periods do not exhibit a significant effect. This suggests that both types of short sales are contrarian, although the effect is stronger for liquidity-providing short sales. In terms of imbalances between different types of sales, we find that liquidity-providing short sales are significantly more contrarian to all returns considered, compared to liquidity-demanding short sales and liquidity-providing long sales. Liquidity-demanding short sales are significantly more contrarian only in response to yesterday's return, and therefore more similar to liquidity-demanding long sales. During the crash period, both liquidity-providing and liquidity-demanding short sellers become significantly less contrarian, particularly with respect to yesterday's return. There is, however, no evidence that liquidity-demanding short sellers turn into momentum traders.

The contrarian behavior of short sellers is consistent with the motive of trading against overreactions (Diether et al., 2009). In addition, an inventory effect can be attributed to the fact that the liquidity-providing short sales are the most contrarian sales type (Comerton-Forde et al., 2016). The rationale is that a substantial share of liquidity-providing short sales likely originates from broker-dealers acting as market makers. Positive returns over the past week can deplete broker-dealers inventory, prompting them to use short sales instead of long sales to fill further customer buy orders.

Turning to the effect of temporary restrictions on aggressive short sales (i.e., SEC Rule 201), we find that the activation of the restriction effectively reduces the aggressiveness of short sellers, as they significantly decrease their liquidity demand (columns "SIS" and "SIS-SIL"). However, they simultaneously increase their liquidity supply (columns "BIS", "BIS-SIS", and "BIS-BIL"), indicating an effort to circumvent the restriction. The presence of the circuit breaker during our sample period may therefore explain why liquidity-demanding short selling does not increase following price declines, as reported by Comerton-Forde et al. (2016).[25]

The control variables provide some additional insights: Activity in both short selling types exhibits positive autocorrelation and cross-autocorrelation, and increases following higher levels of volatility and already established short interest.

We conclude that off-exchange short selling is contrarian with respect to recent returns. This finding aligns with the motive of trading against overreactions and extends on-exchange evidence

[25] In untabulated robustness checks, we confirm that our results hold across three groups formed according to market capitalization and when controlling either for firm-fixed or a time-fixed effects.

	Percentage Proportion of Off-Exchange Sales				
Variable	BIS	SIS	BIS–SIS	BIS-BIL	SIS-SIL
$r_{i,t}^{ON}$	6.05^{***}	1.86^{**}	4.08^{***}	4.67^{**}	-1.95
	(5.15)	(2.81)	(4.07)	(2.58)	(−1.32)
$r_{i,t-1}$	7.55^{***}	1.98^{***}	5.69^{***}	10.59^{***}	6.29^{***}
	(16.14)	(6.51)	(12.58)	(13.61)	(8.08)
$r_{i,t-5\to t-2}$	0.79^{**}	-0.17	1.07^{***}	1.87^{***}	0.49
	(3.01)	(−0.94)	(3.90)	(4.27)	(1.10)
$\mathbf{1}_{i,t}^{Crash} \times r_{i,t}^{ON}$	-1.38	-1.86	0.60	1.74	0.37
	(−0.67)	(−1.23)	(0.31)	(0.58)	(0.13)
$\mathbf{1}_{i,t}^{Crash} \times r_{i,t-1}$	-5.25^{***}	-2.05^{***}	-3.19^{***}	-7.17^{***}	-3.96^{*}
	(−4.66)	(−3.49)	(−3.31)	(−3.85)	(−2.48)
$\mathbf{1}_{i,t}^{Crash} \times r_{i,t-5\to t-2}$	-1.06^{*}	-0.01	-1.12^{*}	-2.13^{**}	-1.49^{*}
	(−2.23)	(−0.02)	(−2.43)	(−3.02)	(−2.18)
$rule_{i,t}$	1.77^{***}	-0.64^{***}	2.42^{***}	1.42^{***}	-1.68^{***}
	(11.39)	(−9.71)	(15.42)	(7.52)	(−10.61)
$pv_{i,t-1}^{D,BIS}$	27.66^{***}	11.44^{***}			
	(25.58)	(23.73)			
$pv_{i,t-1}^{D,SIS}$	14.85^{***}	25.77^{***}			
	(22.47)	(34.38)			
$pv_{i,t-1}^{D,BIS-SIS}$			14.28^{***}		
			(16.81)		
$pv_{i,t-1}^{D,BIS-BIL}$				31.73^{***}	
				(26.48)	
$pv_{i,t-1}^{D,SIS-SIL}$					26.24^{***}
					(26.63)
$pv_{i,t-1}^{D}$	-0.44^{*}	-1.03^{***}	1.30^{***}	0.95^{**}	-0.83^{*}
	(−1.97)	(−6.62)	(5.61)	(2.66)	(−2.22)
$Volatility_{i,t-5\to t-1}$	1.39^{***}	0.40^{*}	1.08^{***}	-0.60	-1.74^{***}
	(4.45)	(2.05)	(3.41)	(−1.05)	(−3.52)
$\log s_{i,t-1}^{quoted}$	0.54^{***}	0.05	0.52^{***}	0.54^{***}	-0.18
	(5.57)	(0.82)	(5.83)	(3.70)	(−1.28)
$SI_{i,t-1}$	4.64^{***}	3.87^{**}	1.09	5.99^{**}	5.03^{*}
	(3.81)	(2.84)	(0.97)	(3.15)	(2.05)
$IO_{i,t-1}$	-2.25^{***}	0.58	-2.81^{***}	-1.05	3.91^{**}
	(−3.36)	(1.30)	(−4.04)	(−1.03)	(3.06)
$\log MarketCap_{i,t-1}$	-0.54^{***}	0.10	-0.64^{***}	-0.63^{**}	0.29
	(−3.65)	(1.31)	(−5.29)	(−2.81)	(1.59)
FE_i	Yes	Yes	Yes	Yes	Yes
FE_t	Yes	Yes	Yes	Yes	Yes
Adj. R^2	13.08	11.41	3.65	10.81	8.03
# Obs.	225K	225K	225K	225K	225K

Table 3.7. ***Previous Returns and Short Selling Restrictions.*** *The table shows the results for the panel regression according to (3.11). The dependent variables in columns two and three are the percentage proportions of buyer-initiated (BIS) or seller-initiated (SIS) off-exchange short sales according to (3.9), and in columns three to five the imbalances between different types of sales according to (3.10). The independent variables are reported in the first column (Variable). All regressions include firm-fixed and time-fixed effects. Coefficients are multiplied by* 10^2*. Inference is based on robust standard errors clustered by time and firm. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The adjusted* R^2 *excludes the explanatory power of the fixed effects. The sample period is 2019 to 2021.*

(Diether et al., 2009). Importantly, our results show that there is no evidence that short sellers exaggerate price declines. The fact that liquidity-providing short sales are most contrarian is also consistent with an inventory effect, emphasizing their importance for broker-dealers' liquidity provision. Finally, we show that when restrictions on aggressive short selling are binding, short sellers reduce their demand for liquidity but increase their supply. This behavior suggests the effectiveness of the rule while also indicating efforts to bypass constraints by adapting order execution strategies – an insight not previously documented in the literature.

3.4.5 Impact on Exchange Liquidity

3.4.5.1 Methodology

The theory of Zhu (2014) predicts that when off-exchange venues attract relatively uninformed order flow away from exchanges, the concentration of informed traders increases on-exchange. This, in turn, elevates on-exchange adverse selection risks, potentially causing market makers to quote wider spreads.[26] Recent empirical studies tend to confirm the detrimental effect of off-exchange trading on exchange liquidity using aggregate off-exchange order flow (Comerton-Forde and Putniņš, 2015; Degryse et al., 2015) and order flow internalized by broker-dealers (Comerton-Forde et al., 2018; Aramian and Nordén, 2021; Hu and Murphy, 2023). Other studies, however, report either no impact or positive effects (Gresse, 2006; O'Hara and Ye, 2011; He and Lepone, 2014; Foley and Putniņš, 2016). One way to reconcile the mixed evidence is that the detrimental effect of off-exchange trading on exchange liquidity is nonlinear and that off-exchange trading has not yet reached critical levels in some markets and time periods studied. In this regard, Comerton-Forde and Putniņš (2015) indicate that exchange liquidity starts to deteriorate when off-exchange trading in individual stocks exceeds 10%.

Our findings so far demonstrate that while off-exchange trades do contain information, they are notably less informed than exchange trades. Moreover, the percentage of off-exchange trading in our sample is above the critical value of 10% on almost every stock-day. We therefore expect that aggregate off-exchange trading activity contributes to widening exchange spreads. Of particular interest to us is whether this adverse effect extends to liquidity-providing short sales. If so, short sales' positive impact on off-exchange liquidity comes at the cost of deteriorating exchange liquidity. This is plausible, as a substantial portion of liquidity-providing short sales is likely used by broker-dealers to internalize relatively uninformed customer orders. Short selling enables broker-dealers to internalize substantially more of these orders compared to when they could only sell off positive inventory via long sales. Without these short sales, the respective buy orders could eventually end up on an exchange, and decrease the order flows' informativeness. In turn, enabling market makers to quote tighter on-exchange spreads (Zhu, 2014).

To measure the impact of off-exchange trading on the displayed exchange liquidity, as measured by the NBBO spread, we adopt the instrumental variables approach of Comerton-Forde

[26] In a related model, Buti et al. (2017) show that adding a dark pool alongside a lit market can cause the spread in the lit market to widen.

and Putniņš (2015) and Foley and Putniņš (2016). In contrast to standard OLS regressions, instrumental variables regressions allow to account for endogeneity. When studying the effect of off-exchange trading on exchange liquidity, off-exchange trading might not be exogenous. For example, an investor's decision to route an order to an off-exchange venue or a broker-dealer's decision to internalize a customer order can be affected by the on-exchange liquidity. This conditionality creates an endogeneity issue between exchange liquidity and off-exchange trading.

To overcome the potential endogeneity issue, we use two instrumental variables in a two-stage least squares (2SLS) panel regression. The first instrumental variable is the average percentage proportion of the respective type of off-exchange sales in all other stocks in the same size tercile ($\overline{pv}_{i,t}^{j,OtherStocks}$). The second instrumental variable is the 1-day lagged percentage proportion of the respective type of off-exchange volume in the same stock ($pv_{i,t-1}^{j}$). Both instrumental variables are widely used in the microstructure literature (e.g., Sarkar and Schwartz, 2009; Degryse et al., 2015; Comerton-Forde and Putniņš, 2015; Foley and Putniņš, 2016). They qualify as instrumental variables because their levels are correlated with the respective off-exchange trading activity in a particular stock, although it is unlikely that their levels are driven by the quoted spread in this particular stock. The first-stage regression for each type of off-exchange trading activity $j \in \mathcal{J}$ is:

$$pv_{i,t}^{j} = \beta_1 \overline{pv}_{i,t}^{j,OtherStocks} + \beta_2 pv_{i,t-1}^{j} + \sum_k \gamma_k X_{i,t}^{k} + FE_i + \epsilon_{i,t}, \tag{3.12}$$

where $pv_{i,t}^{j}$ is the proportion of off-exchange volume of type j over the total volume in stock i on day t, FE_i is a stock fixed effect, and $X_{i,t}^{k}$ represents the control variables $TotalVolume_{i,t}$ (the logarithm of dollar volume across all venues), $Volatility_{i,t}$ (the standard deviation of one-minute midpoint returns), $MarketCap_{i,t}$ (the logarithm of market capitalization), $ConstrainedSpread_{i,t}$ (the proportional time of the day for which the stock's quoted spread is constrained at the minimum tick size), and $\overline{s}_{i,t}^{OtherStocks}$ (the average of the logarithm of time-weighted quoted half-spreads in all other stocks in the same size tercile). The control variables are included to remove the influence of established spread determinants from the literature and to help isolate the causal effect of off-exchange trading in the second-stage regressions. The last two variables deserve explanation: $ConstrainedSpread_{i,t}$ addresses binding size constraints in spreads due to the minimum tick size, while $\overline{s}_{i,t}^{OtherStocks}$ removes co-movement in spreads, isolating effects of off-exchange trading from general spread changes. The second-stage regression is:

$$\log s_{i,t}^{quoted} = \beta_1 \widehat{pv}_{i,t}^{D,BIS} + \beta_2 \widehat{pv}_{i,t}^{D,BIL} + \beta_3 \widehat{pv}_{i,t}^{D,SIS} + \beta_4 \widehat{pv}_{i,t}^{D,SIL} + \sum_k \gamma_k X_{i,t}^{k} + FE + \epsilon_{i,t}, \tag{3.13}$$

where $\log s_{i,t}^{quoted}$ is the logarithm of the proportional time-weighted quoted NBBO half-spread in basispoints, and $\widehat{pv}_{i,t}^{j}$ are the fitted values from first-stage regression. The control variables are the same as in the first stage and FE represents different sets of fixed-effects. Finally, to put the 2SLS results into perspective, we also estimate the regression (3.13) via OLS where the fitted values $\widehat{pv}_{i,t}^{j}$ are replaced with the actual observations $pv_{i,t}^{j}$.

3.4.5.2 Results

Table 3.8 presents the first-stage results of the 2SLS regressions in Panel A. The coefficients of the instrumental variables are significantly positive for each trading activity measure, demonstrating that the instruments are valid. Panel B reports the second-stage 2SLS results, along with the standard OLS results for comparison. Both approaches indicate that all types of off-exchange trading are detrimental to the lit market liquidity. In the baseline version of column (1), the off-exchange trading coefficients capture time-variation due to the stock-fixed effects. Although all types of off-exchange volume tend to contribute to higher spreads, the effect is strongest for buyer-initiated short sales. When we substitute the firm-fixed effect with a time-fixed effect in column (2), the off-exchange trading coefficients capture variability in the cross-section. Again, the results show that higher shares of off-exchange trading tend to widen the spreads of stocks significantly, except for buyer-initiated long sales. Finally, when we control in column (3) for both stock and time specifics, all types of off-exchange trading contribute significantly to wider spreads. Across all model specifications, a marginal increase of buyer-initiated short selling by 1% of the total dollar volume is associated with an increase of the quoted spread between 1% to 4% ($exp(0.01 \times \widehat{\beta}_1) - 1$), all else equal. Given that the average level of off-exchange trading is 33% in our sample, variations in the off-exchange trading level have an economically significant impact on the NBBO.[27]

The results for the control variables confirm previous evidence from the literature (e.g., Comerton-Forde and Putniņš, 2015; Foley and Putniņš, 2016). Particularly, spreads are wider when volatility is high, and trading volume is low. Moreover, smaller stocks tend to have higher spreads compared to larger stocks.

In summary, we find that higher off-exchange trading levels are detrimental to exchange liquidity, with liquidity-providing short sales being most detrimental. Short sales' positive effect on off-exchange liquidity thus comes at the cost of deteriorating exchange liquidity.

[27] The results are robust to various changes. Results not tabulated are qualitatively similar when the quoted spreads are not log-transformed, time fixed-effects in the first-stage regressions are added, and the set of control variables is altered, for example when the variable for commonality in the quoted spread is dropped. They also hold during both the crash period and normal period.

Panel A: First-Stage 2SLS Results				
	Percentage Proportion of Off-Exchange Volume			
Instrumental Variable	$pv_{i,t}^{D,BIS}$	$pv_{i,t}^{D,BIL}$	$pv_{i,t}^{D,SIS}$	$pv_{i,t}^{D,SIL}$
$\overline{pv}_{i,t}^{j,OtherStocks}$	0.66^{***}	0.56^{***}	0.51^{***}	0.64^{***}
	(22.17)	(22.53)	(17.89)	(24.50)
$pv_{i,t-1}^{j}$	0.32^{***}	0.22^{***}	0.29^{***}	0.21^{***}
	(26.07)	(23.64)	(32.89)	(23.65)
Controls	Yes	Yes	Yes	Yes
FE_i	Yes	Yes	Yes	Yes
Adj. R^2	29.25	19.21	20.36	24.49
# Obs.	225K	225K	225K	225K

Panel B: Second-Stage 2SLS Results & OLS Results						
	Log NBBO Spread					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{pv}_{i,t}^{D,BIS}$	2.06^{***}	3.99^{***}	1.64^{***}	1.06^{***}	1.84^{***}	1.02^{***}
	(8.13)	(7.59)	(7.84)	(15.04)	(9.68)	(16.21)
$\widehat{pv}_{i,t}^{D,BIL}$	0.52^{***}	-0.86	0.96^{***}	0.51^{***}	0.12	0.59^{***}
	(3.36)	(-1.45)	(6.41)	(12.59)	(0.79)	(15.41)
$\widehat{pv}_{i,t}^{D,SIS}$	1.12^{***}	1.42^{*}	1.25^{***}	0.73^{***}	0.67^{***}	0.79^{***}
	(5.77)	(2.21)	(7.23)	(12.40)	(3.48)	(13.95)
$\widehat{pv}_{i,t}^{D,SIL}$	1.35^{***}	2.26^{**}	1.64^{***}	0.82^{***}	1.12^{***}	0.86^{***}
	(5.41)	(3.28)	(8.47)	(19.10)	(8.61)	(20.58)
$\log TotalVolume_{i,t}$	-0.26^{***}	-0.30^{***}	-0.27^{***}	-0.24^{***}	-0.27^{***}	-0.25^{***}
	(-18.14)	(-9.74)	(-19.65)	(-19.92)	(-12.98)	(-20.95)
$Volatility_{i,t}$	2.72^{***}	2.53^{***}	2.12^{***}	2.72^{***}	2.54^{***}	2.05^{***}
	(14.29)	(9.98)	(12.62)	(14.17)	(10.57)	(12.26)
$\log MarketCap_{i,t}$	0.07^{*}	-0.09^{*}	0.03	0.05	-0.13^{***}	0.00
	(2.16)	(-2.23)	(0.93)	(1.66)	(-4.32)	(0.14)
$ConstrainedSpread_{i,t}$	-0.62^{***}	-0.84^{***}	-0.53^{***}	-0.64^{***}	-0.88^{***}	-0.55^{***}
	(-9.91)	(-13.67)	(-9.23)	(-10.65)	(-16.12)	(-10.35)
$\log \overline{s}_{i,t}^{OtherStocks}$	0.34^{***}	0.03	0.02	0.34^{***}	0.01	0.02
	(9.10)	(0.62)	(0.80)	(8.91)	(0.23)	(0.59)
Method	2SLS	2SLS	2SLS	OLS	OLS	OLS
FE_i	Yes	No	Yes	Yes	No	Yes
FE_t	No	Yes	Yes	No	Yes	Yes
Adj. R^2	54.65	45.21	42.34	56.31	46.13	43.62
# Obs.	225K	225K	225K	225K	225K	225K

Table 3.8. ***Impact of Off-Exchange Trading on Exchange Liquidity.*** *The table shows the first-stage results of the two-stage least squares (2SLS) panel regressions accroding to (3.12) in Panel A. The dependent variables are the percentage proportions of different types of off-exchange sales over total sales per stock-day. Panel B reports the second-stage results of the 2SLS regressions accroding to (3.13) in columns (1) to (3), and standard OLS regression results with actually observed variables instead of fitted variables in columns (4) to (6). The dependent variable is the log time-weighted average proportional quoted half-spread (NBBO). The independent variables and instrumental variables are reported in the first column. The control variables in the first stage and second stage are identical. The inclusion of firm-fixed effects (FE_i) and time-fixed effects (FE_t) is indicated. Inference is based on robust standard errors clustered by time and firm. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The adjusted R^2 includes (excludes) the explanatory power of the fixed effects in Panel A (B). The sample period is 2019 to 2021.*

3.5 Conclusion

Today, approximately one-third of all U.S. equity trading occurs off-exchange, with short sellers involved in 44% of the off-exchange volume. Given the puzzling prevalence of short selling in this market segment – traditionally known to attract relatively uninformed order flow – we examine its role for liquidity provision and price discovery. To this end,we distinguish between short sales that provide liquidity and those that demand it. By comparing these short sales to respective long sales, we aim to uncover behavioral differences.

Overall, short sales are the primary providers of off-exchange liquidity, accounting for the passive side in 55% of buyer-initiated volume and the active side in 34% of seller-initiated volume. Compared to long sellers, short sellers provide liquidity at wider spreads and demand liquidity at lower spreads, aligning with the theory of Comerton-Forde et al. (2016). Seller-initiated short sales tend to be better informed than long sales, but less informed than exchange sales. In addition, short sellers exhibit a contrarian response to returns over the past week, consistent with motives of trading against overreactions and the evolution of market makers' inventory. Despite their positive contribution to off-exchange liquidity, short sellers' role in segmenting higher levels of relatively uninformed order flow away from exchanges negatively impacts on-exchange liquidity, as measured by the NBBO spread. Our findings strengthen the view that short sales should be considered from a more nuanced perspective.

Appendix to Chapter 3

Types of Off-Exchange Traders

Who are the short sellers that trade off-exchange? The TAQ data do neither provide identities nor broad classifications in terms of who the buyer and the seller in a transaction are. We therefore cannot attribute institutional investors, retail investors, or broker-dealers (market makers) to specific transaction. Aggregate FINRA data, however, reveal that broker-dealers (Non-ATSs) are involved in 69% of the off-exchange volume during our sample period (FINRA, 2023, p. 38). Under the assumptions that broker-dealers take the passive side in their trades and that their trading activity is equally distributed between buyer-initiated and seller-initiated trades, we can deduce that liquidity-providing short selling must be common practice among broker-dealers. This is because liquidity-providing short sales account for 55% of all liquidity-providing sales (cf. Table 3.3). In the hypothetical case where broker-dealers are responsible for all liquidity-providing long sales (45%), they would still need to be involved in 44% ((69% − 45%)/55%) of the liquidity-providing short sales. More likely is, however, that they are responsible for substantially more of the liquidity-providing short sales. Unfortunately, this line of reasoning does not provide further insights, e.g. to whom broker-dealers provide liquidity.

Recently, Boehmer et al. (2021) have proposed a procedure to identify marketable retail trades among the off-exchange trades. The procedure relies on the unique feature of subpenny increments in off-exchange trade prices, and assumes that broker-dealers attract and execute marketable non-directed retail orders off-exchange at small price improvements relative to the NBBO. A crucial assumption for the accuracy of the algorithm, however, is that institutional orders do not trade at prices with subpenny increments. Battalio et al. (2024) challenge this assumption, showing that it does not always hold in reality. For this reason, we do not employ the algorithm in our main analysis. For the interested reader, we nonetheless present results of the volume proportions among buyer-initiated and seller-initiated short sales and long sales that the procedure, as adapted by Barber et al. (2024), assigns to retail investors and institutions. The proportions are calculated for each stock-day based on the traded volume and subsequently averaged. Figure 3.6 reports the composition of buyer-initiated (liquidity-providing) sales in Panel (a), and the composition of seller-initiated (liquidity-demanding) sales in Panel (b).

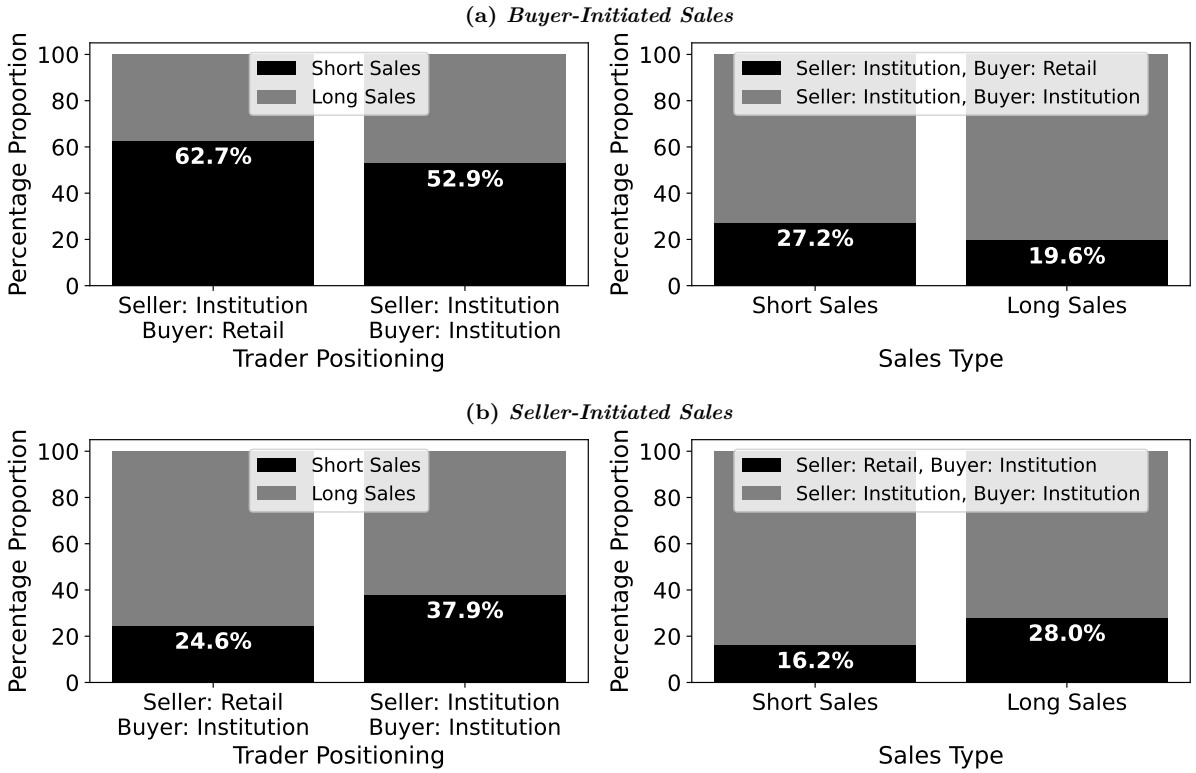

Figure 3.6. ***Composition of Off-Exchange Sales.*** *The figure shows in Panel (a) the composition of buyer-initiated (liquidity-providing) sales. The Panel (b) shows the composition of seller-initiated (liquidity-demanding) sales. The compositions are separately shown based on the traders involved (left) and the type of sale (right). The compositions are calculated based on off-exchange trading volume for each stock-day and subsequently averaged. Retail trades are identified through the procedure of Barber et al. (2024). By assumption of the procedure, the retail investor is always the initiating buyer (seller) in a marketable retail buy (sell) trade. An institution (broker-dealer) takes the passive side. This assumption enables the identification of the buyer and the seller in a retail trade. For example, in a buyer-initiated retail trade that involves a short sale, the institution must be the short seller. In a seller-initiated retail trade that involves a short sale, the retail investor must be the short seller and the institution the buyer. The remaining trades are assumed to be mostly between institutions. The sample period is 2019 to 2021.*

Descriptive Statistics

Variable	Mean	Std.	Min.	1%	10%	25%	Median	75%	90%	99%	Max.
$r_{i,t}^{ON}$	0.0012	0.0122	−0.0755	−0.0269	−0.0078	−0.0031	0.0009	0.0051	0.0105	0.0324	0.0853
$r_{i,t}$	0.0006	0.0247	−0.1295	−0.0627	−0.0231	−0.0105	0.0006	0.0116	0.0239	0.0657	0.1368
$r_{i,t-3\to t}$	0.0023	0.0493	−0.2450	−0.1269	−0.0463	−0.0204	0.0025	0.0251	0.0501	0.1333	0.2533
$rule_{i,t}$	0.0176	0.0779	0.0000	0.0000	0.0000	0.0022	0.0069	0.0113	0.0278	0.2413	0.7481
$pv_{i,t}^{D,BIS}$	0.0880	0.0430	0.0094	0.0216	0.0437	0.0596	0.0807	0.1071	0.1394	0.2269	0.3318
$pv_{i,t}^{D,BIL}$	0.0741	0.0476	0.0023	0.0091	0.0283	0.0440	0.0659	0.0935	0.1243	0.2336	0.4136
$pv_{i,t}^{D,SIS}$	0.0551	0.0323	0.0020	0.0077	0.0238	0.0348	0.0494	0.0682	0.0911	0.1612	0.2735
$pv_{i,t}^{D,SIL}$	0.1118	0.0575	0.0120	0.0255	0.0531	0.0752	0.1037	0.1365	0.1739	0.3037	0.4930
$pv_{i,t}^{D,BIS-SIS}$	0.0329	0.0426	−0.1870	−0.0657	−0.0032	0.0130	0.0291	0.0482	0.0744	0.1651	0.2832
$pv_{i,t}^{D,BIS-BIL}$	0.0139	0.0697	−0.3650	−0.1765	−0.0586	−0.0224	0.0147	0.0523	0.0893	0.1812	0.2897
$pv_{i,t}^{D,SIS-SIL}$	−0.0567	0.0706	−0.4661	−0.2682	−0.1301	−0.0901	−0.0529	−0.0174	0.0169	0.0974	0.2117
$pv_{i,t}^{D}$	0.3291	0.0953	0.1047	0.1477	0.2203	0.2661	0.3190	0.3799	0.4489	0.6065	0.7395
$\overline{pv}_{i,t}^{D,BIS,OtherStocks}$	0.0880	0.0074	0.0792	0.0797	0.0802	0.0806	0.0861	0.0973	0.0979	0.0983	0.0985
$\overline{pv}_{i,t}^{D,BIL,OtherStocks}$	0.0741	0.0072	0.0644	0.0654	0.0663	0.0667	0.0729	0.0830	0.0834	0.0837	0.0838
$\overline{pv}_{i,t}^{D,SIS,OtherStocks}$	0.0551	0.0038	0.0495	0.0501	0.0506	0.0509	0.0553	0.0593	0.0597	0.0599	0.0600
$\overline{pv}_{i,t}^{D,SIL,OtherStocks}$	0.1118	0.0121	0.0938	0.0949	0.0958	0.0963	0.1153	0.1240	0.1246	0.1250	0.1252
$Volatility_{i,t-4\to t}$	0.0870	0.0562	0.0216	0.0268	0.0393	0.0514	0.0723	0.1047	0.1500	0.2869	0.4671
$\log s_{i,t}^{quoted}$	1.7682	1.2234	−0.8569	−0.4118	0.1213	0.7865	1.8395	2.6265	3.3365	4.5394	5.0944
$SI_{i,t}$	0.0421	0.0536	0.0012	0.0037	0.0079	0.0116	0.0214	0.0510	0.1022	0.2480	0.4172
$IO_{i,t}$	0.7842	0.1841	0.0705	0.2725	0.5388	0.6824	0.8109	0.9095	0.9787	1.1562	1.2917
$\log MarketCap_{i,t}$	22.6906	2.3503	18.1739	18.5550	19.6481	20.7470	22.3852	24.9567	25.8128	27.1109	28.0737
$\log TotalVolume_{i,t}$	17.4041	2.4182	10.6455	11.8314	14.1977	15.6691	17.4884	19.4286	20.2936	22.2821	23.2650
$Volatility_{i,t}$	0.1115	0.0627	0.0287	0.0438	0.0583	0.0705	0.0940	0.1328	0.1863	0.3258	0.5238
$ConstrainedSpread_{i,t}$	0.2521	0.3611	0.0000	0.0000	0.0000	0.0009	0.0344	0.4214	0.9592	0.9976	0.9998
$\log \overline{s}_{i,t}^{OtherStocks}$	1.7698	1.0095	0.4865	0.4918	0.5011	0.5087	1.8289	2.9684	2.9777	2.9844	2.9898

Table 3.9. ***Descriptive Statistics of Variables.*** *The table provides descriptive statistics of the main variables in Sections 3.4.4 and 3.4.5. The statistics are calculated for each day and subsequently averaged over all days. The sample period is 2019 to 2021.*

Chapter 4

Interday Cross-Sectional Momentum: Global Evidence and Determinants

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Forthcoming in
Finance (`https://shs.cairn.info/journal-finance`)

Abstract
We examine whether half-hour returns predict half-hour returns on subsequent days at the firm level, using a novel set of high-frequency data on firms that constitute the stock market indices of nine developed markets. We show that interday cross-sectional momentum (ICSM) exists in all markets of our sample. It is most pronounced during the last half hour of a trading day. In the previously studied U.S. market, ICSM has become weaker. Based on trading motives derived from the literature, we propose and test four hypotheses that link the strength of ICSM in the last half hour to firm-level market characteristics. We find that ICSM is stronger when volatility is low, and absolute overnight returns are small, while liquidity has no significant effect. Finally, we show that international investors can save transaction costs of economically significant size by strategically timing trades based on ICSM.

JEL Classification: D4, D82, G14, G15
Keywords: interday momentum, intraday return pattern, liquidity, price efficiency, overnight return

4.1 Introduction

The momentum effect describes the continuation of the direction of past stock returns. A trading strategy in which investors buy stocks that have performed (relatively) well in the past and sell stocks that have performed (relatively) poorly in the past can exploit this effect and generates significantly positive returns (Jegadeesh and Titman, 1993). For formation and holding periods of a few months up to a year, this effect is extensively documented in the literature (e.g., Rouwenhorst, 1998; Griffin et al., 2003; Asness et al., 2013). However, little is known about whether momentum patterns are also present at a higher frequency.[1] For U.S. stocks, Heston et al. (2010, 2011) are the first to show that a stock's half-hour return positively predicts its return in the same interval on subsequent days, particularly during the first and the last half hour of a trading day. The same interday cross-sectional momentum (ICSM) effect is documented for the Indian stock market (Murphy and Thirumalai, 2017).

The theory of slow-moving capital offers an explanation for the existence of ICSM (e.g., Mitchell et al., 2007; Duffie, 2010): Due to transaction costs, informational frictions, institutional constraints, and behavioral biases, investment capital moves slowly and not instantaneously to new trading opportunities. Two strands of literature provide empirical evidence of slow-moving capital that, taken together, are consistent with ICSM. The first strand examines capital flows from investors to institutions, particularly mutual funds. It provides extensive evidence of positive autocorrelation in mutual fund inflows and outflows, indicating that investor behavior is persistent over time (e.g., Del Guercio and Tkac, 2002; Frazzini and Lamont, 2008; Lou, 2012). The second strand examines how capital moves from institutions to individual stocks. It shows that institutional trading is likewise persistent, with institutions tending to buy or sell the same stocks over successive days (e.g., Coval and Stafford, 2007; Campbell et al., 2009; Murphy and Thirumalai, 2017). This behavior results from two main sources: (i) Mutual funds expanding existing holdings following inflows and liquidating positions to meet redemptions, and (ii) institutions building or closing large positions via piece-wise order executions over multiple days.

Importantly, capital flows may not only persist across days, but also exhibit same-time-of-day clustering. For example, index funds frequently use market-on-close orders to reduce the tracking error to benchmarks (Bogousslavsky and Muravyev, 2023), popular trading algorithms overweight the opening and closing periods, as they trade in proportion to the diurnal distribution of trading volume (Białkowski et al., 2008), discretionary liquidity traders may trade near the close to tap high volumes at narrow spreads (Angerer et al., 2018; Lou et al., 2019), and active managers may pass trades to execution desks at fixed times due to scheduling constraints (Heston et al., 2011). If these capital flows are not fully anticipated, their price impact can create ICSM at specific times of day.

[1] An exception is the intraday momentum effect, which is extensively documented for index-level time series returns, as in Gao et al. (2018) and Li et al. (2022), among others. They find that the last half-hour return is positively affected by the previous overnight return and the first half-hour return. We provide more details on this effect in Section 4.5.

While capital flows are well studied, empirical evidence on ICSM remains limited to the above studies.[2] As such, it is an open question whether ICSM holds across international markets and whether it persists over time. For other return patterns, a growing literature documents significant variability along these two dimensions (e.g., Hameed and Kusnadi, 2002; Jacobs and Müller, 2020; Rosa, 2022; Kaplanski, 2023). Cross-market variability can arise from heterogeneity in market size, trading mechanisms, and investor behavior, whereas time variability can result from increased anticipation or shifts in capital flows. In this regard, the growth of index investing (Bae and Kim, 2020) has substantially increased the end-of-day trading demand (e.g., Johann et al., 2019; Raillon, 2020; Bogousslavsky and Muravyev, 2023). This shift could amplify the end-of-day ICSM effect.

In this paper, we provide a global study on ICSM by extending the work of Heston et al. (2010, 2011) and Murphy and Thirumalai (2017). Our study consists of three parts. We first show that ICSM is still present in the previously studied U.S. market, and that it also exists in the eight novel markets of our sample. The pattern is strongest in the last half hour, but barely present during the remainder of the trading day. We then examine determinants of the strength of ICSM in the last half hour by proposing and testing four hypotheses related to firm-level market characteristics and trading motives derived from the literature. We find that ICSM is stronger when volatility is low, and absolute overnight returns are small, while liquidity has no significant effect. Finally, we show that international investors can save transaction costs of economically significant size by strategically timing trades based on ICSM.

The three parts of our study proceed as follows. In the first part, we investigate whether ICSM is a global phenomenon. We build our analysis on a high-frequency data sample, covering firms that constitute the blue chip stock market indices of nine markets across North America, Europe, Asia and Australia. Both our sample period and eight of our sample markets have not been studied before. Using panel regressions, we provide empirical evidence that ICSM is still present in the U.S., and that it also exists in the novel markets of our sample. The pattern is strongest in the last half hour, but barely present during the remainder of the trading day. Comparing the last half-hour U.S. evidence of Heston et al. (2010) to our out-of-sample evidence, we find that the strength of the pattern has weakened by about 75%. The fact that it is still significant and so persistent in the last half hour could be related to favorable conditions for slow-moving capital: The liquidity is high, the volatility is low, and the intraday price discovery is almost completed. This finding is also consistent with the evidence that institutional investors – who are assumed to be the main driver of the pattern – trade more near the market close (Lou et al., 2019). Our cross-market evidence also shows, that ICSM in the last half hour is robust to the market size, and to markets operating under either purely order-driven mechanisms or with designated market makers. Overall, these findings suggest that similar frictions affect investors across markets, giving rise to similar capital flows and thus ICSM at the end of the trading day.

[2] Heston et al. (2010) use data from 2001 to 2005 for the U.S. and extend the sample period to cover 2001 to 2009 in Heston et al. (2011). Murphy and Thirumalai (2017) use data from 2005 to 2006 for India. To the best of our knowledge, these are the only studies that focus on ICSM.

In the second part, we propose four hypotheses related to market characteristics and trading motives, derived from the literature. The first two hypotheses concern liquidity, defined as the ease, costs, and price impact of trading a desired quantity (e.g., Kyle, 1985). These hypotheses are competing and correspond to the two main sources of slow-moving capital flows that may give rise to ICSM. The first source is institutions building or unwinding large positions via the piece-wise execution of orders over time (Białkowski et al., 2008; Murphy and Thirumalai, 2017). This behavior causes repetitive liquidity shocks in the same direction. When liquidity is low, completing an order takes longer, which increases the likelihood that the execution horizon spans multiple days and thus amplifies ICSM. The first hypothesis is therefore that ICSM is stronger in less liquid stocks. The second source relates to mutual funds and index funds managing inflows and outflows, that persist for several quarters (Del Guercio and Tkac, 2002; Frazzini and Lamont, 2008; Lou, 2012). To reduce costs and price impact when managing inflows and outflows, mutual funds tend to focus on buying or selling their most liquid holdings (Popescu and Xu, 2023). Index funds similarly concentrate trading in liquid stocks, either because such stocks carry greater index weights in full-replication strategies or because representative sampling explicitly targets high-liquidity stocks (Vieira et al., 2023). This could amplify ICSM in more liquid stocks, which is our second hypothesis.

The next hypothesis concerns volatility. The empirical literature documents that an increase in volatility tends to increase the autocorrelation at various intraday frequencies (Rosa, 2022; Li et al., 2022; Gao et al., 2019; Bianco and Renò, 2006), yet conversely, it tends to decrease the autocorrelation at the daily frequency (McKenzie and Kim, 2007; McKenzie and Faff, 2003; Säfvenblad, 2000; Sentana and Wadhwani, 1992; LeBaron, 1992). In light of the slow-moving capital theory, this suggests that higher volatility could be associated with an acceleration in the re-allocation speed of capital. Faster moving capital has a higher short-term price impact, increasing the return autocorrelation at intraday frequencies. In turn, the capital flow becomes less persistent at lower frequencies, causing the return autocorrelation to decline at daily frequencies. Our third hypothesis is therefore that ICSM is stronger for less volatile securities.

The last hypothesis is related to two trading motives that connect the trading activity in the morning with the trading activity in the last half hour, and therefore potentially their returns. Outside of the regular trading hours, trading interest and price-relevant information are accumulated. They are incorporated into prices at the open, driving the overnight return. First, incorporating accumulated trading interest into prices at the open may cause a transient liquidity shock. Traders who provide the liquidity buy at discounts or sell at premiums. This can leave them with a sub-optimal portfolio containing excess positions. Unloading these excess positions at a later time can cause another liquidity shock in the same direction as the original one (Bogousslavsky, 2016). Across the trading times of these liquidity providers, price pressure can create momentum in returns. Given that liquidity is better supplied towards the end of the day, liquidity providers may choose to close their excess positions then. Second, there may be late informed traders (Gao et al., 2018). These traders want to trade on overnight information, but do not want to or do not manage to trade immediately at the open. For the same liquidity reasons, they may choose to trade near the close, driving returns in the same direction as in the

morning. Both motives suggest that overnight returns can induce price pressure in the last half hour. This price pressure is distinct from the price pressure that causes the interday momentum effect. It could therefore obscure ICSM at the close. The fourth hypothesis is therefore that ICSM is less pronounced when overnight returns are large.

We then test our hypotheses empirically. Across the majority of the markets, our hypotheses related to volatility and overnight returns are supported. This means that ICSM is stronger when volatility is low, and absolute overnight returns are small. There is, however, no evidence that any of the two hypotheses related to liquidity dominates the other. This indicates that slow-moving capital can create ICSM in a diverse set of stocks, making it a pervasive phenomenon.

In the third part, we show that ICSM is economically significant. To demonstrate this, we take a practitioner perspective and construct the long-short portfolios in the sense of Jegadeesh and Titman (1993). Our results show significantly positive returns in the absence of transaction costs. On average, however, these returns cover only 20% of the quoted bid-ask spread, and 38% of the spread when two rules are added to account for short-run reversals and absolute overnight returns. This has important implications. On the one hand, the effect is small enough to create a limit to arbitrage that could be a reason why the pattern is so persistent (Gromb and Vayanos, 2010). On the other hand, the effect is large enough that the strategic timing of trades allows investors to save transaction costs of economically significant size.

Our paper contributes to the literature in several ways. First, it extends the growing literature on intraday return patterns, with the first analysis of ICSM in a global setting. We show that this momentum pattern is a global phenomenon and that it is less pronounced, compared to previous studies (Heston et al., 2010). This suggests that markets have become more efficient. Second, we relate ICSM to trading motives related to market characteristics. This allows a deeper understanding of the interplay between intraday return patterns and market characteristics.

The rest of the paper is structured as follows. Section 4.2 presents the data and details on the trading mechanism per market. Section 4.3 defines variables and presents descriptive statistics. Section 4.4 provides evidence of the pervasiveness of ICSM. Section 4.5 proposes hypotheses that link ICSM with market characteristics, and subsequently tests them. Section 4.6 examines the economic significance. Section 4.7 concludes.

4.2 Data and Trading Mechanisms

4.2.1 Data

We collect transaction price and volume data, aggregated over 1-minute intervals, for listed firms that constitute the benchmark stock indices of 15 countries.[3] The countries are selected according to market capitalization and data availability. The data are from LSEG and cover the period from August 2021 to May 2023. Additionally, we retrieve the official daily opening and closing auction prices from LSEG as reported by the respective exchange. We broadly follow the literature (Li et al., 2022), and employ data-cleaning steps for each firm to remove non-trading days and recording errors. Specifically, we remove holidays and days in which the exchange closed early and there are no trading records of the first or last half-hour. Finally, the 1-minute intervals where the low (high) is above (below) the daily high (low) are also removed.

Market	Index	Trading Mechanism				Trading Hours			Sample	
		DMM	Shorts	$T+1$	Break	Local	GMT	Intervals	Days	Stocks
Europe	AEX, ATX, BEL20, CAC40, DAX, PSI20 IBEX35	Yes	Yes	No	No	09:00–17:30	GMT+1	17	469	194
Canada	TSX	Yes	Yes	No	No	09:30–16:00	GMT-5	13	455	233
United States	S&P500	Yes	Yes	No	No	09:30–16:00	GMT-5	13	457	504
Australia	ASX200	No	Yes	No	No	10:00–16:00	GMT+11	12	456	200
China	CSI300	No	No	Yes	Yes	09:30–15:00	GMT+8	8	439	300
Hong Kong	HSI	No	Yes	No	Yes	09:30–16:00	GMT+8	11	442	68
Japan	Nikkei225	No	Yes	No	Yes	09:00–15:00	GMT+9	10	447	225
Korea	KOSPI200	Yes	Yes	No	No	09:00–15:30	GMT+9	13	439	200
Taiwan	TWSE50	No	Yes	No	No	09:00–13:30	GMT+8	9	433	50

Table 4.1. ***Sample Overview.*** *The table provides an overview of the markets in our sample along with the respective stock market index, details on the local trading mechanism, the trading hours, and the sample size. With respect to the trading mechanism, the columns indicate, whether the exchange uses Designated Market Makers (DMM), whether short-sales are allowed (Shorts), whether same-day turnaround trades are forbidden ($T+1$), and whether there is a break of at least 30 minutes around midday in the trading hours (Break). For the trading hours, the local time (Local), the time zone as of January 2023 (GMT), and the daily number of half-hour trading intervals are shown. For the cleaned sample, the number of days (Days) and the mean number of stocks per day (Stocks) are shown. The European sample includes Austria, Belgium, France, Germany, the Netherlands, Portugal, and Spain. The sample period is August 2021 to May 2023.*

Furthermore, we retrieve daily end-of-day quoted spreads, foreign exchange rates, and the market capitalization per firm during the sample period from LSEG.

In total, the sample consists of about 2,150 different firms, geographically spanning Europe, North America, Asia and Australia. In Europe, most of the exchanges are identical in terms of the currency (Euro) and regular local trading hours (09:00–17:30). In fact, many European countries even share the same exchange (Euronext). We therefore merge the cross-sections of

[3] For each time-stamped interval, the data provide information on the first, highest, lowest, and last transaction prices as well as the number of shares traded on the primary listing exchange. All prices are in local currency and are adjusted for splits and dividends. Similar data have been used in Li et al. (2022).

European countries and treat Europe as one.[4] Table 4.1 provides an overview of the markets considered along with their respective stock market index, details on the local trading mechanisms, and the trading hours. Treating Europe as one and the other eight countries individually, we refer to these nine entities as markets instead of countries in the following.

4.2.2 Trading Mechanisms

The trading mechanisms of the markets in our international sample are diverse. As reported in Table 4.1, differences exist with regard to whether (i) a market operates purely under an order driven or designated market maker (specialist) system,[5] (ii) short-sales are banned, (iii) same-day turnaround trades are banned (so-called $T+1$ rule), (iv) there is a notable break around noon, and (v) in the length of the regular trading hours. These differences may affect the behavior of market participants. Our international sample therefore provides a rich setting to investigate their relevance for the interday momentum pattern. In this regard, the $T+1$ rule in China is most notable.[6] The limitation to close trades as early as the next day may lead to an intraday overreaction that is corrected on the following days. This could weaken or even reverse the interday momentum pattern.

4.3 Variables and Descriptive Statistics

Following Heston et al. (2010) and Murphy and Thirumalai (2017), we partition the regular trading day into 30-minute intervals.[7] For these intervals, we calculate simple returns. More specifically, the return on firm i, on day t within interval j is

$$r_{i,t,j} = \frac{p_{i,t,j}^{end}}{p_{i,t,j}^{start}} - 1, \tag{4.1}$$

where $p_{i,t,j}^{start}$ ($p_{i,t,j}^{end}$) is the price of stock i, on day t at the start (end) of interval j. In our main results, we take the official auction opening and closing prices as the first and last prices of a trading day.[8] Figure 4.1 summarizes the start and end points for calculating returns in the first (FH), the middle (MH), and the last (LH) half-hour intervals of a trading day, as well as overnight (ON).

[4] For consistency, we do not consider European countries that are different in terms of the currency or the trading hours.

[5] For discussions of the two system, see, e. g., Venkataraman and Waisburd (2007); Menkveld and Wang (2013).

[6] For a detailed description of the trading mechanisms of Chinese exchanges, see, e.g. Gao et al. (2019).

[7] For each market, we focus on the regular trading hours as given in Table 4.1. As such we exclude trading in the pre- and after-hours as well as breaks. Since different exchanges have different trading hours, the number of intraday intervals per trading day varies by market.

[8] Using auction prices appears adequate, as they usually concentrate significant trading volume (Johann et al., 2019; Bogousslavsky and Muravyev, 2023). For robustness, we repeat our analysis and substitute the opening and closing prices from the daily data with the first and the last price from the 1-minute interval data during the regular trading hours, coming to similar results.

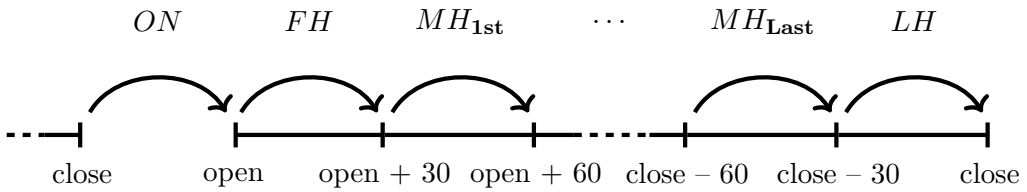

Figure 4.1. ***Partitioning of a Trading Day.*** *The figure shows the points in time used to partition the trading day into intervals. We define the overnight interval (ON), the first half-hour interval (FH), the middle half-hour intervals (MH), and the last half-hour interval (LH).*

To characterize the environment in which the stocks of a firm trade, we define measures for liquidity, price efficiency, size, and volatility. Typically, the degree of a security's liquidity is characterized by the ability to convert a desired quantity of it into cash quickly, cheaply, and with little impact on its market price (Demsetz, 1968; Kyle, 1985; Glosten and Harris, 1988). This includes the dimensions volume, speed, costs and price impact. We cover the dimensions volume and speed by measuring the trading volume per firm i, day t, and interval j as $Volume_{i,t,j}$. To measure costs, we use the end-of-day quoted spread, denoted as $Spread_{i,t}$. Finally, we use the measure of Amihud (2002) as a proxy for the price impact of trading \$1 Mio. within an interval, defined as

$$PriceImpact_{i,t,j} = \frac{|r_{i,t,j}| \cdot 10^6}{Volume_{i,t,j}}. \tag{4.2}$$

To measure high-frequency price inefficiency, we focus on the deviation of return autocorrelation from zero, that is the deviation from a random walk process without any autocorrelation. In our transaction-based data set, this kind of high-frequency predictability could result from autocorrelation in order imbalances (Chordia et al., 2005) and microstructure noise (e.g., the bid-ask bounce effect). We define $Inefficiency_{i,t,j}$ as the absolute value of autocorrelation in 1-minute returns. Large stocks are typically more liquid, and more actively traded by index(ed) funds. We therefore define market capitalization $Size_{i,t}$ as a proxy for liquidity, but also as an indicator of institutional activity through indexing. Finally, we measure a firm's intraday return volatility by the absolute return within an interval, denoted as $Volatility_{i,t,j}$, and its daily return volatility within the sample period by the standard deviation of close-to-close returns, denoted as $Volatility_i$.

Market	Interval	Obs.	Return [BP]					Volume [$ Mio.]				Price Impact [BP/$ Mio.]			Inefficiency			Market Cap. [$ Bn.]			Spread [BP]		
			Mean	Med.	Std.	Kurt.	Daily [%]	Mean	Med.	Std.	Daily [%]	Mean	Med.	Std.	Mean	Med.	Std.	Mean	Med.	Std.	Mean	Med.	Std.
Europe	ON	90,749	3.89	3.03	76	17	19																
	FH	90,749	−1.93	−1.18	83	7	20	5.39	2.32	14	8	153.20	20.66	576	0.18	0.15	0.15						
	MH	1,361,235	0.00	−0.05	39	13	4	2.15	0.94	4	3	132.17	19.26	467	0.20	0.16	0.22						
	LH	90,749	−0.58	−1.16	36	8	5	24.08	13.83	31	39	39.00	1.67	261	0.19	0.16	0.15	33	16	49	11	6	16
Canada	ON	106,023	1.01	−0.30	104	23	19																
	FH	106,023	1.06	1.29	120	8	29	3.66	0.81	12	12	184.76	75.36	262	0.19	0.16	0.14						
	MH	1,166,253	0.03	−0.28	49	14	4	1.11	0.37	2	4	165.60	55.74	258	0.20	0.17	0.20						
	LH	106,023	−0.56	−1.62	39	7	4	14.45	2.19	47	32	38.87	9.53	87	0.19	0.17	0.14	11	3	20	74	62	54
USA	ON	230,182	0.03	1.00	93	43	23																
	FH	230,182	0.90	1.07	92	9	22	16.68	5.54	57	9	17.43	9.62	20	0.17	0.15	0.12						
	MH	2,532,002	0.13	0.36	41	21	4	4.69	1.89	16	3	18.73	10.48	21	0.16	0.14	0.12						
	LH	230,182	−2.09	−2.06	29	8	6	69.86	37.19	126	56	1.24	0.68	3	0.16	0.14	0.11	74	31	188	3	2	3
Australia	ON	91,166	8.20	5.48	127	15	39																
	FH	91,166	−4.09	−4.04	113	9	17	2.12	0.65	5	12	332.47	84.22	669	0.22	0.19	0.16						
	MH	911,660	0.01	−0.27	46	23	4	0.84	0.30	2	5	234.74	49.37	542	0.27	0.25	0.19						
	LH	91,166	0.24	−0.76	61	12	9	6.12	2.09	13	34	105.80	12.61	358	0.30	0.29	0.18	8	2	21	170	128	144
China	ON	131,696	−6.98	-8.34	82	20	13																
	FH	131,696	4.93	−2.90	146	7	37	36.93	18.52	55	25	6.49	3.94	7	0.19	0.17	0.14						
	MH	790,176	−0.16	−3.59	67	11	8	13.85	7.33	20	8	7.11	4.27	8	0.23	0.20	0.16						
	LH	131,696	1.70	0.34	37	11	5	16.42	9.70	20	13	4.01	2.33	5	0.25	0.24	0.17	26	14	43	8	5	8
Hong Kong	ON	30,239	2.13	1.80	109	7	26																
	FH	30,239	−9.91	−9.33	135	5	32	17.39	6.20	36	15	23.78	12.72	28	0.20	0.18	0.14						
	MH	272,151	−0.58	−0.91	56	9	4	6.88	2.66	14	5	20.46	9.50	27	0.26	0.24	0.17						
	LH	30,239	9.35	7.99	37	5	3	21.26	10.10	35	25	4.72	2.43	7	0.29	0.28	0.17	57	26	75	15	13	8
Japan	ON	100,560	5.18	4.54	93	15	43																
	FH	100,560	0.01	−0.72	80	6	22	14.13	5.64	26	20	18.16	8.07	24	0.18	0.15	0.13						
	MH	804,480	−0.03	−0.02	35	16	4	3.95	1.63	8	5	21.62	9.35	28	0.21	0.18	0.15						
	LH	100,560	0.40	0.40	24	7	4	18.43	10.93	23	34	4.08	1.51	9	0.25	0.23	0.17	17	8	28	20	17	11
Korea	ON	87,791	1.08	−3.04	84	15	20																
	FH	87,791	−0.09	−3.18	120	8	30	5.38	1.28	17	18	140.58	53.88	219	0.23	0.21	0.15						
	MH	965,701	−0.42	−0.78	49	24	4	1.56	0.45	5	5	128.08	43.49	213	0.35	0.36	0.17						
	LH	87,791	0.93	0.09	42	9	5	3.18	0.94	10	13	86.37	23.30	172	0.36	0.36	0.18	7	2	26	22	18	11
Taiwan	ON	21621	9.20	6.27	77	6	29																
	FH	21,621	−6.93	−8.28	89	6	25	14.17	3.07	34	21	30.81	15.50	40	0.23	0.21	0.16						
	MH	151,347	0.01	−0.53	42	9	5	4.15	1.21	10	6	30.77	13.62	44	0.34	0.35	0.18						
	LH	21,621	1.75	0.46	41	5	12	11.31	4.03	25	23	13.32	6.08	22	0.36	0.37	0.18	19	5	66	22	18	11

Table 4.2. ***Descriptive Statistics.*** *The table shows the number of observations, the mean, the median, the standard deviation, and the kurtosis for different variables per market and interval of a trading day. For returns, the diurnal percentage contribution per interval towards daily price discovery is provided (Daily). It is defined as the return in an interval divided by the daily return. For trading volume, the diurnal proportional trading volume per half-hour interval is provided (Daily). It is defined as the trading volume in an interval divided by the total daily trading volume. The statistics are calculated for each day and subsequently averaged over all days. Market capitalization and the quoted spread are only available at the end of day. The sample period is August 2021 to May 2023.*

For each market, Table 4.2 provides descriptive statistics of the above variables for different times of the day. To facilitate the comparison across markets in the table, local currencies are converted to U.S. dollar.[9] There is no consistent pattern of intraday seasonality in the sign of returns. However, across all markets, the overnight and first half-hour returns exhibit considerably higher volatility in comparison to returns observed during the remainder of the day. This period also accounts for a significant portion of the daily price discovery, ranging from 39% (Europe) to 65% (Japan), as measured by the average ratio of the return within a given interval to the daily return. Significant information and trading interests are accumulated overnight. Consequently, the process of price discovery in the morning leads to increased volatility in the market (Gao et al., 2018). While the proportional trading volume peaks in the first half-hour for the Chinese (25%) and the Korean (18%) stock markets, all other markets have their peak in the last half hour (23%–56%).[10] This shift in activity from the historic U-shape (Admati and Pfleiderer, 1988) to a concentration at the end of the day is a recent phenomenon observed in several markets (Johann et al., 2019; Raillon, 2020; Bogousslavsky and Muravyev, 2023). Especially the closing auctions allow for the cheap exchange of large quantities (Bogousslavsky and Muravyev, 2023). Consistent with that, our measure of price impact has its daily low in the last half-hour interval. In Europe, Canada and the U.S., price inefficiency, as measured by the absolute autocorrelation in high-frequency returns, is stable over the course of a day. In the remaining markets, there is a slight increase. The mean firm size per market in our sample ranges between \$7 bn. (Korea) and \$75 bn. (USA). Similarly, end-of-day quoted spreads range between 3 basis points (USA) and 170 basis points (Australia). Apart from between-market variability, all variables exhibit substantial within-market variation.

4.4 Interday Cross-Sectional Momentum

4.4.1 Baseline Model and Results

In this section, we investigate whether the interday cross-sectional momentum pattern continues to exist in the U.S. market, and whether it is also present in other markets. To do so, we analyze the relation between the stock returns on day t in half-hour interval j and those lagged by k days. Specifically, we estimate the following univariate panel regression for each market in our sample:

$$r_{i,t,j} = \beta_k \cdot r_{i,t-k,j} + FE_{t,j} + \epsilon_{i,t,j}, \tag{4.3}$$

[9] When comparing the variables across markets, it is important to note that the indices do not encompass the same proportion of the respective local stock market. This discrepancy is attributable to the variation in the number of constituents per index and the total number of stocks across different markets.

[10] The U.S. sample encompasses trading activity on the New York Stock Exchange (NYSE) and NASDAQ. Across all venues, these exchanges collectively account for approximately 30% of the trading volume for respective listed firms (Jurich, 2021). Accordingly, accounting for trading volume on other venues should result in a slight decrease in the relative activity peak observed at the end of the trading day. Nevertheless, given that the exchanges are the leaders in terms of price discovery (Hatheway et al., 2017), it is reasonable to assume that our focus on these two exchanges has no impact on the analysis of return patterns.

where $r_{i,t,j}$ is the return of firm i on day t in interval j, and $FE_{t,j}$ is a time-fixed effect that captures the overall market move on day t within interval j. Following Murphy and Thirumalai (2017), we employ panel regressions rather than Fama-MacBeth regressions, as they allow us to additionally incorporate firm-fixed effects later. Moreover, the panel regressions are estimated based on all observations in a single step and account for dependencies in errors within both firms and days via two-way clustered standard errors, improving accuracy of statistical inference (Petersen, 2009; Cameron et al., 2011). Nonetheless, we have also estimated Fama-MacBeth regressions as a robustness check, coming to the same conclusions. We estimate model (4.3) for each market for the daily lags $k = 1, \ldots, 5$ (i.e., one trading week).[11] To address concerns about the impact of outliers, we winsorize returns at the 1% level for each monthly interval in our main results, following the approach outlined in Heston et al. (2010).

Table 4.3 presents the results per market for our baseline model. As dependent variables, we separately consider returns for the first half-hour interval (FH), the middle half-hour intervals (MH), and the last half-hour interval (LH).

The results of the first half-hour returns show that only Europe and the U.S. feature significant one-day lag interday momentum (Columns *FH*). The coefficients of subsequent lags are insignificant. This result differs from Heston et al. (2010), who find that the momentum pattern in the U.S. is significantly positive in the first half hour for multiples of daily lags.

In the middle half-hour intervals (Columns *MH*), we observe the interday momentum pattern for the one-day lag in the U.S., Australia, Korea, and Taiwan. For further lags, the significance tends to decline. In Hong Kong, the coefficient for the two-day lag is significantly positive, while the coefficient for the one-day lag is not. In China, there is a significantly negative coefficient for the one-day lag, indicating a reversal. This coefficient is also significantly more negative than the average momentum coefficient across all markets. This is consistent with the expected impact of the unique $T + 1$ rule in China: As investors cannot liquidate their newly opened positions on the same day, they tend to do so on the next day if they have a short-term perspective. As a result, they generate one-day lag return reversals instead of continuations.

Finally, the results show that all of our sample markets exhibit statistically significant interday momentum in the last half-hour interval, which can persist for up to five trading days in the majority of markets (Columns *LH*). The U.S. market is an exception, however, with only three significant lags. Once more, in comparison with the findings of Heston et al. (2010), our results indicate a weakening of the interday momentum effect in the last half hour for the U.S. market by about 75%.[12]

[11] We also estimate the model with all lags simultaneously, using a multiple panel regression. Coming to very similar coefficients and significance levels, the univariate panel regression approach appears adequate.

[12] Heston et al. (2010) report results for S&P 500 firms only for respectively sorted long-short portfolios. Due to this methodological difference, our coefficients in this section are not directly comparable to their portfolio returns. However, we adopt their portfolio approach in Section 4.6 (Table 4.9) and as a robustness check (Table 4.15). These results suggest that the size of the effect has declined by about 75% for portfolio returns in the last half hour formed on the basis of one-day lagged returns.

	Returns														
	First half-hour interval (FH)					Middle half-hour intervals (MH)					Last half-hour interval (LH)				
Market	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Europe	2.27^{*}	2.48^{**}	1.47	3.47^{***}	1.45	0.36	0.36	0.34	0.41	−0.21	2.72^{***}	2.98^{***}	2.13^{**}	2.88^{***}	1.60^{*}
	(2.18)	(2.58)	(1.47)	(4.17)	(1.54)	(1.33)	(1.44)	(1.37)	(1.69)	(−0.84)	(3.58)	(4.62)	(3.12)	(4.43)	(2.52)
Canada	−0.64	1.24	0.28	1.02	0.42	0.65	0.12	0.34	0.43	0.59	5.11^{***}	4.04^{***}	2.01^{**}	3.20^{***}	3.22^{***}
	(−0.64)	(1.38)	(0.27)	(1.05)	(0.42)	(1.86)	(0.38)	(1.01)	(1.27)	(1.78)	(7.42)	(5.10)	(3.23)	(4.53)	(4.42)
USA	2.23^{*}	1.07	−1.43	0.73	−1.50	0.85^{*}	0.20	−0.20	0.67^{*}	0.41	2.54^{***}	1.91^{**}	0.75	1.28^{*}	0.80
	(2.02)	(1.09)	(−1.59)	(0.75)	(−1.53)	(2.49)	(0.60)	(−0.61)	(2.01)	(1.24)	(3.50)	(3.05)	(1.04)	(2.00)	(1.23)
Australia	1.27	1.96^{**}	0.51	1.75^{**}	2.29^{***}	0.98^{***}	1.02^{***}	0.38	0.32	0.52^{*}	3.41^{***}	1.98^{**}	2.91^{***}	2.26^{***}	2.56^{***}
	(1.84)	(3.14)	(0.84)	(3.09)	(3.85)	(4.60)	(4.57)	(1.66)	(1.57)	(2.24)	(5.59)	(3.10)	(4.39)	(3.80)	(4.05)
China	−0.78	−1.14	-1.91^{*}	−0.52	0.46	-1.36^{***}	0.30	0.15	0.55	−0.06	4.10^{***}	3.40^{***}	2.57^{***}	2.58^{***}	2.42^{***}
	(−0.85)	(−1.30)	(−2.20)	(−0.60)	(0.53)	(−3.60)	(0.81)	(0.40)	(1.50)	(−0.18)	(7.24)	(7.52)	(5.93)	(5.34)	(5.27)
Hong Kong	1.57	1.39	0.73	1.25	0.55	−0.01	0.99^{*}	−0.08	0.60	0.13	7.78^{***}	6.46^{***}	7.06^{***}	7.13^{***}	5.03^{***}
	(1.34)	(1.33)	(0.69)	(1.03)	(0.53)	(−0.01)	(2.01)	(−0.18)	(1.22)	(0.28)	(7.27)	(6.20)	(6.99)	(7.50)	(5.61)
Japan	−0.89	−0.55	0.76	−0.10	0.20	0.36	−0.15	0.12	−0.13	−0.06	5.54^{***}	4.78^{***}	4.05^{***}	3.59^{***}	2.23^{***}
	(−1.11)	(−0.75)	(1.00)	(−0.16)	(0.28)	(1.31)	(−0.53)	(0.44)	(−0.49)	(−0.23)	(9.70)	(9.36)	(7.59)	(8.01)	(5.03)
Korea	-1.92^{*}	−0.41	2.27^{**}	0.60	1.13	0.60^{**}	0.70^{***}	0.59^{***}	0.47^{**}	0.23	7.22^{***}	7.46^{***}	7.10^{***}	6.35^{***}	5.87^{***}
	(−2.54)	(−0.57)	(3.07)	(0.85)	(1.65)	(3.06)	(3.71)	(3.36)	(2.74)	(1.18)	(11.32)	(13.74)	(13.34)	(13.77)	(12.47)
Taiwan	−1.03	−0.83	−0.00	0.58	0.03	1.86^{***}	1.42^{**}	1.16^{*}	0.81	1.39^{***}	9.23^{***}	6.32^{***}	6.12^{***}	3.79^{**}	4.40^{***}
	(−0.77)	(−0.70)	(−0.00)	(0.62)	(0.03)	(4.12)	(2.66)	(2.36)	(1.83)	(3.86)	(6.73)	(3.81)	(5.40)	(3.25)	(4.32)
$FE_{t,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE_i	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta \log Volume_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Volatility_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta PriceImpact_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Inefficiency_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table 4.3. ***Baseline Model.*** *The table shows the estimation results for the panel regressions according to model (4.3). Each cell represents a separate regression. The second row indicates whether the dependent variable in the regressions is from the first half-hour interval (FH), the middle half-hour intervals (MH), or the last half-hour interval (LH). The third row indicates the lag k for explanatory variables. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects and controls are included. Inference is based on standard errors clustered by time (t,j) and entity i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

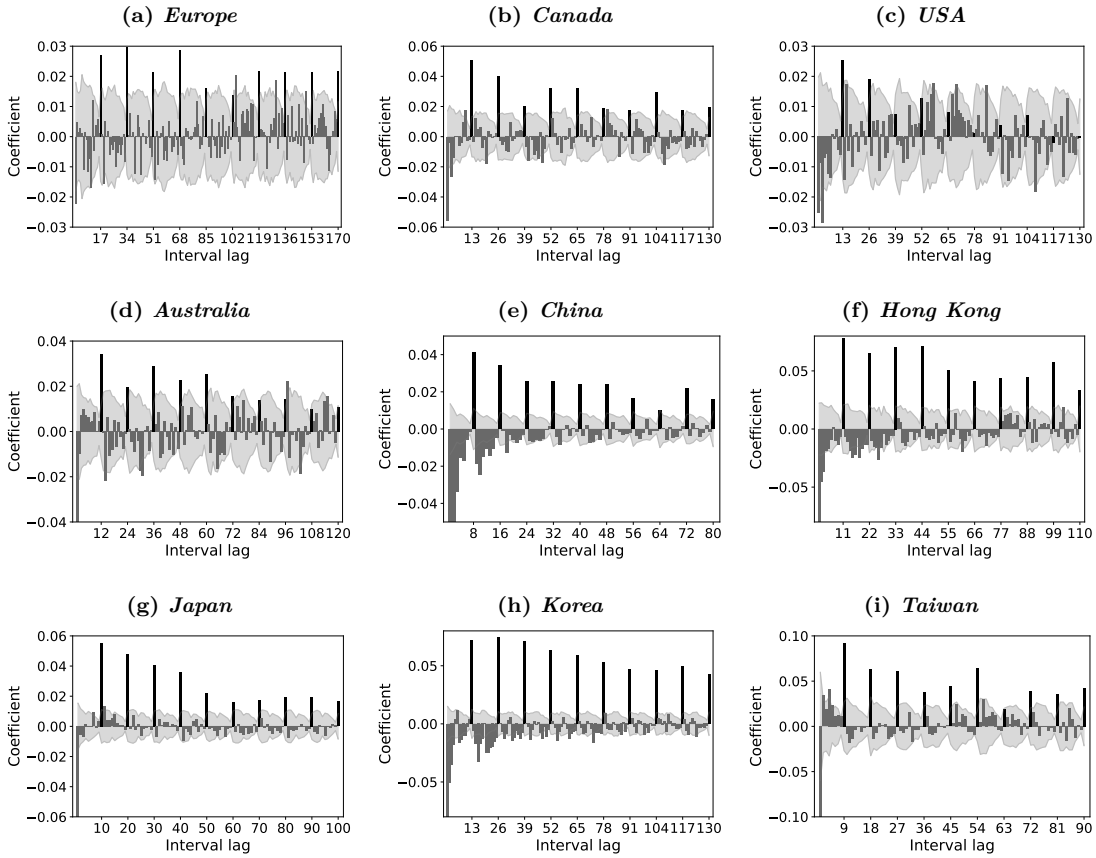

Figure 4.2. ***Coefficients for the Last Half-Hour Returns.*** *The figure shows the estimated beta coefficient for panel regressions according to model (4.3). Each Panel shows the results for a distinct market. In all regressions, returns of the last half-hour interval (LH) per day are the dependent variable. For each market and lag, a separate panel regression is estimated. For each of these regressions, the estimated coefficient is represented by a bar. The x-axis indicates the half-hour interval lag of the explanatory returns. The y-axis indicates the value for the coefficient of the lagged returns. Bars that represent lags of multiples of one trading day, are in black. For each market, Table 4.1 shows the number of daily half-hour intervals. Inference is based on standard errors clustered by time* (t,j) *and entity* i*. Areas shaded in light gray represent 95% confidence intervals for the null hypothesis, that the true coefficient is zero. Bars that range out of the gray shaded area indicate significance (at least) at the 5% level. The sample period is August 2021 to May 2023.*

The above analysis shows that there is a positive and persistent relationship between the last half-hour returns on subsequent trading days in all markets. To investigate whether this relationship differs from the relationship of the last half-hour returns to the lagged returns of other intervals, we re-estimate the model (4.3), covering all half-hour lags of the previous ten trading days.[13] Figure 4.2 shows the estimated coefficients for the lagged returns. The coefficients of lags that are multiples of a full trading day are systematically more pronounced than the coefficients of other lags. This confirms that the interday momentum effect is very distinct and unlikely the outcome of noise. In addition, the figure provides evidence of another systematic pattern: Returns in all markets feature significant mean-reversion – relative to the market return – for the first lag. This effect may result from liquidity imbalances, overreactions or the bid-ask bounce, and is consistent with the literature (Heston et al., 2010; Murphy and Thirumalai, 2017).

[13] Note that the regular trading hours, and therefore the number of daily half-hour intervals, differ across markets. Consequently, the number of intervals that constitutes ten trading days varies.

Overall, our results suggest an increase in market efficiency, such that predictability in the form of interday momentum is sustained primarily in the last half hour and only to a lesser extent. Similar tendencies are observed for other intraday return patterns (Hossain et al., 2021; Rosa, 2022; Huang et al., 2023). This is consistent with evidence from the literature, showing that liquidity providers compete to provide liquidity to predictable capital flows, thereby decreasing their temporary price impact and consequently the return predictability (Admati and Paul, 1991; Bessembinder et al., 2016; Murphy and Thirumalai, 2017). The pervasive and still significant interday momentum in the last half hour is consistent with previous evidence, which documents that the pattern is particularly strong during this interval (Heston et al., 2010). In addition, interday momentum may be reinforced by the trading activity of index(ed) funds, which contribute to the trend of increasing trading volume near the close due to the importance of closing prices (Johann et al., 2019; Raillon, 2020; Bogousslavsky and Muravyev, 2023). Finally, the last half-hour offers favorable conditions for slow-moving capital flows from institutions that build or unwind large positions via the piece-wise execution of orders: The availability of liquidity, in the form of turnover and depth is high (Lee et al., 1993), volatility is low, and the intraday price discovery is almost completed.

4.4.2 Robustness

To test the robustness of the results, we re-estimate the model (4.3) with some modifications. To start, we conduct (i) Fama-MacBeth regressions instead of the panel regression approach, (ii) regressions utilising solely prices from continuous trading, omitting the official auction opening and closing prices, and (iii) regressions based on raw (non-winsorized) returns. In all cases, we obtain similar results. For the sake of brevity, we do not tabulate them here.[14]

We next extend the baseline model (4.3) by including control variables that capture periodic changes in intraday market characteristics, which could potentially explain the return momentum. For instance, a relatively high change in the trading volume during a particular half-hour interval tends to be followed by similar changes in the same half-hour interval over subsequent days (Heston et al., 2010). Accordingly, we control for k-day lagged half-hour differences in the logarithm of trading volume ($\Delta \log Volume_{i,t-k,j}$), volatility ($\Delta Volatility_{i,t-k,j}$), price impact ($\Delta PriceImpact_{i,t-k,j}$), and inefficiency ($\Delta Inefficiency_{i,t-k,j}$).[15] To rule out that the return pattern results from systematically higher or lower returns of a few firms, we also add a firm-fixed effect FE_i to our regression. We then estimate the following model:

$$r_{i,t,j} = \beta_k \cdot r_{i,t-k,j} + \sum_m \gamma_m \cdot X^m_{i,t-k,j} + FE_{t,j} + FE_i + \epsilon_{i,t,j}, \tag{4.4}$$

[14] The results are tabulated in the Appendix to Chapter 4, respectively in the Tables 4.10, 4.11, 4.12, 4.13, and 4.14.

[15] For any variable $\#_{i,t,j}$, the half-hour difference Δ is defined as $\Delta\#_{i,t,j} = \#_{i,t,j} - \#_{i,t,j-1}$.

	Returns														
	First half-hour interval (FH)					Middle half-hour intervals (MH)					Last half-hour interval (LH)				
Market	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Europe	1.37	1.52	0.51	2.58^{**}	0.50	0.35	0.35	0.32	0.39	−0.23	1.81^{*}	2.01^{**}	1.22	1.94^{**}	0.68
	(1.33)	(1.57)	(0.52)	(3.11)	(0.54)	(1.27)	(1.37)	(1.29)	(1.61)	(−0.91)	(2.57)	(3.26)	(1.94)	(3.24)	(1.14)
Canada	−1.32	0.52	−0.47	0.30	−0.32	0.62	0.09	0.29	0.40	0.55	3.97^{***}	2.93^{***}	0.91	2.13^{**}	2.11^{**}
	(−1.33)	(0.59)	(−0.47)	(0.31)	(−0.33)	(1.77)	(0.27)	(0.87)	(1.19)	(1.68)	(5.83)	(3.75)	(1.48)	(3.03)	(2.88)
USA	1.85	0.69	-1.82^{*}	0.35	−1.89	0.83^{*}	0.18	−0.23	0.65	0.40	2.08^{**}	1.47^{*}	0.22	0.80	0.30
	(1.67)	(0.70)	(−2.01)	(0.36)	(−1.94)	(2.42)	(0.53)	(−0.68)	(1.94)	(1.19)	(2.85)	(2.32)	(0.30)	(1.24)	(0.46)
Australia	0.65	1.34^{*}	−0.10	1.11^{*}	1.69^{**}	0.94^{***}	0.98^{***}	0.33	0.27	0.48^{*}	2.74^{***}	1.32^{*}	2.32^{***}	1.55^{*}	1.91^{**}
	(0.95)	(2.18)	(−0.17)	(2.02)	(2.83)	(4.37)	(4.40)	(1.46)	(1.32)	(2.05)	(4.46)	(1.98)	(3.46)	(2.56)	(3.12)
China	−1.54	−1.49	-2.20^{*}	−1.07	0.12	-1.30^{***}	0.21	0.11	0.50	−0.08	3.20^{***}	2.46^{***}	1.58^{***}	1.63^{***}	1.60^{***}
	(−1.62)	(−1.66)	(−2.50)	(−1.21)	(0.14)	(−3.40)	(0.56)	(0.29)	(1.35)	(−0.23)	(5.63)	(5.29)	(3.66)	(3.40)	(3.38)
Hong Kong	0.76	0.69	0.03	0.48	−0.25	−0.07	0.91	−0.12	0.54	0.06	4.72^{***}	3.67^{***}	4.25^{***}	3.71^{***}	2.03^{**}
	(0.65)	(0.68)	(0.03)	(0.41)	(−0.25)	(−0.13)	(1.88)	(−0.27)	(1.10)	(0.12)	(5.14)	(3.95)	(5.61)	(4.27)	(2.66)
Japan	−1.31	−0.99	0.38	−0.52	−0.22	0.34	−0.18	0.09	−0.15	−0.08	4.76^{***}	4.00^{***}	3.27^{***}	2.81^{***}	1.44^{**}
	(−1.62)	(−1.33)	(0.50)	(−0.82)	(−0.30)	(1.23)	(−0.63)	(0.33)	(−0.56)	(−0.29)	(8.37)	(7.77)	(6.16)	(6.22)	(3.25)
Korea	-2.23^{**}	−0.86	1.80^{*}	0.11	0.66	0.61^{**}	0.63^{***}	0.55^{**}	0.40^{*}	0.18	5.66^{***}	5.89^{***}	5.55^{***}	4.76^{***}	4.37^{***}
	(−3.01)	(−1.21)	(2.46)	(0.16)	(0.95)	(3.08)	(3.41)	(3.07)	(2.35)	(0.90)	(9.16)	(11.22)	(11.08)	(10.41)	(9.96)
Taiwan	−1.25	−1.13	−0.28	0.27	−0.34	1.69^{***}	1.26^{*}	1.06^{*}	0.66	1.20^{***}	8.43^{***}	5.30^{**}	5.29^{***}	2.82^{*}	3.44^{***}
	(−0.93)	(−0.97)	(−0.26)	(0.28)	(−0.39)	(3.69)	(2.34)	(2.13)	(1.47)	(3.37)	(5.96)	(3.05)	(4.42)	(2.39)	(3.37)
$FE_{t,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta \log Volume_{i,t-k,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta Volatility_{i,t-k,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta PriceImpact_{i,t-k,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta Inefficiency_{i,t-k,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.4. ***Baseline Model with Controls.*** *The table shows the estimation results for the panel regressions according to model (4.4). Each cell represents a separate regression. The second row indicates whether the dependent variable in the regressions is from the first half-hour interval (FH), the middle half-hour intervals (MH), or the last half-hour interval (LH). The third row indicates the lag k for explanatory variables. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects and controls are included. Control variables include k-day lagged half-hour differences in the logarithm of trading volume ($\Delta \log Volume_{i,t-k,j}$), the absolute half-hour return ($\Delta Volatility_{i,t-k,j}$), the scaled Amihud (2002) ratio of absolute half-hour return over trading volume ($\Delta PriceImpact_{i,t-k,j}$), and the absolute autocorrelation in 1-minute returns ($\Delta Inefficiency_{i,t-k,j}$). Inference is based on standard errors clustered by time (t,j) and entity i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

where $X^m_{i,t-k,j}$ represents the control variables and the other variables are as before. Table 4.4 reports the estimation results for model (4.4). We find that the interday momentum pattern remains statistically significant, although its significance is slightly reduced. This means that the interday momentum pattern cannot be attributed to periodic patterns in the intraday changes of trading volume, volatility, price impact, and inefficiency. Furthermore, the average firm-level return in an interval cannot explain the interday momentum pattern. Interday momentum therefore appears to be a distinct return feature rather than an artifact of periodicity in changes of related market characteristics.

Overall, our empirical results – robust to various modifications – suggest that the interday momentum pattern is widely present in international markets. Regarding the diurnal distribution of its strength, the pattern is barely present in the first half hour, slightly present in the middle of the day, but strongest in the last half hour. Compared to previous studies, the pattern is weaker in our sample. The pervasiveness and persistence of this pattern in the last half-hour may be associated with favorable conditions for slow-moving capital and the importance of closing prices for index-related investment strategies.

4.5 Determinants

In this section, we examine potential determinants of the strength of interday cross-sectional momentum. In Section 4.5.1, we propose four hypotheses that link interday momentum in the last half hour to trading motives associated with market characteristics. Our focus is on the last half hour, as this interval exhibits the strongest interday momentum across all sample markets. In Section 4.5.2, we test these hypotheses empirically.

4.5.1 Hypotheses Development

4.5.1.1 Liquidity

The literature attributes slow-moving capital flows that persist over successive days to two main sources. For each source, we derive a competing hypothesis about its relationship with liquidity – defined as the ease, costs, and price impact of trading a desired quantity (e.g., Kyle, 1985) – and, therefore, the potential effect of liquidity on interday momentum. The first hypothesis (1a) concerns the behavior of institutions when building or unwinding large positions. To reduce costs and price impact, institutions tend to spread the execution of orders over time (e.g., Białkowski et al., 2008; Murphy and Thirumalai, 2017). This behavior causes repetitive but smaller liquidity shocks in the same direction over the execution period, rather than a single large shock. The length of the execution period depends on both order size and stock liquidity. For a given order size, lower liquidity extends the execution horizon. When the execution horizon spans multiple days, time-of-day patterns in the execution strategy can create patterns in liquidity shocks that are consistent with interday momentum. Specifically, several

factors may cause liquidity shocks to cluster in the last half-hour period. For example, popular trading algorithms overweight the last half-hour period to align with the diurnal trading volume distribution (Białkowski et al., 2008), and discretionary traders may be drawn to the end-of-day concentration of high volumes at narrow spreads, as well as the closing auction (Angerer et al., 2018; Lou et al., 2019; Bogousslavsky and Muravyev, 2023). Consequently, we expect that lower liquidity increases the likelihood that capital flows from the piece-wise building or unwinding of large positions spread over successive days and amplify last half-hour interday momentum.

The second hypothesis (1b) focuses on how mutual funds and index funds manage inflows and outflows, which tend to persist for several quarters (e.g., Del Guercio and Tkac, 2002; Frazzini and Lamont, 2008; Lou, 2012) Typically, funds use inflows to expand existing holdings and liquidate positions to pay for redemptions (e.g., Coval and Stafford, 2007; Campbell et al., 2009). To reduce costs and price impact when managing inflows and outflows, mutual funds tend to focus on buying or selling their most liquid holdings (Popescu and Xu, 2023). Similarly, index funds tend to buy or sell liquid stocks more, either due to the full replication of indices – where larger, more liquid stocks have higher weights – or representative sampling strategies that concentrate on liquid stocks (Vieira et al., 2023). This flow-induced trading activity creates price pressure, even in larger, more liquid stocks (Lou, 2012). Given the increased popularity of index investing in recent decades (Bae and Kim, 2020), such repetitive, flow-induced trading can be substantial, especially within our sample of index constituents. Importantly, liquidity shocks from this source of slow-moving capital are likely concentrated near the close: Index funds frequently use market-on-close orders to reduce the tracking error to their benchmarks (Bogousslavsky and Muravyev, 2023), and end-of-day trading is generally attractive to large, liquidity-seeking traders due to high turnover and narrow spreads (Angerer et al., 2018; Lou et al., 2019). Accordingly, we expect stronger last half-hour interday momentum in more liquid stocks, driven by persistent buying or selling over successive days due to funds' inflow and outflow management.

Hypothesis 1a. *Interday cross-sectional momentum is stronger for securities that are less liquid.*

Hypothesis 1b. *Interday cross-sectional momentum is stronger for securities that are more liquid.*

Since Hypotheses 1a and 1b compete with each other, the net effect of liquidity on interday momentum depends on the degree to which the two underlying forces counteract each other. In addition, given the positive relationship between liquidity, price efficiency, and firm size (Amihud, 2002; Conrad et al., 2015), we expect that these three variables have a similar effect on interday momentum.

4.5.1.2 Volatility

The empirical literature indicates that the level of volatility significantly affects return autocorrelations. Increased volatility tends to increase the autocorrelation at various intraday frequencies (Bianco and Renò, 2006; Gao et al., 2019; Li et al., 2022; Rosa, 2022), yet conversely, it tends to decrease the autocorrelation at the daily frequency (LeBaron, 1992; Sentana and Wadhwani, 1992; Säfvenblad, 2000; McKenzie and Faff, 2003; McKenzie and Kim, 2007). In light of the slow-moving capital theory, this suggests that higher volatility could be associated with an acceleration in the re-allocation speed of capital. Faster moving capital has a higher short-term price impact, increasing the return autocorrelation at intraday frequencies. In turn, the capital flow becomes less persistent at lower frequencies, causing the return autocorrelation to decline at daily frequencies. This could result in a less pronounced interday momentum effect. We therefore expect that the interday momentum effect is inversely related to volatility.

Hypothesis 2. *Interday cross-sectional momentum is stronger for less volatile securities.*

4.5.1.3 Overnight Returns

Financial markets facilitate liquidity and price discovery. Outside of the regular trading hours, trading interest and price-relevant information are accumulated. They are incorporated into prices at the open, driving the overnight return. Bogousslavsky (2016) and Gao et al. (2018) each propose a channel that connects the trading activity in the morning with the trading activity in the last half hour, and therefore potentially their returns. This relationship is referred to as intraday momentum in the literature.[16] First, incorporating accumulated trading interest into prices at the open may cause a transient liquidity shock. Traders who provide the liquidity buy at discounts or sell at premiums. This can leave them with a sub-optimal portfolio containing excess positions. Unloading these excess positions at a later time can cause another liquidity shock in the same direction as the original one (Bogousslavsky, 2016). Across the trading times of these liquidity providers, price pressure can create momentum in returns. Given that liquidity is better supplied towards the end of the day, liquidity providers may choose to close their excess positions then. Second, there may be late informed traders (Gao et al., 2018). These traders want to trade on overnight information, but do not want to or do not manage to trade immediately at the open. For the same liquidity reasons, they may choose to trade

[16] The seminal work of Gao et al. (2018) provides empirical evidence that the overnight return and the first half-hour return predict the last half-hour return of the aggregate U.S. stock market index. This index-level effect is also found in China (Chu et al., 2019), Australia (Ho et al., 2021), and a subset of 16 developed markets (Li et al., 2022). Moreover, there is evidence for various futures contracts, including stock index futures (Baltussen et al., 2021), commodity futures (Jin et al., 2020; Wen et al., 2021), volatility futures (Huang et al., 2023), bond futures (Zang et al., 2021), foreign exchange rates (Elaut et al., 2018), and Bitcoin (Shen et al., 2022). However, the evidence in Asia-Pacific is mixed (Lai et al., 2022; Limkriangkrai et al., 2023), and some studies suggest a time-variability or recent disappearance of the pattern (Hossain et al., 2021; Rosa, 2022; Huang et al., 2023). Firm-level evidence is rare: For China, Gao et al. (2019) find that the overnight return has more predictive power than the first half-hour return. For the U.S., Komarov (2017) provides evidence that the positive relation between returns in the morning and in the last half-hour disappeared or even reversed after 2001. Neither study accounts for interday momentum.

near the close, driving returns in the same direction as in the morning. Both channels suggest that overnight returns can induce price pressure in the last half hour. This price pressure is distinct from the price pressure that causes the interday momentum effect. It could therefore obscure the interday momentum effect at the close. If this conjecture holds, then the magnitude of overnight returns should decrease the interday momentum.

Hypothesis 3. *Interday cross-sectional momentum is less pronounced when overnight returns are large.*

4.5.2 Hypothesis Testing

4.5.2.1 Firm-Level Evidence

We start our hypothesis testing by investigate whether differences in the interday momentum effect at the firm level are driven by differences in firm-level market characteristics. In this setting, we test the Hypotheses 1a, 1b, and 2, which are related to the levels of the market characteristics liquidity, efficiency, size, and volatility.[17] To conduct this analysis, we use a two-stage regression approach.

In the first stage, we obtain an interday momentum coefficient for each firm in our sample by re-estimating the time-series version of model (4.3) for each firm individually:[18]

$$\tilde{r}_{i,t,LH} = \alpha_i + \beta_i^{MOM} \cdot \tilde{r}_{i,t-1,LH} + \epsilon_{i,t,LH}. \tag{4.5}$$

To be consistent with the panel models, we use excess returns defined as $\tilde{r}_{i,t,LH} = r_{i,t,LH} - \bar{r}_{m,t,LH}$, where $\bar{r}_{m,t,LH}$ is the average return in market m on day t in the last half-hour interval. The coefficient α_i then captures the average excess return, while β_i^{MOM} represents the firm-specific momentum. We estimate this model for the last half-hour returns and a one-day lag. In total, we obtain 2,076 firm-level momentum proxies.

Table 4.5 presents descriptive statistics for the estimated momentum coefficients per market. We find that the average firm-level coefficients have signs and values that are consistent with those of the panel models, confirming our previous results.[19] We find that the percentage of positive momentum coefficients ranges between 61% (Europe) and 92% (Taiwan). Moreover,

[17] We investigate hypotheses that are related to changes in market characteristics separately in the Section 4.5.2.2.

[18] For stability of the estimates, we require at least 100 observations for a firm, to be included in the sample.

[19] The closest match among the tabulated panel data models is model (4.4). Just like the firm-by-firm time-series regressions, the panel model controls for the time-fixed and firm-fixed effects. However, differences in the estimates arise primarily for two reasons: First, the panel model (4.4) additionally controls for changes in several market characteristics. Second, statistics on the firm-by-firm momentum weight each firm equally, while the panel model does not, as the constituents of an index may change over time. Finally, as a robustness check, we re-estimate model (4.5) without α_i. In this case the the mean interday momentum coefficients resemble the respective coefficients of the panel data model (4.3), tabulated in Table 4.3. The subsequent results on the role of market characteristics are robust to this change in methodology.

Market	Mean	Median	> 0	$> 0^*$	$> 0^{**}$	$> 0^{***}$	# Firms
Europe	1.71	1.09	61.27	31.86	23.53	10.29	204
Canada	4.29	4.24	77.56	44.49	31.89	13.39	254
USA	2.12	1.93	65.20	24.47	15.49	5.54	523
Australia	2.66	2.85	64.19	25.58	17.21	6.51	215
China	3.14	3.02	66.37	31.87	18.42	7.02	342
Hong Kong	5.28	4.73	79.22	38.96	24.68	10.39	77
Japan	5.35	5.33	77.83	46.09	31.74	17.39	230
Korea	6.06	5.81	82.50	51.00	39.00	21.00	200
Taiwan	8.79	7.74	92.00	56.00	40.00	30.00	50

Table 4.5. ***Firm-Level Interday Momentum****. The table reports descriptive statistics for the firm-by-firm momentum coefficients in the last half hour for the one-day lag, estimated according to model (4.5). For each market, the table shows the mean, median, and percentage of positive coefficients (> 0). The percentages of significantly positive coefficients are indicated at the 10% level ($> 0^*$), the 5% level ($> 0^{**}$), and the 1% level ($> 0^{***}$). Inference is based on heteroscedasticity and autocorrelation robust standard errors. All values are shown in percentage points. The last column shows the number of firms with estimated coefficients.*

between 24% (U.S.) and 56% (Taiwan) of the firms per market feature significantly positive momentum at the 10% level. These results indicate that the interday momentum effect is also widely present at the firm level.

In the second stage, we explore whether the estimated firm-level momentum proxies β_i^{MOM} are systematically related to firm-level market characteristics, measured as time-series averages. We estimate the following cross-sectional regression for all firms in our sample:

$$\begin{aligned}\widehat{\beta_i^{MOM}} = \alpha &+ \beta_1 \cdot Volatility_i + \beta_2 \cdot Illiqudity_i \\ &+ \beta_3 \cdot Inefficiency_i + \beta_4 \cdot Size_i + FE_m + \epsilon_i.\end{aligned} \tag{4.6}$$

Here, α is a constant capturing average momentum, while the explanatory variables represent firm-level volatility ($Volatility_i$), liquidity ($Illiqudity_i$), price efficiency ($Inefficiency_i$), and size ($Size_i$).[20] To account for market-level effects, we include a fixed effect per market FE_m. For ease of comparability, the independent variables are normalized within each market by subtracting the mean and dividing by the standard deviation.[21] The coefficients then reflect the change in momentum for a one standard deviation change in the respective variable. We estimate the model for all markets pooled together and one market at a time.

[20] $Illiquidity_i$ is the first principal component of the variables $Spread_i$, $Volume_i$, and $PriceImpact_i$. Although these variables measure different dimensions of liquidity, they are correlated. For brevity and to prevent econometric issues, we use their first principal component. However, we get similar results when we use any of the three liquidity measures instead. The firm-level variables $Spread_i$, $Volume_i$, $PriceImpact_i$, $Size_i$, and $Inefficiency_i$ are constructed per firm i by averaging $Spread_{i,t}$, $Volume_{i,t,j}$, $PriceImpact_{i,t,j}$, $Size_{i,t}$, and $Inefficiency_{i,t,j}$ over the sample period.

[21] The results remain qualitatively similar without normalization.

	Firm Momentum Coefficients									
Variables	Pooled	Europe	Canada	USA	Australia	China	Hong Kong	Japan	Korea	Taiwan
α	3.57^{***}	1.71^{***}	4.29^{***}	2.12^{***}	2.66^{***}	3.14^{***}	5.28^{***}	5.35^{***}	6.06^{***}	8.79^{***}
	(25.41)	(3.78)	(10.09)	(8.62)	(5.97)	(8.36)	(8.52)	(13.4)	(12.87)	(9.12)
$Volatility_i$	-0.47^{**}	-0.53	-1.25^{**}	0.07	0.47	-0.08	-2.18^{***}	-1.11^{*}	-1.62^{**}	-1.56
	(-3.15)	(-1.3)	(-3.05)	(0.24)	(0.86)	(-0.19)	(-3.51)	(-2.48)	(-2.72)	(-0.87)
$Illiquidity_i$	-0.00	0.68	-1.05	-0.28	-1.50	1.06	-2.31	1.59	-0.45	0.64
	(-0.02)	(1.02)	(-1.28)	(-0.42)	(-1.92)	(1.94)	(-1.63)	(1.57)	(-0.73)	(0.31)
$Inefficiency_i$	0.21	1.43^{*}	0.01	0.31	0.21	-0.70	0.83	-0.49	-1.04	-0.40
	(1.41)	(2.22)	(0.02)	(1.32)	(0.41)	(-1.29)	(1.03)	(-1.24)	(-1.83)	(-0.48)
$Size_i$	0.14	0.42	-2.13^{**}	-0.09	-0.06	1.31^{**}	-1.14	1.57	0.52	-0.32
	(0.58)	(0.49)	(-3.07)	(-0.15)	(-0.07)	(2.81)	(-0.84)	(1.56)	(0.80)	(-0.21)
FE_m	Yes	No	No	No	No	No	No	No	No	No
# Firms	2076	201	249	515	213	342	77	229	200	50
Adj. R^2	7.15	8.94	5.81	0.37	5.18	2.79	17.00	9.29	5.88	8.83

Table 4.6. ***Firm-Level Market Characteristics.*** *The table shows the estimation results for the regressions according to model (4.6). The regressions are based on momentum coefficients per firm, calculated from last half-hour interval (LH) returns according to (4.5). Firm momentum coefficients are used as dependent variables. The explanatory variables are standardized per market and currencies are converted to USD. All estimated parameters are shown in percentage points. The last rows indicate whether market-fixed effects are included, show the number of firms included in the regressions, and the adjusted R^2. Inference is based on heteroscedasticity robust standard errors. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

The results are presented in Table 4.6. The coefficients on illiquidity, inefficiency and size are almost entirely insignificant. This indicates that interday momentum is neither especially strong in the least liquid nor the most liquid stocks – meaning that neither Hypothesis 1a nor Hypothesis 1b dominates. Accordingly, the two opposing forces that we hypothesize to amplify interday momentum in less liquid stocks (capital flows from the piece-wise building or unwinding of large institutional positions) and more liquid stocks (capital flows from the persistent buying or selling from funds' management of persistent inflows and outflows) appear to offset each other, resulting in a net neutral effect. An alternative explanation lies in the composition of our sample, which consists exclusively of index constituents – stocks that tend to be large and liquid. This composition likely reduces cross-sectional variation in liquidity, efficiency, and size, thereby limiting our ability to detect strong effects along these dimensions. In contrast, the coefficient on volatility is significantly negative in the pooled regression, consistent with Hypothesis 2. This suggests that higher volatility is associated with an acceleration in the speed of capital flows, such that flows become less persistent across days and interday momentum declines. On the market level, however, the evidence is weaker, with only four out of nine markets exhibiting significantly negative coefficients. One possible explanation is that volatility is time-varying, while our two-stage approach uses time-averaged measures, potentially masking dynamic interactions between volatility and interday momentum. We explore this possibility in the next section.

To further investigate the roles of volatility and illiquidity in explaining the interday momentum effect, we re-estimate model (4.6) with several modifications. For brevity, these results are discussed below but only tabulated in the Appendix to Chapter 4 (Table 4.16).

Intraday seasonality in return volatility is well documented (e.g., Engle and Sokolska, 2012). Moreover, prior research suggests that volatility earlier in the day is more likely to reflect price discovery from information-driven trading activity, whereas volatility near the market close tends to result from uninformed price pressure (e.g., Bogousslavsky and Muravyev, 2023). To examine the sensitivity of the interday momentum effect to volatility during specific periods of the day, we successively replace the variable $Volatility_i$ – a measure of the daily close-to-close standard deviation of returns – with alternative measures that capture the standard deviation of (i) overnight plus first half-hour returns, (ii) middle half-hour returns, and (iii) last half-hour returns. All other regression variables are unchanged and we estimate a separate regression for each volatility specification.

We find that volatility in overnight and middle half-hour returns tends to reduce the strength of interday momentum, consistent with the effect observed for daily return volatility. In contrast, volatility in the last half-hour exerts a considerably weaker impact, reaching statistical significance in only two markets. These findings are consistent with Hypothesis 2, which posits that volatility from fast-moving capital flows – typically associated with information-driven trading – can weaken or obscure the effects of slow-moving capital flows, which are expected to drive interday momentum. This suggests that the capital flows underlying interday momentum are unlikely to be driven by short-term information, consistent with their lack of reliance on immediacy. Additionally, these results offer preliminary support for Hypothesis 3, which posits

that interday momentum is less pronounced when overnight returns are large. We explore this channel in greater detail in the next section.

We also examine whether the statistical insignificance of the illiquidity coefficient could be driven by multicollinearity between the variables $Illiqudity_i$ and $Size_i$, which exhibit a correlation of -0.72. All other variable correlations are weaker, ranging between 0.08 and 0.48 in absolute terms. To address this concern, we omit the variable $Size_i$ and instead sort firms within each market into groups of small and large firms based on the median market capitalization. To construct balanced pooled samples, we randomly select 50 firms from each size group per market. If fewer than 50 firms are available (Hong Kong, Taiwan), all firms in the size group are selected. This sampling method ensures that no single market disproportionately influences the pooled results. For each size group, we re-estimate model (4.6) without the variable $Size_i$. We find that the coefficient on the variable $Illiqudity_i$ remains insignificant across all small-stock groups and in nine out of ten large-stock groups. Similar results hold when additional regressors are omitted. We therefore conclude that the lack of a significant illiquidity effect on interday momentum is unlikely to be driven by multicollinearity.

To summarize, we find that interday momentum in the last half hour is inversely related to volatility, supporting Hypothesis 2. As the effect is not significant in all markets, this could be due to time-varying volatility, which cannot be captured in the two-stage regression approach. Moreover, interday momentum in our sample of blue chip index constituents – which are large and liquid stocks – is mostly independent of illiquidity, inefficiency and size, suggesting that neither Hypothesis 1a nor Hypothesis 1b dominates. Interday momentum is therefore a pervasive phenomenon, and not limited to hard-to-trade stocks.

4.5.2.2 Panel-Level Evidence

We further investigate our hypotheses in the presence of time-variability in the market characteristics, using a panel regression approach. This allows us to analyze whether interday momentum is affected by short-run changes in market characteristics. In this setting, we test the Hypotheses 2 and 3, which are related to the market characteristics volatility and overnight returns. These variables may exhibit meaningful time-variability.

We start by revisiting Hypothesis 2. A given stock may experience periods of both high and low volatility. The omission of this time-variability may be a reason for the mixed evidence on the moderating role of the level of volatility in the previous section. Therefore, we perform an additional analysis which accounts for the time-variability of volatility. To this end, we follow Moskowitz et al. (2012) and measure the variance of daily returns based on exponentially weighted squared daily returns of the previous 60 days:

$$\sigma_{i,t}^2 = \frac{1}{w} \cdot \sum_{j=1}^{60} \alpha \cdot (1-\alpha)^{j-1} \cdot r_{i,t-j}^2, \tag{4.7}$$

	Returns in the last half-hour interval (LH)									
Variables	Pooled	Europe	Canada	USA	Australia	China	Hong Kong	Japan	Korea	Taiwan
$r_{i,t-1,LH}$	5.18***	3.36	5.23***	4.45***	2.80*	5.61***	8.56***	8.32***	9.24***	16.27***
	(10.68)	(1.94)	(4.03)	(3.49)	(2.51)	(4.78)	(5.07)	(6.69)	(9.23)	(5.28)
$r_{i,t-1,LH} \cdot \sigma_{r_{i,t}}$	−72.52***	−84.60	−40.66	−102.14	−13.18	−87.22*	−116.12*	−190.61**	−146.35***	−379.59**
	(−4.05)	(−1.02)	(−0.93)	(−1.77)	(−0.37)	(−2.16)	(−2.32)	(−3.21)	(−3.87)	(−2.71)
$\sigma_{r_{i,t}}$	0.19	0.02	−0.07	−0.46	0.80	0.46	0.62	0.42	0.24	−0.87
	(1.45)	(0.07)	(−0.21)	(−1.50)	(1.81)	(1.68)	(1.16)	(1.74)	(0.63)	(−0.78)
$r_{i,t,MH_{Last}}$	−9.80***	−2.03*	−5.56***	−2.24*	−11.35***	−12.37***	−15.26***	−8.62***	−20.61***	−15.39***
	(−25.90)	(−2.23)	(−6.28)	(−2.21)	(−13.86)	(−17.59)	(−13.73)	(−10.86)	(−26.84)	(−5.31)
$FE_{t,LH}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.82	0.06	0.41	0.10	0.46	2.19	2.83	0.82	3.79	2.13

Table 4.7. ***Volatility.*** *The table shows the estimation results for the panel regressions according to model (4.8). The last half-hour returns (LH) are the dependent variable in the regressions. The second row indicates the market used in the regressions. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects are included, and the adjusted R^2 net of the explanatory power of fixed effects. Inference is based on standard errors clustered by time (t,j) and entity i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

where $r_{i,t}$ is the daily return, $w = \sum_{j=1}^{60} \alpha \cdot (1-\alpha)^{j-1}$ is the sum of the weights, $\frac{1}{w}$ is a scaling factor which assures that the scaled weights add up to one, and $\alpha = 0.03$ such that 54% of the weight is given to the most recent 20 days (one month).[22]

Based on the variance measure (4.7), we estimate the following panel regression:

$$\begin{aligned} r_{i,t,LH} =& \beta_1 \cdot r_{i,t-1,LH} + \beta_2 \cdot r_{i,t-1,LH} \cdot \sigma_{i,t} + \beta_3 \cdot \sigma_{i,t} \\ &+ \beta_4 \cdot r_{i,t,MH_{Last}} + FE_{t,LH} + FE_i + \epsilon_{i,t,LH}. \end{aligned} \tag{4.8}$$

While β_1 captures the average momentum effect as before, β_2 captures the deviation from this average that is attributable to volatility, measured by the variable $\sigma_{i,t}$. Furthermore, we control for the direct effects of volatility and the penultimate half-hour return ($r_{i,t,MH_{Last}}$) to capture short-run mean-reversion that could result from liquidity imbalances, overreactions or the bid-ask bounce. The existence of short-run mean-reversion is evident from Figure 4.2. Finally, we control for time-specific and firm-specific effects.

Table 4.7 presents the results for the regression (4.8). The coefficient on the interaction term $r_{i,t-1,LH} \cdot \sigma_{i,1}$ is negative in all markets and significantly negative in five markets (China, Hong Kong, Japan, Korea, Taiwan). This consistency in sign across markets suggests that the slightly weaker evidence in Table 4.6 is indeed likely due to unaccounted time-variation in volatility. These results support the view that higher volatility accelerates the speed of capital flows, thereby reducing the persistence of slow-moving capital that underpins interday momentum. Interday momentum therefore declines when volatility increases, in line with Hypothesis 2. Moreover, the coefficients of the variable $r_{i,t,MH_{Last}}$ are significantly negative in all markets. This reflects short-run mean-reversion of the returns in the last half hour compared to the returns in the penultimate half hour.

We next investigate Hypothesis 3. We expect that the absolute overnight returns have a negative effect on the interday momentum effect during the last half-hour interval. The greater the magnitude of the overnight return, the lower the interday momentum on that day. The rationale is that the overnight return affects the last half-hour return, potentially due to infrequent (intraday) rebalancing (Bogousslavsky, 2016) and late informed trading (Gao et al., 2018).[23] These intraday effects could obscure the interday momentum effect. To formally test this, we estimate the following model:

[22] The subsequent results are robust to other parameter choices.

[23] Absolute short-horizon returns also serve as volatility proxies (e.g., Andersen and Bollerslev, 1998). Therefore, the absolute overnight return can be viewed as an alternative to the volatility measure $\sigma_{i,t}$. However, both measures aim to capture different types of price variability, reflecting distinct economic drivers of ICSM's strength (Section 4.5.1). Absolute overnight returns aim to reflect intraday trading needs, which can introduce price pressure that masks the end-of-day effects of slow-moving capital flows. In contrast, $\sigma_{i,t}$ captures longer-term volatility over recent weeks, which we interpret as reflecting the general speed of capital flows.

$$\begin{aligned} r_{i,t,LH} =& \beta_1 \cdot r_{i,t-1,LH} + \beta_2 \cdot r_{i,t-1,LH} \cdot |r_{i,t,ONFH}| + \beta_3 \cdot |r_{i,t,ONFH}| \\ &+ \beta_4 \cdot r_{i,t,ON} + \beta_5 \cdot r_{i,t,FH} + \beta_6 \cdot r_{i,t,MH_{Last}} + FE_{t,LH} + FE_i + \epsilon_{i,t,LH}. \end{aligned} \tag{4.9}$$

While β_1 captures the average momentum effect as before, β_2 captures the deviation from this average, that is due to the absolute overnight return, measured by the variable $|r_{i,t,ONFH}|$. This variable is based on the cumulative overnight (ON) and first half-hour (FH) return. Including the first half-hour return is motivated by the rationale that it may take up to 30 minutes to fully incorporate the trading interest and information accumulated overnight. This approach also aligns with the intraday momentum literature, ensuring consistency.[24] We additionally control for the direct effects of the absolute overnight return ($|r_{i,t,ONFH}|$), the signed overnight return ($r_{i,t,ON}$), and the first half-hour return ($r_{i,t,FH}$). Moreover, we add the penultimate half-hour return ($r_{i,t,MH_{Last}}$) to capture short-run mean-reversion, as before. In addition, we control for time-specific and firm-specific effects.

Table 4.8 presents the results for model (4.9), per market and for all markets pooled together. We find that interday momentum persists in all markets, as indicated by the significantly positive coefficients of the variable $r_{i,t-1,LH}$. Consistent with our expectation, we find that the coefficient for the interaction term $r_{i,t-1,LH} \cdot |r_{i,t,ONFH}|$ is negative in all markets and significantly negative in five markets (China, Hong Kong, Japan, Korea, Taiwan). The results support Hypothesis 3, suggesting that the interday momentum effect is less pronounced when the absolute overnight returns are large. Furthermore, the significantly positive coefficients of the variables $r_{i,t,ON}$ and $r_{i,t,FH}$ provide evidence of intraday momentum with respect to the overnight return (China and Hong Kong) and the first half-hour returns (Australia, Japan, Korea, and Taiwan). In Europe and Canada, there is no significant intraday momentum. In the U.S., the last half-hour return is negatively affected by the overnight return and the first half-hour return. Although the U.S. evidence does not support the theories of late informed trading and infrequent rebalancing, it is consistent with the empirical findings of Komarov (2017). Finally, the coefficients of the variable $r_{i,t,MH_{Last}}$ are again significantly negative in all markets.

Overall, we find that increases in volatility and larger absolute overnight returns lead to a decline in interday momentum during the last half-hour of trading. This effect is statistically significant in five Asian markets (China, Hong Kong, Japan, Korea, Taiwan) and confirms the Hypotheses 2 and 3. The return in the last half-hour interval is moreover affected by intraday momentum related to overnight (China, Hong Kong) and early trading returns (Australia, Japan, Korea, Taiwan), although the U.S. shows a contrary pattern. Additionally, there is consistent evidence of short-run mean-reversion between the penultimate and the last half-hour return across all markets. We conclude that interday momentum, intraday momentum, and short-run mean-reversion are distinct features of last half-hour returns.

[24] We get qualitatively similar results when we exclude the first half-hour return.

	Returns in the last half-hour interval (LH)									
Variables	Pooled	Europe	Canada	USA	Australia	China	Hong Kong	Japan	Korea	Taiwan
$r_{i,t-1,LH}$	4.55^{***}	2.93^{***}	4.86^{***}	2.80^{***}	3.89^{***}	4.61^{***}	7.39^{***}	5.99^{***}	7.12^{***}	10.99^{***}
	(14.02)	(3.58)	(6.08)	(3.33)	(4.59)	(7.54)	(6.75)	(7.95)	(9.75)	(7.12)
$r_{i,t-1,LH} \cdot \lvert r_{i,t,ONFH} \rvert$	-78.75^{***}	-111.03	-55.81	-62.43	-61.50	-85.46^{***}	-128.95^{**}	-116.32^{**}	-92.53^{*}	-198.93^{*}
	(-4.44)	(-1.49)	(-1.33)	(-1.29)	(-1.37)	(-3.37)	(-2.59)	(-2.66)	(-2.43)	(-2.54)
$\lvert r_{i,t,ONFH} \rvert$	-0.06	-0.01	-0.15	-0.22	-0.07	-0.11	0.30	-0.37^{*}	0.05	0.77
	(-0.71)	(-0.04)	(-0.54)	(-0.97)	(-0.20)	(-0.70)	(0.92)	(-2.29)	(0.25)	(1.69)
$r_{i,t,ON}$	0.10	-0.27	-0.22	-0.70^{*}	0.62	0.73^{**}	1.40^{**}	0.40	0.11	-0.31
	(0.71)	(-0.63)	(-0.53)	(-2.09)	(1.59)	(2.90)	(2.75)	(1.92)	(0.37)	(-0.49)
$r_{i,t,FH}$	0.04	0.17	-0.16	-0.58^{*}	0.76^{*}	-0.04	-0.27	0.51^{**}	0.72^{***}	1.57^{**}
	(0.43)	(0.48)	(-0.60)	(-2.20)	(2.12)	(-0.26)	(-0.94)	(2.60)	(3.55)	(3.23)
$r_{i,t,MH_{Last}}$	-10.01^{***}	-2.10^{*}	-5.54^{***}	-2.27^{*}	-12.82^{***}	-12.37^{***}	-15.25^{***}	-8.61^{***}	-20.68^{***}	-15.38^{***}
	(-26.02)	(-2.32)	(-6.25)	(-2.25)	(-12.50)	(-17.79)	(-13.75)	(-10.93)	(-27.00)	(-5.22)
$FE_{t,LH}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.85	0.09	0.42	0.15	0.61	2.21	3.02	0.87	3.83	2.17

Table 4.8. ***Overnight Returns.*** *The table shows the estimation results for the panel regressions according to model (4.9). The last half-hour returns (LH) are the dependent variable in the regressions. The second row indicates the market used in the regressions. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects are included, and the adjusted R^2 net of the explanatory power of fixed effects. Inference is based on standard errors clustered by time (t,j) and entity i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

4.6 Economic Significance

In this section, we determine the economic significance of trading strategies that exploit the intraday return patterns at the end of the trading day. Building on the previous analysis, we expect that portfolios based on past winners in the last half-hour interval continue to have higher returns in the last half-hour interval than portfolios based on past losers. To provide intuition for this rationale, we create ten equal-sized portfolios by sorting stocks according to their returns during the last half-hour interval on the previous day in ascending order. For these ten portfolios, equal-weighted returns are calculated during the last half-hour interval today. The average decile portfolio returns for the nine markets are shown in Figure 4.3. We observe that decile portfolio returns tend to increase approximately linear with past returns in all markets.

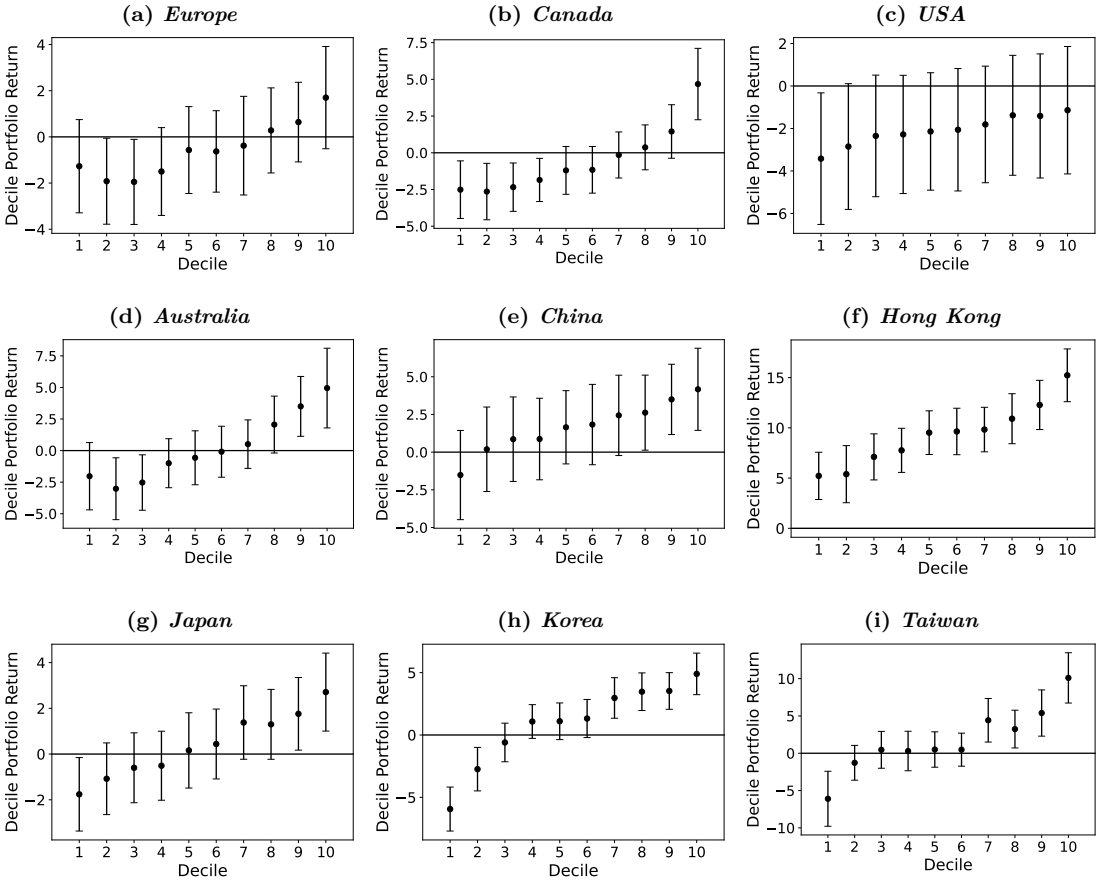

Figure 4.3. ***Average Decile Portfolio Returns in the Last Half-Hour Interval.*** *Ten equal-sized portfolios are formed by sorting stocks according to their returns during the last half-hour interval on the previous day in ascending order (formation period). For these ten portfolios, equal-weighted returns are calculated during the last half-hour interval today (holding period). Per panel, the average decile portfolio returns (in basis points) of a given market are represented by dots. The whiskers span 95% confidence intervals. Inference is robust to heteroscedasticity and autocorrelation. The sample period is August 2021 to May 2023.*

In the spirit of Jegadeesh and Titman (1993), we now analyze the returns of long-short portfolios based on past winners and losers. As our baseline strategy, we form portfolios of winners (losers)

based on stocks with the 10% highest (lowest) returns, in the last half-hour interval on the previous day. These portfolios are held in the last half-hour interval today. We then calculate equal-weighted returns for each portfolio and subtract the average return of the losers (short) from that of the winners (long). These returns do not account for any transaction costs yet. We therefore investigate, whether the returns suffice to cover the bid-ask spread quoted at the end of the day. To this end, we calculate the average percentage proportion of the spread that is earned by the long-short portfolio. We thereby assume that each each leg of the portfolio has to pay the quoted spread in order to create and close it. This is a rather conservative assumption, as trades often happen inside of the spread. Our results thus provide a lower bound for the profitability.

Table 4.9 reports descriptive statistics for the long-short portfolio returns in Panel A.[25] Consistent with our previous results, the long-short portfolios provide significantly positive returns in all markets. The returns in the last half hour range from 2.28 basis points (U.S.) to 16.20 basis points (Taiwan).[26] They are positive on more than 50% of the days. The baseline strategy, however, earns, on average across all markets, only 20% of the quoted spread. On the market level, the percentage of the quoted spread earned ranges between 9.44% (Japan) to 38.32% (China), with the exceptions of very low profitability in Australia (1.84%) and Canada (4.09%). As a consequence, the pattern cannot be exploited if an investor pays the liquidity premium and has no other motives to trade. This is consistent with previous results for the U.S. (Heston et al., 2010). However, if an investor has other motives to trade, the strategic timing of trades allows for a significant reduction in transaction costs.

The results in Section 4.5 show that interday momentum in a stock tends to be more pronounced when its overnight return was low, and that its return in the last half hour is inversely related to the return in the penultimate half hour. We incorporate these insights into the baseline strategy by applying two threshold filters to the daily stock universe: (i) The absolute overnight return must be less than 2%, and (ii) the penultimate half-hour return must be negative (positive) for stocks in the long (short) portfolio.[27] To prevent over-fitting, we make no attempt to optimize these thresholds.

Table 4.9 reports the results for the threshold strategy in Panel B. The filters tend to increase the strategy's return to 38% of the quoted spread, on average across all markets. On the market level, the percentage of the quoted spread earned ranges between 15.96% (Japan) to 99.21% (China), while the exceptions of rather low profitability in Australia (4.61%) and Canada (3.87%) persist. Although the threshold strategy remains unable to produce profits net of the bid-ask spread, the potential savings in transaction costs for investors who time their trades are substantially increased.

[25] Please note that the $T + 1$ rule would prevent an implementation of the suggested strategy in China. For completeness, we nonetheless present the results for all markets.

[26] These returns are for holding the portfolios for 30 minutes. By multiplying them with a factor of 250, they can be translated into annualized returns.

[27] The 2% absolute overnight return threshold corresponds to quantiles ranging between 88% (Australia) and 96% (China).

	Decile Portfolio Spread Return [BP]							Quoted Spread
Market	Mean	Std.	1%	25%	50%	75%	99%	Earned [%]
Panel A: Baseline Strategy								
Europe	2.97**	18.10	−37.45	−8.34	2.65	15.02	46.08	10.78
Canada	7.19***	19.04	−38.48	−5.92	7.33	19.67	53.63	4.09
USA	2.28**	16.04	−30.18	−7.80	1.77	10.77	50.80	29.75
Australia	6.98***	30.74	−67.03	−11.57	5.11	24.47	82.77	1.84
China	5.69***	14.95	−32.30	−2.69	6.20	13.95	46.26	38.32
Hong Kong	10.02***	25.45	−52,69	−7,82	9,94	25,37	77,14	30.79
Japan	4.46***	9.82	−19.36	−1.84	4.54	10.36	28.20	9.44
Korea	10.84***	17.45	−25.63	−0.08	9.88	20.60	61.35	22.81
Taiwan	16.20***	43.48	−81.01	−8.73	13.85	34.86	159.66	32.95
Panel B: Threshold Strategy								
Europe	3.49**	22.47	−42.41	−8.10	1.93	14.75	51.98	16.46
Canada	5.97***	20.06	−37.88	−6.48	5.44	16.26	57.63	3.87
USA	2.95***	17.18	−47.10	−5.20	2.25	11.48	46.39	47.40
Australia	13.94***	38.97	−62.38	−1.80	12.03	28.86	151.26	4.61
China	13.86***	18.92	−37.47	2.34	13.84	22.84	66.13	99.21
Hong Kong	16.48***	29.67	−53.29	0.71	15.79	32.80	87.09	53.98
Japan	6.47***	12.66	−24.55	0.05	6.95	13.73	37.51	15.96
Korea	23.60***	23.05	−38.44	10.83	22.73	36.11	84.44	54.23
Taiwan	21.92***	47.69	−82.94	−1.10	19.22	44.85	176.28	48.13

Table 4.9. ***Decile Portfolio Spread Returns.*** *The table shows descriptive statistics for the average decile portfolio spread return per market. The holding period is the last half-hour interval (LH). The formation period is the last half-hour interval on the previous day. In Panel A, the portfolios are formed of winners (losers), that had the 10% highest (lowest) returns during the formation period. For these portfolios, equal-weighted returns are calculated. Subsequently, the average return of the losers (short) is subtracted from the average return of the winners (long). In Panel B, the stock universe is filtered as follows before creating the daily spread portfolios: (i) the absolute overnight return must be less than 2%, and (ii) the penultimate half-hour return must be negative (positive) for stocks in the long (short) portfolio. For each strategy, the decile portfolio spread return (Mean) is reported in basis points per half hour. Furthermore, the standard deviation (Std.), quantiles of the return distribution, and the percentage proportion of the quoted spread that is earned on average by the decile spread portfolio (Quoted Spread Earned) are shown. Significant returns are indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). Inference is robust to heteroscedasticity and autocorrelation. The sample period is August 2021 to May 2023.*

Overall, the trading strategies based on long-short portfolios yield positive returns in all sample markets. These returns, however, do not cover the whole bid-ask spread, on average. This has important implications. On the one hand, the effect is small enough to create a limit to arbitrage that could be a reason why the pattern is so persistent (Gromb and Vayanos, 2010). On the other hand, the effect is large enough that the strategic timing of trades allows investors to save transaction costs of economically significant size. This is applicable for institutional as well as retail investors and across international markets.

4.7 Conclusion

Interday cross-sectional momentum (ICSM) has not yet been analyzed extensively across markets and time periods, making it difficult to assess its prevalence (Heston et al., 2010, 2011; Murphy and Thirumalai, 2017). We therefore examine nine international stock markets to provide new evidence on its prevalence and determinants of its strength.

We show that ICSM is present in all our sample markets and that it is most pronounced during the last half hour of a trading day. In the previously studied U.S market (Heston et al., 2010), ICSM has become weaker. This suggests that markets have become more efficient over time, although investors across markets are still subject to frictions, causing them to move capital slowly.

Furthermore, we examine determinants of the strength of ICSM in the last half hour by proposing and testing four hypotheses related to firm-level market characteristics and trading motives derived from the literature. We find that ICSM is stronger when volatility is low, and absolute overnight returns are small, while liquidity has no significant effect. Moreover, we show that interday momentum, intraday momentum, and short-run mean-reversion are distinct features of last half-hour returns. This enhances the understanding of intraday return patterns.

Finally, we show that long-short portfolio strategies that aim to exploit ICSM produce significantly positive returns in the absence of transaction costs. Although the returns do not cover the full bid-ask spread, the strategic timing of trades based on ICSM can save investors an economically significant amount of transaction costs.

Appendix to Chapter 4

	Returns														
	First half-hour interval (FH)					Middle half-hour intervals (MH)					Last half-hour interval (LH)				
Market	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Europe	1.50	2.26*	1.14	3.28***	1.16	0.24	0.29	0.17	0.35	−0.51*	1.99*	2.74***	2.16**	2.38***	1.03
	(1.30)	(2.26)	(1.14)	(4.09)	(1.21)	(0.90)	(1.12)	(0.66)	(1.42)	(−1.98)	(2.39)	(4.20)	(2.96)	(3.55)	(1.43)
Canada	−1.14	1.20	0.23	0.77	0.65	0.56	−0.14	0.29	0.43	0.51	5.03***	3.41***	2.02**	3.19***	2.83***
	(−1.11)	(1.35)	(0.23)	(0.82)	(0.66)	(1.58)	(−0.42)	(0.84)	(1.22)	(1.55)	(7.15)	(3.97)	(3.10)	(4.27)	(3.70)
USA	2.05	0.96	−1.36	0.60	−1.98*	0.56	−0.30	0.07	0.31	0.16	1.84*	1.99*	1.01	1.63	0.58
	(1.89)	(1.00)	(−1.56)	(0.63)	(−2.06)	(1.15)	(−0.74)	(0.14)	(0.75)	(0.46)	(1.98)	(2.50)	(1.31)	(1.81)	(0.88)
Australia	1.29	1.93**	0.58	1.61*	1.87**	1.00***	1.02***	0.45	0.18	0.54*	3.12***	1.76*	2.74***	2.39***	2.01**
	(1.65)	(2.93)	(0.75)	(2.53)	(3.06)	(4.22)	(4.13)	(1.83)	(0.67)	(2.13)	(5.14)	(2.53)	(4.04)	(3.49)	(3.03)
China	−0.41	−1.22	−1.88*	−0.46	0.56	−1.40***	0.30	0.14	0.47	−0.09	3.43***	2.97***	2.39***	2.55***	1.93***
	(−0.45)	(−1.40)	(−2.18)	(−0.53)	(0.64)	(−3.72)	(0.80)	(0.35)	(1.29)	(−0.26)	(5.27)	(5.83)	(4.94)	(4.68)	(3.91)
Hong Kong	1.93	1.35	2.04	1.25	0.27	−0.46	0.87	−0.23	0.40	−0.26	6.78***	5.84***	6.71***	6.97***	4.33***
	(1.56)	(1.19)	(1.35)	(0.97)	(0.26)	(−0.81)	(1.56)	(−0.48)	(0.77)	(−0.57)	(5.53)	(5.29)	(6.50)	(6.21)	(4.54)
Japan	−1.66	−0.23	0.41	−0.21	0.30	0.28	−0.17	−0.34	−0.31	−0.10	4.67***	4.14***	3.71***	3.31***	1.85***
	(−1.56)	(−0.27)	(0.50)	(−0.33)	(0.39)	(0.92)	(−0.61)	(−0.79)	(−1.09)	(−0.38)	(6.59)	(8.00)	(6.69)	(7.21)	(3.75)
Korea	−2.01**	−0.19	1.91*	0.41	0.81	0.49*	0.65**	0.52**	0.40*	0.13	6.22***	6.33***	5.70***	6.17***	4.94***
	(−2.60)	(−0.28)	(2.48)	(0.60)	(1.13)	(2.50)	(3.06)	(2.96)	(2.20)	(0.65)	(8.73)	(8.12)	(6.63)	(10.92)	(9.67)
Taiwan	−0.83	−0.64	−0.20	0.52	−0.16	1.57***	1.24*	0.93	0.58	1.15**	9.35***	5.19**	5.08***	3.53**	3.71***
	(−0.61)	(−0.56)	(−0.19)	(0.57)	(−0.18)	(3.39)	(2.27)	(1.87)	(1.22)	(3.20)	(6.59)	(2.70)	(3.34)	(2.80)	(3.71)
$FE_{t,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE_i	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta \log Volume_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Volatility_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta PriceImpact_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Inefficiency_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table 4.10. ***Panel Regression: Raw Returns, Official Opening and Closing Prices*** *The table shows the estimation results for the panel regressions according to model (4.3). Each cell represents a separate regression. The second row indicates whether the dependent variable in the regressions is from the first half-hour interval (FH), the middle half-hour intervals (MH), or the last half-hour interval (LH). The third row indicates the lag k for explanatory variables. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects and controls are included. Inference is based on standard errors clustered by time (t,j) and entity i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

	Returns														
	First half-hour interval (FH)					Middle half-hour intervals (MH)					Last half-hour interval (LH)				
Market	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Europe	2.55^{**}	2.48^{***}	1.97^{**}	2.39^{***}	2.03^{**}	0.37	0.24	0.18	0.46^{*}	−0.23	2.88^{***}	3.23^{***}	2.04^{***}	2.68^{***}	1.46^{**}
	(3.21)	(3.46)	(2.89)	(3.72)	(2.82)	(1.85)	(1.20)	(0.95)	(2.38)	(−1.24)	(4.40)	(5.29)	(3.51)	(4.52)	(2.67)
Canada	−0.26	1.31	1.13	0.78	1.36	0.31	−0.04	0.14	0.33	0.39	5.14^{***}	3.86^{***}	2.30^{***}	2.81^{***}	2.64^{***}
	(−0.34)	(1.55)	(1.57)	(1.00)	(1.55)	(1.24)	(−0.14)	(0.56)	(1.30)	(1.59)	(8.47)	(5.35)	(3.62)	(4.98)	(3.81)
USA	2.46^{*}	1.08	−1.24	0.49	−0.96	0.46	−0.04	−0.03	0.51^{*}	0.06	2.00^{**}	1.92^{***}	0.76	1.43^{*}	0.71
	(2.51)	(1.17)	(−1.47)	(0.60)	(−1.04)	(1.94)	(−0.14)	(−0.13)	(2.06)	(0.27)	(2.83)	(3.72)	(1.30)	(2.37)	(1.13)
Australia	1.07	1.94^{**}	0.49	1.60^{**}	2.10^{**}	0.39	0.56	0.27	0.31	0.67	4.08^{***}	2.44^{***}	3.73^{***}	2.41^{***}	2.84^{***}
	(1.69)	(3.26)	(0.79)	(2.71)	(3.25)	(1.20)	(1.59)	(0.87)	(0.94)	(1.51)	(5.27)	(3.46)	(5.03)	(3.92)	(4.20)
China	−0.43	-1.56^{*}	-1.67^{*}	−0.53	0.50	-0.81^{**}	0.03	0.15	0.33	0.06	4.16^{***}	3.69^{***}	2.79^{***}	2.50^{***}	1.94^{***}
	(−0.47)	(−2.17)	(−2.19)	(−0.60)	(0.59)	(−2.71)	(0.09)	(0.50)	(1.26)	(0.22)	(8.78)	(9.43)	(6.24)	(5.01)	(3.84)
Hong Kong	1.80	2.24^{*}	0.84	1.21	0.90	0.42	0.84^{*}	0.22	0.40	0.40	8.22^{***}	7.74^{***}	6.98^{***}	7.55^{***}	5.63^{***}
	(1.60)	(2.07)	(0.76)	(1.03)	(0.85)	(1.28)	(2.43)	(0.64)	(1.20)	(1.15)	(10.44)	(9.93)	(8.30)	(8.42)	(7.32)
Japan	−1.05	0.15	0.31	−0.27	0.41	0.57^{*}	−0.39	0.22	−0.05	−0.20	5.64^{***}	4.65^{***}	4.26^{***}	3.66^{***}	2.14^{***}
	(−1.40)	(0.20)	(0.43)	(−0.41)	(0.58)	(2.44)	(−1.67)	(0.99)	(−0.25)	(−0.90)	(11.00)	(9.43)	(9.63)	(7.60)	(4.60)
Korea	-2.22^{**}	0.16	1.46^{*}	0.24	0.83	0.37^{*}	0.60^{***}	0.62^{***}	0.30^{*}	0.23	7.30^{***}	7.41^{***}	6.90^{***}	6.70^{***}	5.72^{***}
	(−3.13)	(0.25)	(2.10)	(0.43)	(1.23)	(2.34)	(3.69)	(4.15)	(1.97)	(1.53)	(15.37)	(12.78)	(10.22)	(12.73)	(12.06)
Taiwan	−0.58	−0.47	−0.56	0.64	0.09	1.58^{***}	0.87	1.35^{***}	0.95^{*}	1.25^{**}	10.34^{***}	6.15^{***}	6.80^{***}	4.75^{***}	4.94^{***}
	(−0.52)	(−0.52)	(−0.65)	(0.59)	(0.09)	(3.62)	(1.96)	(3.39)	(2.47)	(2.96)	(9.08)	(5.75)	(6.11)	(5.00)	(4.28)
$FE_{t,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta \log Volume_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Volatility_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta PriceImpact_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Inefficiency_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table 4.11. ***Fama-MacBeth Regression: Raw Returns, Official Opening and Closing Prices.*** *The table shows the estimation results for the Fama-MacBeth version of the model (4.3). Each cell represents a separate regression. The second row indicates whether the dependent variable in the regressions is from the first half-hour interval (FH), the middle half-hour intervals (MH), or the last half-hour interval (LH). The third row indicates the lag k for explanatory variables. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects and controls are included. Inference is based on robust standard errors. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

	Returns														
	First half-hour interval (FH)					Middle half-hour intervals (MH)					Last half-hour interval (LH)				
Market	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Europe	2.85^{***}	2.51^{***}	2.18^{***}	2.61^{***}	2.22^{**}	0.48^{*}	0.32	0.28	0.42^{*}	−0.12	3.10^{***}	3.39^{***}	2.17^{***}	3.00^{***}	1.72^{**}
	(3.72)	(3.55)	(3.30)	(4.02)	(3.12)	(2.49)	(1.70)	(1.53)	(2.25)	(−0.64)	(5.25)	(6.06)	(4.05)	(5.32)	(3.27)
Canada	0.22	1.23	1.09	0.83	1.17	0.36	0.04	0.15	0.28	0.34	5.17^{***}	4.16^{***}	2.14^{***}	2.88^{***}	2.88^{***}
	(0.28)	(1.47)	(1.47)	(1.05)	(1.42)	(1.52)	(0.16)	(0.64)	(1.17)	(1.45)	(9.16)	(6.10)	(3.43)	(5.48)	(4.32)
USA	2.40^{*}	1.29	−1.39	0.67	−0.46	0.47^{*}	0.23	−0.07	0.59^{**}	0.04	2.25^{***}	1.98^{***}	0.84	1.39^{*}	0.92
	(2.44)	(1.37)	(−1.65)	(0.84)	(−0.50)	(2.23)	(1.02)	(−0.31)	(2.67)	(0.19)	(3.39)	(4.11)	(1.58)	(2.48)	(1.57)
Australia	1.14^{*}	1.87^{***}	0.42	1.78^{***}	2.46^{***}	0.35	0.61^{*}	0.11	0.41	0.46	4.58^{***}	2.58^{***}	3.86^{***}	2.44^{***}	3.16^{***}
	(2.10)	(3.30)	(0.76)	(3.53)	(3.90)	(1.20)	(1.99)	(0.43)	(1.33)	(1.47)	(6.76)	(4.36)	(6.58)	(5.02)	(5.41)
China	−0.60	-1.46^{*}	-1.72^{*}	−0.57	0.32	-0.88^{**}	0.04	0.12	0.47	0.01	4.30^{***}	3.68^{***}	2.77^{***}	2.69^{***}	2.35^{***}
	(−0.64)	(−2.02)	(−2.23)	(−0.64)	(0.38)	(−3.14)	(0.16)	(0.45)	(1.88)	(0.03)	(9.91)	(10.64)	(6.94)	(6.20)	(5.55)
Hong Kong	1.72	1.94	0.41	1.26	0.82	0.60^{*}	0.83^{**}	0.23	0.53	0.49	8.49^{***}	7.74^{***}	7.17^{***}	7.58^{***}	5.76^{***}
	(1.61)	(1.90)	(0.42)	(1.25)	(0.80)	(1.98)	(2.60)	(0.72)	(1.74)	(1.54)	(11.58)	(11.06)	(8.83)	(8.81)	(7.76)
Japan	−0.77	−0.08	0.74	−0.29	0.38	0.46^{*}	−0.25	0.26	0.02	−0.17	5.83^{***}	4.98^{***}	4.33^{***}	3.72^{***}	2.24^{***}
	(−1.11)	(−0.11)	(1.09)	(−0.45)	(0.59)	(2.14)	(−1.16)	(1.24)	(0.11)	(−0.80)	(11.98)	(10.07)	(10.71)	(8.29)	(4.98)
Korea	-2.11^{**}	−0.11	1.87^{**}	0.44	1.08	0.49^{***}	0.66^{***}	0.62^{***}	0.44^{**}	0.29^{*}	7.87^{***}	8.13^{***}	7.44^{***}	6.72^{***}	6.15^{***}
	(−3.21)	(−0.18)	(2.77)	(0.77)	(1.66)	(3.39)	(4.46)	(4.64)	(3.21)	(2.13)	(17.36)	(22.65)	(16.32)	(15.53)	(14.79)
Taiwan	−0.74	−0.56	−0.20	0.73	0.05	1.71^{***}	1.07^{**}	1.38^{***}	0.94^{**}	1.25^{**}	10.00^{***}	6.78^{***}	6.78^{***}	4.45^{***}	5.33^{***}
	(−0.69)	(−0.67)	(−0.24)	(0.72)	(0.05)	(4.34)	(2.66)	(3.81)	(2.76)	(3.25)	(9.27)	(7.21)	(6.56)	(5.07)	(4.97)
$FE_{t,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta \log Volume_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Volatility_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta PriceImpact_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Inefficiency_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table 4.12. ***Fama-MacBeth Regression: Winsorized Returns, Official Opening and Closing Prices.*** *The table shows the estimation results for the Fama-MacBeth version of the model (4.3). Each cell represents a separate regression. The second row indicates whether the dependent variable in the regressions is from the first half-hour interval (FH), the middle half-hour intervals (MH), or the last half-hour interval (LH). The third row indicates the lag k for explanatory variables. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects and controls are included. Inference is based on robust standard errors. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

	Returns														
	First half-hour interval (FH)					Middle half-hour intervals (MH)					Last half-hour interval (LH)				
Market	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Europe	1.50	2.27*	1.18	3.25***	1.15	0.24	0.29	0.17	0.35	−0.51*	−1.07	0.44	0.05	0.60	−0.30
	(1.31)	(2.30)	(1.20)	(4.09)	(1.21)	(0.90)	(1.12)	(0.66)	(1.42)	(−1.98)	(−1.34)	(0.60)	(0.07)	(0.83)	(−0.41)
Canada	−1.14	1.20	0.23	0.77	0.65	0.56	−0.14	0.29	0.43	0.51	4.01***	2.56**	1.75*	2.45***	2.30**
	(−1.11)	(1.35)	(0.23)	(0.82)	(0.65)	(1.58)	(−0.42)	(0.84)	(1.22)	(1.55)	(5.54)	(3.06)	(2.43)	(3.45)	(2.97)
USA	1.97	0.87	−1.34	0.58	−1.91*	0.56	−0.30	0.07	0.31	0.16	1.72	1.91*	0.93	1.59	0.51
	(1.88)	(0.95)	(−1.59)	(0.64)	(−2.05)	(1.15)	(−0.74)	(0.14)	(0.75)	(0.46)	(1.87)	(2.42)	(1.19)	(1.79)	(0.76)
Australia	1.15	1.98**	0.73	1.71*	2.20***	1.00***	1.02***	0.45	0.18	0.54*	2.54**	−0.84	0.71	−0.98	0.75
	(1.44)	(2.90)	(1.08)	(2.49)	(3.48)	(4.22)	(4.13)	(1.83)	(0.67)	(2.13)	(2.86)	(−0.93)	(0.76)	(−1.08)	(0.63)
China	−0.44	−1.30	−1.93*	−0.37	0.55	−1.40***	0.30	0.14	0.47	−0.09	3.00***	2.49***	1.86***	2.20***	1.69***
	(−0.48)	(−1.46)	(−2.23)	(−0.41)	(0.62)	(−3.72)	(0.80)	(0.35)	(1.29)	(−0.26)	(4.77)	(5.13)	(3.80)	(4.04)	(3.42)
Hong Kong	1.15	1.12	1.96	1.28	−0.04	−0.46	0.87	−0.23	0.40	−0.26	1.56	2.03*	2.82***	4.39***	2.16**
	(0.90)	(0.96)	(1.26)	(0.94)	(−0.03)	(−0.81)	(1.56)	(−0.48)	(0.77)	(−0.57)	(1.57)	(2.18)	(3.88)	(4.89)	(2.86)
Japan	−1.66	−0.23	0.41	−0.21	0.30	0.28	−0.17	−0.34	−0.31	−0.10	4.56***	4.30***	3.84***	3.16***	1.49**
	(−1.56)	(−0.27)	(0.50)	(−0.33)	(0.39)	(0.92)	(−0.61)	(−0.79)	(−1.09)	(−0.38)	(5.75)	(8.02)	(6.73)	(6.40)	(2.94)
Korea	−2.30**	−0.50	1.72*	0.33	0.72	0.49*	0.65**	0.52**	0.40*	0.13	4.61***	4.44***	4.03***	3.78***	3.22***
	(−2.95)	(−0.68)	(2.18)	(0.47)	(0.98)	(2.50)	(3.06)	(2.96)	(2.20)	(0.65)	(6.43)	(7.84)	(4.92)	(7.00)	(5.86)
Taiwan	−0.83	−0.64	−0.20	0.52	−0.16	1.57***	1.24*	0.93	0.58	1.15**	5.38***	1.12	2.25	0.90	1.65
	(−0.61)	(−0.56)	(−0.19)	(0.57)	(−0.18)	(3.39)	(2.27)	(1.87)	(1.22)	(3.20)	(5.28)	(0.65)	(1.27)	(0.71)	(1.55)
$FE_{t,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE_i	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta \log Volume_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Volatility_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta PriceImpact_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Inefficiency_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table 4.13. ***Panel Regression: Raw Returns, Continuous Trading.*** *The table shows the estimation results for the panel regressions according to model (4.3). Each cell represents a separate regression. The second row indicates whether the dependent variable in the regressions is from the first half-hour interval (FH), the middle half-hour intervals (MH), or the last half-hour interval (LH). The third row indicates the lag k for explanatory variables. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects and controls are included. Inference is based on standard errors clustered by time (t,j) and entity i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

	Returns														
	First half-hour interval (FH)					Middle half-hour intervals (MH)					Last half-hour interval (LH)				
Market	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Europe	2.25^{*}	2.53^{**}	1.55	3.46^{***}	1.47	0.36	0.36	0.34	0.41	−0.21	−0.44	0.67	−0.36	0.69	0.13
	(2.19)	(2.65)	(1.56)	(4.21)	(1.57)	(1.33)	(1.44)	(1.37)	(1.69)	(−0.84)	(−0.54)	(0.94)	(−0.48)	(1.01)	(0.18)
Canada	−0.64	1.24	0.28	1.02	0.42	0.65	0.12	0.34	0.43	0.59	4.08^{***}	3.11^{***}	1.62^{*}	2.54^{***}	2.75^{***}
	(−0.64)	(1.37)	(0.27)	(1.05)	(0.42)	(1.86)	(0.38)	(1.01)	(1.27)	(1.78)	(5.70)	(3.98)	(2.52)	(3.65)	(3.66)
USA	2.24^{*}	1.05	−1.44	0.75	−1.54	0.85^{*}	0.20	−0.20	0.67^{*}	0.41	2.43^{***}	1.85^{**}	0.67	1.27^{*}	0.73
	(2.05)	(1.08)	(−1.61)	(0.78)	(−1.59)	(2.49)	(0.60)	(−0.61)	(2.01)	(1.24)	(3.37)	(2.96)	(0.93)	(1.97)	(1.13)
Australia	1.04	2.06^{**}	0.81	1.71^{**}	2.53^{***}	0.98^{***}	1.02^{***}	0.38	0.32	0.52^{*}	2.28^{**}	0.13	1.27	−0.36	1.52
	(1.49)	(3.20)	(1.35)	(2.90)	(4.05)	(4.60)	(4.57)	(1.66)	(1.57)	(2.24)	(2.88)	(0.19)	(1.91)	(−0.50)	(1.73)
China	−0.81	−1.20	-1.97^{*}	−0.42	0.44	-1.36^{***}	0.30	0.15	0.55	−0.06	3.62^{***}	2.79^{***}	2.14^{***}	2.12^{***}	2.22^{***}
	(−0.86)	(−1.34)	(−2.26)	(−0.48)	(0.50)	(−3.60)	(0.81)	(0.40)	(1.50)	(−0.18)	(6.76)	(6.43)	(4.89)	(4.51)	(4.78)
Hong Kong	0.73	1.04	0.67	1.27	0.23	−0.01	0.99^{*}	−0.08	0.60	0.13	1.91^{*}	2.21^{**}	3.00^{***}	4.25^{***}	2.71^{***}
	(0.60)	(0.98)	(0.61)	(1.00)	(0.21)	(−0.01)	(2.01)	(−0.18)	(1.22)	(0.28)	(2.30)	(2.62)	(4.22)	(5.64)	(3.75)
Japan	−0.89	−0.55	0.76	−0.10	0.20	0.36	−0.15	0.12	−0.13	−0.06	5.61^{***}	4.94^{***}	4.07^{***}	3.45^{***}	1.89^{***}
	(−1.11)	(−0.75)	(1.00)	(−0.16)	(0.28)	(1.31)	(−0.53)	(0.44)	(−0.49)	(−0.23)	(9.86)	(9.31)	(7.49)	(7.23)	(4.15)
Korea	-2.23^{**}	−0.75	2.06^{**}	0.53	1.04	0.60^{**}	0.70^{***}	0.59^{***}	0.47^{**}	0.23	5.63^{***}	4.94^{***}	4.88^{***}	4.08^{***}	3.72^{***}
	(−2.91)	(−1.00)	(2.72)	(0.74)	(1.47)	(3.06)	(3.71)	(3.36)	(2.74)	(1.18)	(9.41)	(9.74)	(9.00)	(8.80)	(8.02)
Taiwan	−1.03	−0.83	0.00	0.58	0.03	1.86^{***}	1.42^{**}	1.16^{*}	0.81	1.39^{***}	4.25^{***}	2.65^{*}	2.96^{*}	0.68	1.38
	(−0.77)	(−0.70)	(0.00)	(0.62)	(0.03)	(4.12)	(2.66)	(2.36)	(1.83)	(3.86)	(4.54)	(1.99)	(2.52)	(0.63)	(1.40)
$FE_{t,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE_i	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta \log Volume_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Volatility_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta PriceImpact_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
$\Delta Inefficiency_{i,t-k,j}$	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table 4.14. ***Panel Regression: Winsorized Returns, Continuous Trading.*** *The table shows the estimation results for the panel regressions according to model (4.3). Each cell represents a separate regression. The second row indicates whether the dependent variable in the regressions is from the first half-hour interval (FH), the middle half-hour intervals (MH), or the last half-hour interval (LH). The third row indicates the lag k for explanatory variables. All estimated parameters are shown in percentage points. The last rows indicate which fixed effects and controls are included. Inference is based on standard errors clustered by time (t,j) and entity i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample period is August 2021 to May 2023.*

	Average Decile Portfolio Spread Returns														
	First half-hour interval (FH)					Middle half-hour intervals (MH)					Last half-hour interval (LH)				
Market	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days	1 Day	2 Days	3 Days	4 Days	5 Days
Europe	8.14^{**}	5.17^{*}	4.64^{*}	9.19^{***}	6.48^{**}	0.35	0.21	0.26	0.46	−0.28	2.97^{**}	4.20^{***}	2.69^{**}	3.59^{***}	1.76^{*}
	(3.02)	(1.97)	(2.01)	(3.61)	(2.90)	(1.29)	(0.84)	(0.99)	(1.75)	(−1.13)	(3.25)	(4.56)	(3.27)	(4.08)	(2.08)
Canada	−1.79	6.68	1.70	2.33	6.37	0.53	−0.15	0.43	0.59	0.74	7.19^{***}	5.24^{***}	2.72^{**}	3.56^{***}	3.82^{***}
	(−0.38)	(1.63)	(0.49)	(0.69)	(1.41)	(1.18)	(−0.35)	(0.98)	(1.31)	(1.74)	(7.81)	(5.48)	(2.79)	(3.30)	(3.84)
USA	7.27^{*}	4.38	-4.56^{*}	3.21	−3.56	0.55	0.10	−0.17	0.56	0.15	2.28^{**}	2.03^{***}	0.92	1.13	0.92
	(2.01)	(1.63)	(−2.08)	(1.42)	(−1.19)	(1.69)	(0.33)	(−0.56)	(1.84)	(0.49)	(2.68)	(3.49)	(1.26)	(1.67)	(1.36)
Australia	3.97	7.38^{**}	−0.05	6.63^{**}	7.78^{**}	1.36^{***}	1.20^{***}	0.60	0.33	0.77^{*}	6.98^{***}	4.85^{***}	6.40^{***}	4.65^{***}	4.51^{***}
	(1.38)	(2.96)	(−0.02)	(2.63)	(2.89)	(4.24)	(4.00)	(1.92)	(1.01)	(2.56)	(4.68)	(3.42)	(4.26)	(3.40)	(3.32)
China	−4.89	−6.48	−7.26	−3.87	2.06	-2.27^{**}	0.33	0.45	0.62	−0.08	5.69^{***}	4.68^{***}	3.79^{***}	3.35^{***}	2.74^{***}
	(−1.00)	(−1.18)	(−1.81)	(−0.70)	(0.46)	(−3.09)	(0.44)	(0.69)	(0.89)	(−0.12)	(7.18)	(6.64)	(6.85)	(5.43)	(3.90)
Hong Kong	7.39	5.87	5.86	3.02	4.15	0.02	1.57^{*}	0.38	0.67	0.94	10.02^{***}	7.77^{***}	9.81^{***}	8.99^{***}	5.30^{***}
	(1.29)	(1.09)	(0.92)	(0.57)	(0.71)	(0.03)	(2.31)	(0.58)	(0.99)	(1.53)	(8.62)	(6.04)	(8.21)	(8.42)	(4.55)
Japan	−2.47	0.06	0.61	−1.63	−0.68	0.40	−0.27	0.11	−0.33	−0.12	4.46^{***}	3.68^{***}	3.28^{***}	2.86^{***}	1.56^{***}
	(−1.03)	(0.03)	(0.30)	(−0.79)	(−0.38)	(1.42)	(−0.99)	(0.37)	(−1.16)	(−0.47)	(8.66)	(7.49)	(6.75)	(6.21)	(4.04)
Korea	-11.10^{**}	0.73	7.50^{**}	1.20	3.01	0.66^{*}	1.20^{***}	0.85^{**}	0.62^{*}	0.48	10.84^{***}	10.52^{***}	10.46^{***}	10.31^{***}	8.83^{***}
	(−3.22)	(0.20)	(2.64)	(0.29)	(0.90)	(2.13)	(4.18)	(3.08)	(2.34)	(1.67)	(13.98)	(12.27)	(12.39)	(13.06)	(11.23)
Taiwan	−1.47	−5.21	−4.01	4.92	−0.27	2.42^{***}	1.71^{**}	1.59^{**}	1.55^{**}	1.58^{*}	16.20^{***}	9.45^{***}	8.32^{***}	5.53^{**}	6.32^{***}
	(−0.35)	(−1.37)	(−1.18)	(1.29)	(−0.07)	(3.78)	(2.63)	(2.66)	(2.63)	(2.54)	(6.80)	(4.65)	(5.34)	(3.27)	(4.07)

Table 4.15. ***Average Decile Portfolio Spread Returns.*** *The table shows the average decile portfolio spread return per market and k-period lagged formation interval. The spread returns are reported in basis points per half-hour without accounting for any costs. The second row indicates whether the formation and holding period are based on the first half-hour interval (FH), the middle half-hour intervals (MH), or the last half-hour interval (LH). Portfolios are formed of winners (losers), that had the 10% highest (lowest) returns k periods ago. For these portfolios, equal-weighted returns are calculated. Subsequently, the average return of the losers (short) is subtracted from the average return of the winners (long). For example, the value* 7.99 *basis points in the first cell represents the average 30-minute return for creating a long-short portfolio (according to the rules above) at the open and and closing it 30 minutes later. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). Inference is robust to heteroscedasticity and autocorrelation. The sample period is August 2021 to May 2023.*

	Firm Momentum Coefficients									
Variables	Pooled	Europe	Canada	USA	Australia	China	Hong Kong	Japan	Korea	Taiwan
Panel A: Effects of Volatility based on Intraday Measures										
$Volatility_i^{ONFH}$	-0.55^{***}	-1.21^{*}	-1.40^{**}	0.09	0.18	0.09	-1.98^{*}	-1.35^{**}	-1.53^{*}	-1.68
	(-3.62)	(-2.40)	(-3.00)	(0.32)	(0.38)	(0.17)	(-2.54)	(-3.15)	(-2.34)	(-1.05)
$Volatility_i^{MH}$	-0.55^{***}	-0.94^{*}	-1.48^{***}	0.03	0.29	0.31	-1.57^{*}	-1.55^{***}	-1.50^{**}	-0.80
	(-3.78)	(-2.05)	(-3.33)	(0.11)	(0.58)	(0.69)	(-2.17)	(-3.69)	(-2.76)	(-0.63)
$Volatility_i^{LH}$	-0.42^{**}	-1.07^{*}	-0.85	-0.13	0.21	0.47	-0.52	-1.02^{*}	-0.92	-0.07
	(-3.00)	(-2.18)	(-1.93)	(-0.48)	(0.40)	(0.98)	(-0.79)	(-2.51)	(-1.74)	(-0.07)
Panel B: Effects of Liquidity within Separate Size Groups										
$Illiquidity_i$										
... within Small Firms	0.23	0.40	-0.89	0.24	-1.26	0.56	-1.06	0.08	-0.73	1.49
	(0.65)	(0.63)	(-1.13)	(0.63)	(-1.87)	(0.83)	(-0.87)	(0.14)	(-1.07)	(0.88)
... within Large Firms	-0.23	-1.91	0.87	0.21	-0.76	0.43	-1.82^{*}	-0.09	-0.61	0.34
	(-0.78)	(-1.71)	(1.18)	(0.76)	(-0.95)	(0.72)	(-2.45)	(-0.16)	(-1.03)	(0.16)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE_m	Yes	No	No	No	No	No	No	No	No	No

Table 4.16. ***Firm-Level Market Characteristics: Further Analysis.*** *The table shows the estimation results for modifications of model (4.6). In Panel A, the variable $Volatility_i$ is successively replaced with the standard deviation of overnight plus first half-hour returns ($Volatility_i^{ONFH}$), middle half-hour returns ($Volatility_i^{MH}$), and last half-hour returns ($Volatility_i^{LH}$). All other regression variables are unchanged and we estimate a separate regression for each volatility specification. The estimated volatility coefficients are reported. In Panel B, firms within each market are sorted into groups of small and large firms according to the market's median market capitalization. To construct balanced pooled samples, we randomly select 50 firms from each size group per market. If fewer than 50 firms are available (Hong Kong, Taiwan), all firms in the size group are selected. This approach ensures that no single market disproportionately influences the pooled results. Then, model (4.6) is estimated for each size group without the variable $Size_i$. Estimated coefficients for $Illiquidity_i$ are reported. In both Panels, the explanatory variables are standardized per market and currencies are converted to USD. All estimated parameters are shown in percentage points. The last rows indicate whether control variables and market-fixed effects are included. Inference is based on heteroscedasticity robust standard errors. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).*

Chapter 5

The Term Structure of Intraday Return Autocorrelations

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Abstract
Using high-frequency data on the cross-section of U.S. stocks, we analyze intraday return autocorrelations across a fine grid of different horizons: the term structure of intraday return autocorrelations. While average return autocorrelations are mostly negative, the degree of autocorrelation depends on the return horizon. On 15-minute horizons, return reversals are most pronounced. On sub-minute horizons, return continuations occur in relatively larger stocks, during periods of market stress, and in the first half hour of trading. Drawing on the literature, we derive and test hypotheses that link intraday return autocorrelations to major sources of market frictions and trading needs that systematically depend on past returns. We find evidence that return autocorrelations depend on the ease with which intermediaries can mean-revert their inventories, the degree of informational asymmetry, and dynamic hedge adjustments of option market makers.

JEL Classification: D4, D53, D82, G14
Keywords: return autocorrelation, intraday, price pressure, option gamma

5.1 Introduction

In frictionless and weak-form efficient markets, return autocorrelations should be zero (Fama, 1970). In real-world markets, however, return autocorrelations often deviate moderately from zero. This stylized fact is well documented for intraday returns (e.g., Conrad et al., 2015; Dong et al., 2017), as well as for returns over longer horizons (e.g., Jegadeesh and Titman, 1993; Avramov et al., 2006; Hendershott and Menkveld, 2014). The literature attributes these deviations to various sources of market frictions (Stoll, 2000; Duffie, 2010) and trading behavior that systematically depends on past returns (Sentana and Wadhwani, 1992; Baltussen et al., 2021; Barbon et al., 2021; Huang et al., 2023). Importantly, different reasons may generate opposing effects on return autocorrelation. For instance, liquidity-motivated trading of asynchronously arriving buyers and sellers with a risk-averse intermediary tends to induce negative return autocorrelation (e.g., Stoll, 1978; Ho and Stoll, 1981; Grossman and Miller, 1988; Hendershott and Menkveld, 2014), whereas informed trading in the presence of asymmetric information typically generates zero or positive return autocorrelation (e.g., Glosten and Milgrom, 1985; Sadka, 2006; Dong et al., 2017; Van Kervel and Menkveld, 2019). Given the presence of multiple and opposing forces, their relative importance could vary depending on the time horizon, in turn, altering return autocorrelations across frequencies.

Studies on stock-level intraday return autocorrelations typically analyze a single or a limited set of return horizons. As a consequence, little is known about how intraday return autocorrelations depend on the return horizon.[1] Our study addresses this gap by constructing and analyzing a term structure of intraday return autocorrelations. While computationally challenging, this approach allows us to examine two key questions: At which horizons are patterns of return continuations and reversals most pronounced, and how do specific market characteristics shape the term structure of return autocorrelations?

To answer these questions, we analyze high-frequency data on U.S. stocks. We start by computing return autocorrelations across a wide range of intraday frequencies, ranging from one second up to half a trading day. Additionally, we consider correlations between overnight and daytime returns. Together, these correlations form the term structure of intraday return autocorrelations, which we document for the first time in the literature. We find that average intraday return autocorrelations are significantly negative across most intraday return horizons and also between overnight returns and subsequent daytime returns. Most interestingly, however, the term structure exhibits a distinct shape: Return autocorrelations are close to zero for sub-minute returns, decline to a minimum for 15-minute returns, and then gradually revert toward zero for longer return horizons. This pattern indicates that reversals predominate in intraday returns. Moreover, we find that reversals are more pronounced and occur over longer horizons in smaller firms, which provides a first indication that market frictions affect the term structure. Lastly, on sub-minute horizons, we observe return continuations in relatively large stocks, during periods of market stress, and in the first half hour of trading – likely related to

[1] An exception is the finding that stock-level returns tend to mean-revert relative to contemporaneous market returns at high intraday frequencies (Heston et al., 2010).

information-motivated trading. Overall, the results – robust to various modifications – confirm that the return horizon affects the strength of reversals and continuations in intraday returns.

We then draw on the literature on major market frictions and trading needs that depend systematically on past returns to develop three hypotheses that link intraday return autocorrelations to intermediaries' inventory-control procedures, asymmetric information, and dynamic hedging activities of option market makers. The first hypothesis is that the magnitude and the speed of price reversals depend on the ease with which intermediaries can mean-revert their inventories. When buyers and sellers arrive asynchronously, intermediaries absorb demand shocks in the absence of natural counterparties. As intermediaries are typically risk-averse or subject to position limits, they charge a bid-ask spread and respond to trades with transitory quote adjustments that reflect an inventory-control mechanism (Glosten and Harris, 1988; Grossman and Miller, 1988). That is, they revise their quotes to attract an offsetting order flow imbalance that allows them to mean-revert their non-optimal inventories to a desired level (Stoll, 2000). Once the offsetting order flow materializes, the transitory price impact is dropped and quotes rebound – given no change in the fundamental value estimate. This induces negative autocorrelation into mid-quote returns. Building on this framework, we expect that reversals are more pronounced and take longer to occur when it is more difficult for intermediaries to mean-revert their inventories. As intermediaries' inventories are not directly observable, we measure this difficulty based on trading volume, realized spreads, and internalized retail trading activity.

The second hypothesis is that return autocorrelations increase when the informational asymmetry is heightened because informed traders execute their orders more gradually in this environment. The rationale is as follows. When there is informational asymmetry, the direction of trades carries information, as some traders exploit their private information by submitting market orders (Glosten and Milgrom, 1985). To mitigate losses from such trades, liquidity providers charge an additional component in the bid-ask spread and permanently revise their fundamental value estimate and thus their mid-quote after a trade (Glosten and Harris, 1988). The impact of this price-setting policy on return autocorrelations depends on the persistence of order flow imbalances. Positive return autocorrelations can arise when information-motivated traders split their orders and execute them over time, a practice widely observed (Sadka, 2006; Murphy and Thirumalai, 2017; Van Kervel and Menkveld, 2019). We expect that information-motivated traders execute their orders relatively more gradual when informational asymmetry is heightened. This is because liquidity providers impose a larger permanent price impact in such environments, making rapid execution more expensive. To assess informational asymmetry, we measure the permanent price impact of trades.

The third hypothesis is that dynamic hedging activities of option market makers affect return autocorrelations. Option market makers dynamically adjust their hedges in the underlying stock to remain delta-neutral, and the direction of these adjustments depends on the option portfolio's sign of gamma. Prior evidence shows that such hedge adjustments systematically affect stock price dynamics at the end of the trading day (e.g., Baltussen et al., 2021; Barbon et al., 2021) and on daily horizons (e.g., Ni et al., 2021; Soebhag, 2023). Specifically, negative gamma requires hedgers to trade in the direction of past returns – inducing positive autocorrelation,

while positive gamma requires them to trade in the opposite direction of past returns – inducing negative autocorrelation. We expect that hedge adjustments do not only affect end-of-day returns but return autocorrelations throughout the trading day. In this regard, our multi-period approach can shed light on the approximate return horizon where hedge adjustments start to affect price dynamics. Following Baltussen et al. (2021), Soebhag (2023), and Huang et al. (2023), we estimate option market makers' gamma based on public data.

We test these hypotheses empirically using the above market characteristics. We find support for all three hypotheses. This means that when market conditions make it more difficult for intermediaries to mean-revert their inventories, return autocorrelations are more negative. In addition, when informational asymmetries are relatively high, return autocorrelations are more positive (less negative), particularly on short horizons. Finally, when option market makers' gamma exposure is positive (negative), return autocorrelations are significantly more negative (positive). This effect is most pronounced for return horizons of 30 minutes and longer, but limited to stocks of medium and large size. Overall, our results indicate that market characteristics related to inventory control and asymmetric information exert a relatively more pronounced effect on intraday return autocorrelations than hedge adjustments of option market makers.

We contribute to the literature in several ways. We extend the literature that documents price reversals and connects them to transitory price effects from intermediaries' inventory-control procedures (Hendershott and Menkveld, 2014; Boyarchenko et al., 2023; Krohn et al., 2024). Our findings provide insights into the specific intraday horizons at which these reversals occur and the factors that influence their magnitude. We also extend the empirical evidence that return autocorrelations increase when information-driven trading is more pronounced (Dong et al., 2017). In addition, we contribute to the growing body of evidence showing that hedge adjustments of option market makers systematically impact underlyings' price dynamics (Baltussen et al., 2021; Barbon et al., 2021; Huang et al., 2023). Our analysis indicates that hedge adjustments affect price dynamics not only at the end of the day, as previously shown, but also within the day. Finally, our paper relates to studies that use absolute return autocorrelations to assess price efficiency (e.g., Comerton-Forde and Putniņš, 2015). However, rather than focusing on non-directional deviations from zero, we investigate signed return autocorrelations.

Our results have important implications. While we document distinct patterns in the autocorrelations of intraday returns that are consistent with expected patterns in the presence of market frictions and systematic trading needs, we also find that their magnitude is modest on average. This suggests that deviations from weak-form market efficiency are relatively minor after all.

The remainder of the paper is organized as follows: Section 5.2 reviews the literature on intraday return autocorrelations and derives our hypotheses in more detail. Section 5.3 describes the data and the variables. Section 5.4 studies the shape of the term structure of intraday return autocorrelations and tests our hypotheses. Section 5.5 concludes.

5.2 Literature Review and Hypotheses Development

5.2.1 Return Autocorrelations

There are two strands of literature that explore intraday stock-level return autocorrelations.[2] Studies in the first strand measure stock returns relative to the contemporaneous market return (Heston et al., 2010, 2011; Murphy and Thirumalai, 2017). These studies find that first-order excess-return autocorrelations are significantly negative for short horizons, ranging from 1 minute to 30 minutes. However, the significance tends to deteriorate at longer horizons. This indicates reversals in short-term stock returns relative to the market return. The second strand of literature examines stock returns without adjusting for market-wide returns (Chordia et al., 2005, 2008; Conrad et al., 2015; Dong et al., 2017). These studies focus on a single or a limited set of return horizons and provide mixed evidence. For large stocks and high-frequency returns of about 1 minute, autocorrelations are typically close to zero or positive (Conrad et al., 2015). However, as the return frequency decreases or stock size shrinks, autocorrelations tend to become more negative. Specifically, small stocks exhibit negative autocorrelations even at high frequencies (Conrad et al., 2015), and stocks across all sizes tend to show negative autocorrelations at 5-minute (Chordia et al., 2005, 2008) and 10-minute (Dong et al., 2017) return horizons. Furthermore, daytime returns have a tendency to revert previous overnight returns (Akbas et al., 2022; Ham et al., 2023; Hajiyev et al., 2024). However, the reverse effect – whether overnight returns revert prior daytime returns – has not yet been explored. Although these studies cover different time periods and subsets of the cross-section, they collectively provide a first indication that intraday return autocorrelations depend on the return horizon and firm-level market characteristics. Our study extends this second strand of literature by analyzing return autocorrelations across a wide range of intraday frequencies and the entire cross-section of stocks.

5.2.2 Hypotheses

An important source of market friction arises from the asynchronous arrival of buyers and sellers (Glosten and Harris, 1988). If there is no natural counterparty available, intermediaries absorb demand shocks and temporarily hold positions until a natural counterparty arrives. However, as intermediaries are typically risk-averse or subject to position limits, they require compensation for holding non-optimal inventories (e.g., Stoll, 1978; Amihud and Mendelson, 1980; Ho and Stoll, 1981; Grossman and Miller, 1988; Hendershott and Menkveld, 2014). To this end, they charge a transitory price impact as part of the bid-ask spread and revise their mid quote after a trade. This transitory change in the mid quote, also known as price pressure, reflects an inventory-control mechanism that allows an intermediary to mean-revert his inventory to a

[2] On short, non-intraday horizons, stock-level return autocorrelations are generally negative. This pattern has been documented for daily returns (e.g., Stoll, 2000; Hendershott and Menkveld, 2014) and weekly returns (e.g., Avramov et al., 2006). However, over longer horizons, return autocorrelations tend to turn positive, reflecting momentum effects (e.g., Jegadeesh and Titman, 1993).

desired level (Stoll, 2000). The intuition is as follows: When sales to an intermediary raise his inventory above a desired level, he lowers both the bid and the ask to discourage further sales and to encourage purchases. Once the offsetting order flow imbalance materializes and his inventory has mean-reverted, the transitory price impact is dropped and quotes rebound to their former level – given no change in the fundamental value estimate. This process induces negative autocorrelation into mid-quote returns, as price pressure from inventory-control dynamics is transitory. Previous empirical evidence shows that not only traditional market makers, but also high-frequency traders acting as voluntary liquidity providers use price pressure (Menkveld, 2013). This suggests the existence of price pressure effects on various intraday horizons. Moreover, price pressure is economically sizable, and more pronounced and longer-lasting for smaller stocks (Hendershott and Menkveld, 2014). We therefore hypothesize that the magnitude and the speed of price reversals from intermediaries' usage of price pressure depends on the difficulty with which they can mean-revert their inventories.

Hypothesis 1. *Intraday return autocorrelations decrease when the difficulty with which intermediaries can mean-revert their inventories increases.*

To gauge difficulties in inventory control, we use three closely related variables: Trading volume, realized spread, and retail trading activity – as intermediaries' inventories are not directly observable.

Another major source of market friction is informational asymmetry (Glosten and Harris, 1988). When there is informational asymmetry, some traders submit market orders to exploit their informational advantage. As a consequence, the direction of orders carries information. To protect against losses to information-motivated trades, liquidity providers add a permanent price impact component to the bid-ask spread and revise their mid quote after a trade (e.g., Glosten and Milgrom, 1985). Specifically, liquidity providers permanently revise their fundamental value estimate and thus their mid quote upward after executing buy trades and downward after executing sell trades. The impact of this price-setting policy on return autocorrelations depends on the autocorrelation in the order flow. Positive return autocorrelation can arise when information-motivated traders split their orders into smaller pieces and execute them over time, a practice widely observed in financial markets (e.g., Sadka, 2006; Murphy and Thirumalai, 2017; Van Kervel and Menkveld, 2019). Importantly, this illustrates a fundamental difference between the effects of liquidity-motivated and information-motivated trading on return autocorrelations (cf. Hypothesis 1). While the former causes temporary price deviations that tend to revert, the latter contributes to permanent price changes. We hypothesize that return autocorrelations depend on the degree of informational asymmetry. The rationale is as follows. When the proportion of information-motivated traders is high, liquidity providers will charge a relatively larger permanent price impact. In this environment it could be particularly attractive for information-motivated traders to spread their trades over time to reduce their impact on the price, contributing to positive (less negative) return autocorrelation. To quantify the degree of informational asymmetry, we estimate the permanent price impact of trades.

Hypothesis 2. *Intraday return autocorrelations increase when the informational asymmetry increases.*

Traders who systematically trade in the direction (opposite direction) of past returns can generate positive (negative) return autocorrelation (Sentana and Wadhwani, 1992). Among these traders are option market makers who dynamically adjust their hedges. To immunize the value of an option portfolio against changes in the price of the option's underlying, market makers engage in delta-hedging (e.g., Hull, 2021, ch. 19). The delta of an option at time t, defined as $\Delta_t = \frac{\delta V_t}{\delta P_t}$, represents the sensitivity of the option's price V_t to changes in the underlying stock price P_t. Delta-hedging an option portfolio against small changes in P_t thus requires to buy or sell an amount of shares of the underlying equal to $-\Delta_t$. This delta-hedge has to be adjusted to remain effective, as Δ_t fluctuates with changes in P_t. The rate at which Δ_t changes when P_t changes is defined as gamma, $\Gamma_t = \frac{\delta^2 V_t}{\delta P_t^2}$. The sign of gamma thus determines whether hedgers have to buy or sell in response to positive or negative returns in the underlying. In other words, the sign of gamma determines whether the price impact of hedge adjustments has the potential to amplify ($\Gamma_t < 0$) or reverse ($\Gamma_t > 0$) recent returns and thus affects the degree of return autocorrelation.

A growing literature provides empirical evidence that hedge adjustments of option market makers exert systematic and economically sizable price pressure on the option's underlying, consistent with the above rationale.[3] On the daily horizon, the net gamma exposure of delta-hedgers is negatively related to the volatility of the underlying stock (Ni et al., 2021; Soebhag, 2023). This is plausible, as negative (positive) return autocorrelation suppresses (amplifies) volatility. On the intraday horizon, the price pressure from delta-hedge adjustments induces a negative ($\Gamma_t > 0$) or positive ($\Gamma_t < 0$) correlation between the last half-hour return and the return in previous part of the day for stocks, indices, and various futures (Baltussen et al., 2021; Barbon et al., 2021; Huang et al., 2023). This effect is statistically and economically significant. However, the broader impact of delta-hedging or anticipatory front-running on return autocorrelations across different parts of the day and return intervals is yet unexplored. While trading costs likely prevent hedge adjustments at very high frequencies, it is reasonable to expect adjustments at medium frequencies throughout the day, e.g. due to risk limits. Identifying the return horizons at which hedge adjustments begin to affect return autocorrelations is an empirical question that we aim to address. Therefore, we hypothesize that hedge adjustments of option market makers due to gamma exposure affect the term structure of intraday return autocorrelations.

Hypothesis 3. *Intraday return autocorrelations decrease when the gamma exposure of option market makers increases.*

[3] Similar systematic price pressure results from the rebalancing of the exposure of leveraged exchange traded funds at the end of the day (Brøgger, 2021; Todorov, 2024). In addition, there are theoretical, model-driven investigations on the effect of delta-hedging on market quality in the underlying (Frey and Stremme, 1997; Sornette et al., 2022; Buis et al., 2022; Egebjerg and Kokholm, 2024).

5.3 Data and Variables

5.3.1 Data

We base our analysis on the cross-section of U.S. stocks from January 2017 through December 2021. We select sample stocks as follows: Among NYSE- and NASDAQ-listed common stocks, we require that the respective identifiers are not duplicated and do not change during the sample period, that the market capitalization is at least \$100 Mio., and that the stock price is at least \$1. The last two requirements are made to exclude thinly traded stocks and possible tick-size effects of penny stocks.

The sample includes both normal periods and the COVID-induced crash in February and March 2020. For the sample stocks, we retrieve tick-level national best bid and offer (NBBO) quotes and all trades reported to the consolidated tape, both from the Trade and Quote (TAQ) database. Based on these data, we calculate intraday return autocorrelations and trade and quote related variables.

We apply a two-stage cleaning procedure for both quotes and trades to assure accuracy and consistency of the data, motivated by the literature (e.g., Bogousslavsky and Muravyev, 2023; Barbon et al., 2021). In the first stage, we clean the quote data: We retain only quotes with a correct timestamp and positive values for bid, ask, bid size, offer size, and bid-ask spread. Moreover, we retain only quotes with bid (ask) prices that are at most 0.5% below (above) the daily low (high) of the quoted bid (ask) according to the daily CRSP files. In the second stage, we clean the trade data: We retain only trades with a correct timestamp, trade correction indicators 00 (correctly recorded trades) and 01 (late corrected trades, that reflect the actual trade price at the time), a positive trade price, and a positive volume. Moreover, we require that trade prices are at most 0.5% below (above) the daily low (high) of the quoted bid (ask) according to the daily CRSP files. Finally, we use only stock-days where there are at least 390 NBBO updates. This corresponds to one price update per minute of continuous trading, on average. This ensures price variation as the basis for the calculation of autocorrelations.

In addition, we use daily stock-level option data from OptionMetrics, specifically the gamma and the open interest, to estimate the daily net gamma exposure of options market makers. We further use stock-level data from the Center for Research in Security Prices (CRSP), including opening prices, closing prices, market capitalization, and trading volume. All datasets are merged on the stock-day level.

5.3.2 Return Autocorrelations

Let p_τ be the log stock price at time τ, measured in seconds at a given trading day.[4] The one-second log return at time τ (from time $\tau-1$) is then $r_\tau = p_\tau - p_{\tau-1}$ and the q-seconds log return

[4] To improve readability, we suppress the indices i for individual stocks and t for days in the variables.

is $r_\tau(q) = \sum_{k=1}^{q} r_{\tau-k+1}$. With this, the standard estimator for the first-order autocorrelation of q-seconds log returns for a time period from τ to $\tau + mq$ is defined as

$$\widehat{\rho_{\tau,m}(q)} = \frac{\frac{1}{m-1}\sum_{j=1}^{m-1} r_{\tau+(j-1)q}(q) \cdot r_{\tau+jq}(q)}{\frac{1}{m}\sum_{j=0}^{m-1} r_{\tau+jq}(q)^2}. \tag{5.1}$$

We assume that expected returns on these high frequencies are zero, aligning with the literature (e.g., Aït-Sahalia et al., 2011).[5] The standard estimator is, however, subject to potential sampling effects caused by (arbitrary) starting times in q-second return calculations. To reduce these effects, we average over multiple first-order autocorrelations calculated from overlapping q-second returns, leading to the estimator

$$\widehat{\rho(q)} = \frac{1}{|\mathcal{K}(q)|} \sum_{k \in \mathcal{K}(q)} \widehat{\rho_{q+k,m_k}(q)}, \tag{5.2}$$

where $m_k = \lfloor (n-k)/q \rfloor$, $\mathcal{K}(q)$ is the set of time shifts $k \in \{0, 1, \ldots, q-1\}$ for which $m_k \geq 2$, and $|\mathcal{K}(q)|$ is the number of elements in $\mathcal{K}(q)$. The autocorrelation according to (5.2) is simple in interpretation: If there is positive (negative) return autocorrelation, i.e. returns trend (mean-revert), then its value is greater (smaller) than zero.

In addition, we augment the measure (5.1) to estimate the correlation between the overnight return r_{Night^-} and the subsequent daytime return r_{Day}, as well as the correlation between the daytime return and the subsequent overnight return r_{Night^+}:

$$\widehat{\rho}^{\langle N^-, D \rangle} = \frac{r_{Night^-} \times r_{Day}}{\frac{1}{2}(r_{Night^-}^2 + r_{Day}^2)}, \tag{5.3}$$

$$\widehat{\rho}^{\langle D, N^+ \rangle} = \frac{r_{Day} \times r_{Night^+}}{\frac{1}{2}(r_{Day}^2 + r_{Night^+}^2)}. \tag{5.4}$$

Following Akbas et al. (2022), we compute overnight and daytime returns using opening and closing prices from CRSP. These prices are considered most representative, as they reflect auction prices that attract substantial trading volume (Bogousslavsky and Muravyev, 2023).

For each stock i and day t, we use tick-level NBBO quotes to calculate mid-quote prices during regular trading hours, from 9:31 and 15:59.[6] We then span a grid of 1-secondly time stamps

[5] The measure equals the estimate of β in the univariate return regression $r_\tau = \beta r_{\tau-1} + \epsilon_\tau$ (here for $q = 1$). Alternative measures are closely related, but do not show the term structure of return autocorrelations straight away. For example, the variance ratio defined as $VR(h) = \frac{Var[r_\tau(h)]}{h \times Var[r_\tau]}$, reveals the term structure of autocorrelations only via the relation $\rho(q) \approx \frac{VR(2q)}{VR(q)} - 1 \; \forall \; q > 1$.

[6] We rely on mid-quote prices to mitigate the bid-ask bounce effect that can exist in high-frequency trade prices. We exclude the first and last minutes of trading to avoid potential distortions from the opening and closing call auctions, as well as data errors. In a robustness check reported later, we repeat the analysis while additionally omitting the first and last 30 minutes of trading, coming to similar conclusions.

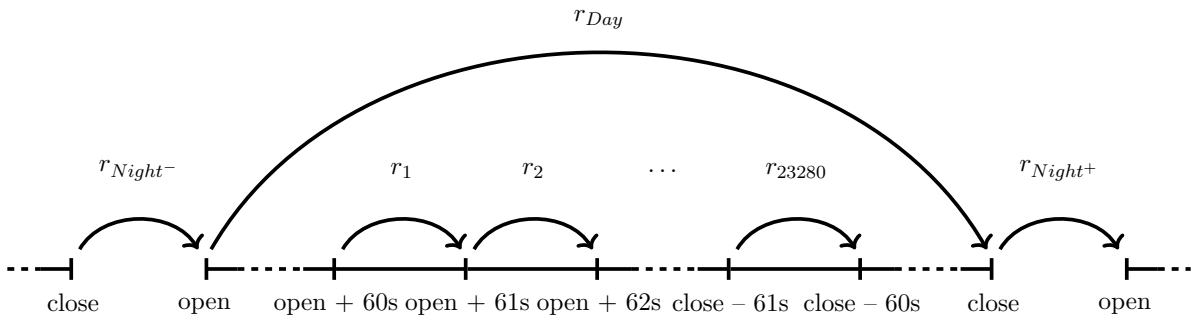

Figure 5.1. ***Intraday Returns.*** *The Figure summarizes the partitioning of a trading day for the calculation of returns. We exclude both the first and the last minute (60 seconds) of trading in the calculation of 1-second intraday returns to avoid potential distortions from the opening and closing of continuous trading.*

over the trading day and use the mid-quote prices at or immediately before the knots. This results in a clock-time grid of 23,280 1-second observations per stock-day. Using Equation (5.2), we compute intraday return autocorrelations $\widehat{\rho_{i,t}(q)}$ for return horizons ranging from $q = 1$ (1-second log returns) to $q = 11{,}640$ (half-day log returns). This allows us to examine whether the relation between subsequent returns depends on the length of the return interval. Additionally, we employ Equations (5.3) and (5.4) to estimate correlations between day and night periods. Figure 5.1 summarizes all returns used in our calculations.

5.3.3 Market Characteristics

In the following, we define the variables used to measure the difficulty of inventory-control management, the degree of asymmetric information, and the net gamma exposure of option market makers.

Volume. Our first measure related to inventory control is trading volume, which captures overall market activity and therefore the ease of finding natural counterparties (Lou and Shu, 2017). Therefore, higher trading activity facilitates inventory management by allowing intermediaries to unwind positions more easily. We denote the logarithmic dollar trading volume from CRSP in stock i on day t as $Volume_{i,t}$.

Realized Spread. Our second measure related to inventory control is the realized spread, which reflects revenues earned by intermediaries that net out losses to better-informed traders (Conrad et al., 2015). The realized spread can be interpreted as the part of the effective spread that compensates intermediaries for the risk of temporarily holding inventory.[7] This compensation should be higher, when it is more difficult for an intermediary to unwind inventory. In these situations, return reversals from the usage of price pressure should be more pronounced. We estimate the realized half spread of trade ψ in stock i on day t as the difference between the transaction price $T_{i,t,\psi}$ and the mid-quote 60 seconds later $M_{i,t,\psi}^{+60s}$, formally given by

[7] More precisely, the realized spread compensates for all risks and costs faced by intermediaries, net of adverse selection costs, such as order processing costs. However, inventory risk likely constitutes a significant portion of this compensation.

$$Spread_{i,t,\psi} = \frac{(T_{i,t,\psi} - M_{i,t,\psi}^{+60s}) \times q_{i,t,\psi}}{M_{i,t,\psi}}, \tag{5.5}$$

where $M_{i,t,\psi}$ is the mid-quote immediately prevailing the trade, and $q_{i,t,\psi}$ is 1 (-1) if trade $\langle i,t,\psi \rangle$ is buyer (seller) initiated.[8] The horizon of 60 seconds is often chosen in the literature (e.g., Comerton-Forde et al., 2016). It should be long enough such that prices can adjust to the trade's permanent price impact, but not too long to introduce unrelated noise. We denote $Spread_{i,t}$ as the average of the realized half-spreads between 9:31 and 15:59 for each stock-day. To mitigate the influence of outliers, we winsorize the spreads at the 1st and 99th percentiles before averaging.

Retail Trading Activity. The third measure related to inventory control concerns retail trading activity. In the U.S. stock market, most retail orders are executed off-exchange by broker-dealers (Boehmer et al., 2021; Barber et al., 2024). Regulatory data reveal that at least 87% of all customer orders initiated through U.S. retail brokers are executed against the inventories of broker-dealers (SEC, 2024, p. 373). Compared to institutional order flow, retail order flow is more balanced (Hoffmann and Jank, 2024). In addition, imbalances in retail order flow are negatively correlated with imbalances in institutional order flow (Barardehi et al., 2025). These properties of retail order flow ease intermediaries' inventory-control because imbalances within the retail and overall order flow become less pronounced. As a consequence, we expect that a higher retail share in the order flow reduces price reversals caused by inventory-control mechanisms, thereby increasing return autocorrelations (i.e., making them less negative). We use the algorithm of Barber et al. (2024) to identify marketable non-directed retail orders that were executed by broker-dealers. The algorithm classifies off-exchange trades as retail trades when they have subpenny price-improvements and deviate from the prevailing mid-quote by at least 10% of the quoted spread.[9] The percentage proportion of retail trading activity for stock i on day t is then computed by summing up the trading volume over all retail trades and scaling it by the total trading volume:

$$Retail_{i,t} = \frac{Volume_{i,t}^{Retail}}{Volume_{i,t}^{Total}}, \tag{5.6}$$

where $Volume_{i,t}^{Retail}$ denotes the retail trading volume and $Volume_{i,t}^{Total}$ is the total trading volume.

Permanent Price Impact. Due to informational asymmetry, trades have a permanent impact on prices (Glosten and Milgrom, 1985). When informational asymmetry is more pronounced, the permanent price impact of trades is higher, raising the costs of trading.[10] We expect that

[8] We use the Lee and Ready (1991) algorithm to sign trades.

[9] Although this algorithm measures retail trading activity with an error (Battalio et al., 2024), the identified order flow still exhibits properties consistent with Hypothesis 1 (Barardehi et al., 2025).

[10] Using absolute intraday returns to proxy for price discovery and informational asymmetry, we empirically verify on the stock level that permanent price impacts in the subsequent trading session increase significantly with the magnitude of the informational asymmetry.

these elevated trading costs incentivize informed traders to execute their orders more gradually over time to reduce price impact. This gradual execution leads to a more persistent order flow, thereby increasing return autocorrelations (i.e., making them less negative). We measure the permanent price impact as the change in the mid-quote prevailing the trade and the mid-quote 60 seconds later, formally given by

$$Impact_{i,t,\psi} = \frac{(M_{i,t,\psi}^{+60s} - M_{i,t,\psi}) \times q_{i,t,\psi}}{M_{i,t,\psi}}. \tag{5.7}$$

We then take the average of the price impact between 9:31 and 15:59 for each stock-day and denote this variable as $Impact_{i,t}$. Prior to averaging, we winsorize the price impacts at the 1st and 99th percentile.

Option Gamma Exposure. The literature provides evidence that option market makers tend to be net-long calls (Lakonishok et al., 2007; Cici and Palacios, 2015) and net-short puts (Bollen and Whaley, 2004; Gârleanu et al., 2009; Cici and Palacios, 2015).[11] Following Baltussen et al. (2021), Soebhag (2023), and Huang et al. (2023), we exploit this positioning pattern to estimate the net gamma exposure (NGE) of option market makers. To this end, we assume that market makers take long positions in calls and short positions in puts and engage in delta-hedging, while end customers do not. We compute the NGE for a call option on stock i, on day t, with strike s, and maturity m as:

$$NGE_{i,t,s,m}^{Call} = \Gamma_{i,t,s,m}^{Call} \times OI_{i,t,s,m}^{Call} \times 100 \times P_{i,t}, \tag{5.8}$$

where $\Gamma_{i,t,s,m}^{Call}$ is the call option's gamma, $OI_{i,t,s,m}^{Call}$ is the call option's open interest, 100 denotes the adjustment from the option contracts to the number of shares of the underlying, and $P_{i,t}$ is the stock price. For a put option, the NGE is similarly defined as

$$NGE_{i,t,s,m}^{Put} = -1 \times \Gamma_{i,t,s,m}^{Put} \times OI_{i,t,s,m}^{Put} \times 100 \times P_{i,t}, \tag{5.9}$$

where the additional term -1 reflects the net-short positioning in puts. The total (scaled) NGE is obtained by summing over all option contracts:

$$NGE_{i,t} = \underbrace{\left(\sum_s \sum_m NGE_{i,t,s,m}^{Call} + \sum_s \sum_m NGE_{i,t,s,m}^{Put} \right)}_{\text{NGE in \$}} \times \underbrace{\frac{P_{i,t}}{100} \times \frac{1}{\overline{Volume_{i,t}}}}_{\text{Scaling Factors}}, \tag{5.10}$$

where the first term represents the NGE in dollar terms. This is the amount that market makers must trade for a change of one dollar in $P_{i,t}$. After applying the scaling factors, where $\overline{Volume_{i,t}}$

[11] Studies using more granular trader-level data to estimate the option gamma exposure come to similar conclusions (Ni et al., 2021; Barbon et al., 2021).

Panel A: Cross-Sectional Summary Statistics					
	Volume	*Spread*	*Retail*	*Impact*	*NGE*
Mean	16.72	2.43	7.43	4.72	0.94
Std.	1.79	4.83	4.81	3.96	2.35
0.01	12.98	−2.27	1.13	0.53	−3.70
0.10	14.35	−0.29	2.89	1.24	−0.43
0.25	15.40	0.11	4.22	2.06	−0.01
0.50	16.69	0.78	6.14	3.55	0.31
0.75	18.01	2.62	9.18	6.00	1.19
0.90	19.11	6.97	13.82	9.65	2.97
0.99	20.84	27.48	25.68	21.74	13.46
Panel B: Cross-Sectional Correlations					
	Volume	*Spread*	*Retail*	*Impact*	*NGE*
Volume	1.00	–	–	–	–
Spread	−0.52	1.00	–	–	–
Retail	−0.01	0.12	1.00	–	–
Impact	−0.61	0.41	0.27	1.00	–
NGE	0.22	−0.09	0.06	−0.13	1.00

Table 5.1. ***Descriptive Statistics.*** *The table provides descriptive statistics of the independent variables. Panel A reports the mean, the standard deviation and quantiles of the variables. Panel B reports correlations between the variables. The statistics are calculated for each day and subsequently averaged over all days. All variables are winsorized at the* 1% *and* 99% *quantiles for each day. Volume represents the logarithmic dollar trading volume, Spread is the average realized spread per trade, Retail is the percentage proportion of retail trading volume over the total trading volume, Impact is the average permanent price impact per trade, and NGE is the net gamma exposure of option market makers. The variables Spread and Impact are reported in basis points, the variables Retail and NGE are reported in percentage points. The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

is the average dollar trading volume over the previous 21 trading days (1 month), $NGE_{i,t}$ can be interpreted as the percentage proportion of the average trading volume that market makers need to trade for a 1% change in the price of the underlying.

Table 5.1 provides descriptive statistics of the market characteristics. Panel A reports time-series averages of the cross-sectional mean, standard deviation, and quantiles of the variables. The results indicate substantial cross-sectional variation, suggesting a rich setting for investigating their impact on return autocorrelations. Notably, retail trading is sizable, accounting for an average of 7.43% of the daily volume. Moreover, NGE ranges from −3.70% (1% quantile) to 13.46% (99% quantile), consistent with values reported by Soebhag (2023). This highlights that hedging flows from option market makers are economically sizable and have the potential to both amplify and reverse recent returns. In addition, Panel B reports correlations between the variables. The volume exhibits a substantially negative correlation with both the realized spread (0.52) and the permanent price impact (0.61). This indicates that in stocks with a lot of trading activity – typically large firms – intermediaries can control their inventory more easily and traders possess less private information. Apart from these relationships, absolute

correlations between all other variables are rather weak, ranging between 0.01 and 0.41 in absolute terms.

5.4 Empirical Analysis

5.4.1 Term Structure

5.4.1.1 Baseline Analysis

We now examine the term structure of intraday return autocorrelations. To this end, we use the term structures from the stock-day level, consisting of the autocorrelations $\widehat{\rho_{i,t}(q)}$ for return horizons ranging from $q = 1$ (1-second log returns) to $q = 11{,}640$ (half-day log returns), as well as the correlations between day and night periods ($\widehat{\rho}^{\langle N^-,D\rangle}, \widehat{\rho}^{\langle D,N^+\rangle}$), and average them across all stock-days.

Figure 5.2 shows the average term structure of intraday return autocorrelations for the full cross-section (Pooled) and for three size groups (Small, Medium, Large) formed according to market capitalization. For selected points along the term structure, the corresponding values are also reported in Table 5.2. The pooled results indicate that average intraday return autocorrelations are negative, mostly significantly, across almost all return horizons during continuous trading. The term structure exhibits a distinct shape: Autocorrelations start at -0.66% for 1-second returns, increase toward zero (-0.03%) for 20-second returns, decline to a minimum of -2.70% for 15-minute returns, and then gradually revert toward zero for longer return horizons. This suggests that return reversals are most pronounced at approximately the 15-minute horizon, a finding consistent with transitory price pressures arising from inventory-control procedures. In addition, the convergence of autocorrelations toward zero at shorter return intervals aligns with the presence of positive autocorrelations in order flow imbalances, which could result from the piecewise execution of large parent orders (Chordia et al., 2005; Sadka, 2006). This practice partially offsets the negative return autocorrelation from inventory-control mechanisms. Finally, the sharper drop in autocorrelations at the shortest intervals may reflect price pressures exerted by liquidity-providing high-frequency traders (Menkveld, 2013).[12]

Turning to the correlations between returns during the night and the day, we find mixed evidence for return reversals. The correlation between the previous overnight return and the daytime return is significantly negative at -1.89%. However, the correlation between the daytime return and the return in the following overnight interval is statistically insignificant. We interpret this asymmetric pattern as follows. Overnight, trading interest and price-relevant information accumulate and are incorporated into prices at the market opening, contributing to the overnight return. Intermediaries likely provide liquidity at the market opening while

[12] Reversals in high-frequency mid-quote returns are also consistent with the gradual replenishing of depth in an order book after a marketable order has removed liquidity. The speed of this process is referred to as resilience (Foucault et al., 2015).

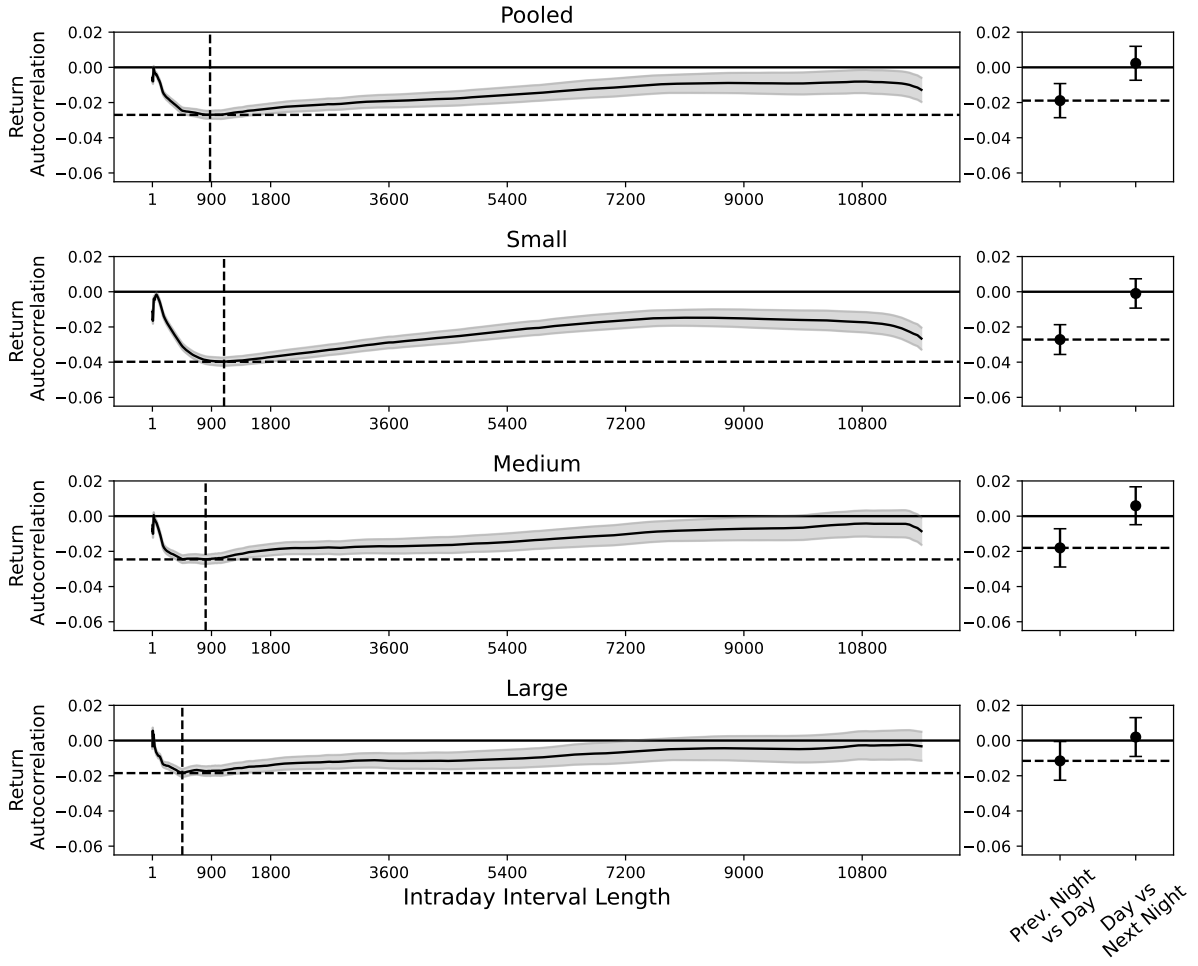

Figure 5.2. ***Term Structure of Intraday Return Autocorrelations.*** *The figure shows the average autocorrelation of intraday returns for different lengths of return intervals. The intraday interval length is given in seconds. The term structure is computed as follows: First, the autocorrelation is calculated from Equation (5.2) for each stock-day and interval length q. Second, the autocorrelations are averaged for each interval length. Prior to averaging, the autocorrelations for each day and interval length are winsorized at the* 1% *and* 99% *quantiles.* 95% *confidence intervals are shown in gray and by whiskers. Inference is based on robust standard errors clustered by firm and day. Results are shown for the entire cross-section (Pooled), and for three size groups (Small, Medium, Large) formed according to terciles of 1-day lagged market capitalization. The dashed lines mark the lowest values. The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

imposing a transitory price impact. When the accumulated trading interest is substantial, the transitory component of the overnight return can be pronounced. As natural counterparties arrive during the day, this transitory price impact dissipates, leading to a return reversal and explaining the observed negative correlation between the previous overnight return and the daytime return. But what accounts for the absence of a significant correlation between the daytime return and the subsequent overnight return? Intermediaries may use price pressure during the day to actively mean-revert their inventory toward desired levels by market close. As a result, end-of-day inventories are likely closer to intermediaries' desired levels than at the start of the day (Bogousslavsky, 2016). Consequently, end-of-day price pressures are less pronounced, reducing the absolute correlation between daytime returns and subsequent overnight returns.

	$\widehat{\rho(q)}$			
q	Pooled	Small	Medium	Large
1	-0.66^{***}	-1.12^{***}	-0.53^{***}	-0.32^{***}
20	-0.03	-0.44^{***}	$+0.06$	$+0.28^{***}$
40	-0.33^{***}	-0.32^{***}	-0.23^{**}	-0.43^{***}
60	-0.40^{***}	-0.16^{*}	-0.36^{***}	-0.68^{***}
300	-1.98^{***}	-2.23^{***}	-2.15^{***}	-1.56^{***}
600	-2.55^{***}	-3.55^{***}	-2.41^{***}	-1.71^{***}
900	-2.69^{***}	-3.93^{***}	-2.42^{***}	-1.72^{***}
1800	-2.33^{***}	-3.70^{***}	-1.90^{***}	-1.39^{***}
3600	-1.92^{***}	-2.88^{***}	-1.71^{***}	-1.16^{***}
5400	-1.56^{***}	-2.19^{***}	-1.46^{***}	-1.04^{***}
7200	-1.08^{***}	-1.60^{***}	-1.00^{***}	-0.64^{*}
9000	-0.90^{**}	-1.52^{***}	-0.72^{*}	-0.45
10800	-0.81^{*}	-1.74^{***}	-0.42	-0.27
11640	-1.28^{***}	-2.66^{***}	-0.85^{*}	-0.33
$\langle N^{-}, D\rangle$	-1.89^{***}	-2.72^{***}	-1.80^{**}	-1.15^{*}
$\langle D, N^{+}\rangle$	$+0.23$	-0.10	$+0.59$	$+0.20$

Table 5.2. ***Term Structure of Intraday Return Autocorrelations.*** *The table reports return autocorrelations for various intervals q (seconds) and size groups formed according to terciles of 1-day lagged market capitalization (Pooled, Small, Medium, Large). All variables are winsorized at the* 1% *and* 99% *quantiles for each day. All coefficients are multiplied by the factor* 10^2*. Inference is based on standard errors clustered by time t and firm i. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

The term structures calculated separately for the three size groups exhibit the same overall pattern as described above. However, both the strength of reversals and the return interval at which they are most pronounced tend to increase for smaller stocks. In the top tercile (Large), the most negative return autocorrelation is -1.85% at approximately 8-minute intervals. In the middle tercile (Medium), the lowest return autocorrelation is -2.46% at around 14-minute intervals. In the bottom tercile (Small), return autocorrelations reach their lowest point at -3.98% on approximately 18-minute intervals. We observe a similar shift in the correlation between overnight returns and daytime returns, which becomes increasingly negative as firm size decreases. Interpreting market capitalization as a proxy for the presence of various market frictions, the results suggest that specific frictions which are associated with negative return autocorrelations (e.g., asynchronously arriving buyers and sellers) are relatively more present in smaller stocks. While prior studies document increasingly negative autocorrelations for smaller stocks at fixed intraday and daily frequencies (Conrad et al., 2015; Hendershott and Menkveld, 2014), our results extend this evidence by showing that firm size affects not only the magnitude but also the horizon over which return autocorrelations are most pronounced. Finally, it is noteworthy that average return autocorrelations remain relatively close to zero, implying that deviations from weak-form market efficiency, while systematic, are modest overall.

In summary, we establish that average intraday return autocorrelations are significantly negative across most intraday return horizons. Similarly, correlations between overnight returns and subsequent daytime returns are also significantly negative. The term structure exhibits a distinct shape, with the most pronounced negative autocorrelations occurring at return intervals ranging from approximately 8 minutes for large stocks to 18 minutes for small stocks. These findings indicate the presence of short-term return reversals, which are more pronounced in smaller firms that are subject to greater market frictions.

5.4.1.2 Further Analysis

To provide further insights and test the robustness of the distinct shape of the term structure, we re-estimate the return autocorrelations with some modifications. We start by investigating the sensitivity of intraday return autocorrelations to the time of day. To this end, we partition the continuous trading hours into three segments: The middle of the day (10:00 to 15:30), the first half hour (9:31 to 10:00), and the last half hour (15:30 to 15:59). Prior empirical evidence suggests that the composition of informed and uninformed traders varies throughout the trading day (e.g., Anand et al., 2005; Dong et al., 2017). While both trader types are similarly present during midday, the opening and closing periods are distinct. The morning period sees heightened activity from informed traders who incorporate private information into prices, whereas the end-of-day period is dominated by uninformed traders executing trades for non-informational reasons. As the informational component of a trade's price impact is permanent (e.g., Glosten and Milgrom, 1985), and private information is incorporated into prices gradually through multiple trades (e.g., Chordia et al., 2005; Comerton-Forde et al., 2016), return reversals are less likely when informed traders are relatively more active. As a consequence, we expect return autocorrelations to increase during periods when informed traders are particularly active.

Panel A of Table 5.3 reports the return autocorrelations separately for the three partitions of the continuous trading session. During the middle of the day, the term structure of intraday return autocorrelations closely resembles our baseline results, both for the pooled sample and across all three size groups. From that, we conclude that our baseline results are robust. In addition, we find that return autocorrelations in the first half hour tend to be higher than in the last half hour for return horizons up to 5 minutes. Notably, return autocorrelations are significantly positive for most intervals ranging from 1 second to 60 seconds in the first half hour. In contrast, all return intervals in the last half hour exhibit negative autocorrelations. These differences between the opening and closing periods align with variations in the informativeness of the traders operating during these times. Furthermore, this evidence supports and extends prior findings that intraday return autocorrelations tend to be higher in the first half of the trading day than in the second half (Dong et al., 2017).

	$\widehat{\rho(q)}$											
Panel A: Separating Middle of the Day, First Half Hour and Last Half Hour Periods												
	10:00 to 15:30				9:31 to 10:00				15:30 to 15:59			
q	Pooled	Small	Medium	Large	Pooled	Small	Medium	Large	Pooled	Small	Medium	Large
1	-0.85^{***}	-1.14^{***}	-0.76^{***}	-0.64^{***}	0.35^{***}	-0.12^{*}	0.55^{***}	0.63^{***}	-0.71^{***}	-1.16^{***}	-0.82^{***}	-0.15^{*}
20	-0.15^{**}	-0.57^{***}	-0.06	0.18^{*}	1.56^{***}	1.77^{***}	1.60^{***}	1.31^{***}	-0.98^{***}	-1.31^{***}	-0.99^{***}	-0.65^{***}
40	-0.40^{***}	-0.39^{***}	-0.31^{***}	-0.52^{***}	1.41^{***}	2.11^{***}	1.55^{***}	0.57^{***}	-1.36^{***}	-1.73^{***}	-1.59^{***}	-0.76^{***}
60	-0.46^{***}	-0.15^{*}	-0.43^{***}	-0.79^{***}	1.33^{***}	2.21^{***}	1.47^{***}	0.32^{**}	-1.44^{***}	-1.97^{***}	-1.68^{***}	-0.66^{***}
300	-1.98^{***}	-2.20^{***}	-2.10^{***}	-1.64^{***}	-0.47^{**}	0.19	-0.96^{***}	-0.65^{***}	-1.50^{***}	-2.39^{***}	-1.15^{***}	-0.95^{**}
600	-2.54^{***}	-3.42^{***}	-2.35^{***}	-1.85^{***}	-1.25^{***}	-1.92^{***}	-1.42^{***}	-0.40	-0.82^{**}	-1.93^{***}	-0.53	-0.01
900	-2.69^{***}	-3.85^{***}	-2.35^{***}	-1.88^{***}								
1800	-2.33^{***}	-3.70^{***}	-1.89^{***}	-1.40^{***}								
3600	-1.75^{***}	-2.69^{***}	-1.54^{***}	-1.03^{***}								
5400	-1.34^{***}	-1.84^{***}	-1.28^{***}	-0.89^{**}								
7200	-0.99^{***}	-1.39^{***}	-0.93^{**}	-0.64								
9000	-0.77^{*}	-1.28^{***}	-0.65	-0.40								
Panel B: Shifting Day and Night Periods												
	±15 Minutes				±30 Minutes							
q	Pooled	Small	Medium	Large	Pooled	Small	Medium	Large				
$\langle N^{-}, D\rangle$	-0.81	-1.18^{**}	-0.77	-0.48	-0.63	-1.05^{**}	-0.66	-0.19				
$\langle D, N^{+}\rangle$	-0.42	-1.57^{***}	-0.12	0.44	-0.09	-1.12^{**}	0.27	0.57				

Table 5.3. ***Term Structure of Intraday Return Autocorrelations with Modified Specifications.*** *The table reports return autocorrelations for various intervals q (seconds) and size groups. Panel A shows results separately for returns during the middle of the day (10:00 to 15:30), the first half hour (9:31 to 10:00), and the last half hour (15:30 to 15:59). Panel B reports results for modified day and night periods, where the day (night) period is shorted (extended) by shifting the start of the day period 15 (30) minutes after the open and the end 15 (30) minutes before the close. All variables are winsorized at the* 1% *and* 99% *quantiles for each day. All coefficients are multiplied by the factor* 10^2*. Inference is based on standard errors clustered by time t and firm i. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

	$\widehat{\rho(q)}$					
q	2017	2018	2019	2020a	2020b	2021
1	0.02	1.08^{***}	0.11	-1.58^{***}	-1.36^{***}	-2.27^{***}
20	0.02	0.56^{***}	-0.30^{**}	-0.09	1.39^{**}	-0.45^{***}
40	-0.50^{***}	0.26^{**}	-0.69^{***}	-0.13	2.20^{***}	-0.83^{***}
60	-0.79^{***}	0.11	-0.79^{***}	-0.21	2.71^{***}	-0.75^{***}
300	-2.23^{***}	-1.79^{***}	-2.07^{***}	-2.19^{***}	0.35	-2.03^{***}
600	-2.95^{***}	-2.20^{***}	-2.83^{***}	-2.28^{***}	-1.64	-2.63^{***}
900	-2.55^{***}	-2.19^{***}	-3.24^{***}	-2.55^{***}	-2.13^{*}	-2.90^{***}
1800	-2.78^{***}	-1.63^{***}	-2.70^{***}	-2.13^{***}	-2.80^{***}	-2.31^{***}
3600	-2.71^{***}	-0.86	-2.07^{***}	-2.26^{***}	-2.67^{*}	-1.66^{***}
5400	-2.73^{***}	-0.14	-1.45^{**}	-1.68^{**}	-2.24	-1.70^{***}
7200	-2.04^{***}	0.72	-1.40^{**}	-0.94	-0.61	-1.63^{**}
9000	-1.43^{**}	1.16	-1.39^{*}	-0.87	0.05	-1.79^{**}
10800	-1.30^{*}	0.88	-1.38^{*}	-0.48	1.33	-1.77^{**}
11640	-1.55^{*}	0.10	-1.57^{*}	-0.83	-0.05	-2.35^{***}
$\langle N^{-}, D\rangle$	-2.85^{***}	-3.03^{**}	-0.50	-2.58	7.54^{*}	-2.26^{*}
$\langle D, N^{+}\rangle$	-1.22	-1.10	0.14	2.11	-0.59	1.12

Table 5.4. ***Term Structure of Intraday Return Autocorrelations by Subperiod.*** *The table reports the return autocorrelations for various intervals q (seconds) and calendar years. The year 2020 is split into the period of the COVID crash during February and March (2020b) and the remaining period excluding the crash (2020a). All variables are winsorized at the 1% and 99% quantiles for each day. All coefficients are multiplied by the factor 10^2. Inference is based on standard errors clustered by time t and firm i. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

We also investigate the sensitivity of the correlations between overnight and daytime returns to modifications in the definition of the time periods. Specifically, we consider two modifications: first, we adjust the daytime period to span from 9:45 to 15:45 (±15 Minutes), and second, we modify it to last from 10:00 to 15:30 (±30 Minutes). In turn, we extend the overnight periods to match these changes. Panel B of Table 5.3 reports the average correlations between returns in the modified daytime and overnight intervals. We observe that the average correlation between the return during the previous night and the return during the day becomes less negative in the pooled sample as well as in each size group, for both modifications. The correlation remains significantly negative only in the small-stock group. This suggests that night-to-day reversals materialize quickly around the opening time. Moreover, the average correlation between the daytime return and the subsequent overnight return is significantly negative only for the small-stock group. This confirms our earlier conclusion that there is few evidence of reversals between daytime returns and the subsequent night returns.

Next, we explore whether the distinct shape of the term structure persists over time. For this purpose, we re-compute the term structure separately for each calendar year. In addition, we split the year 2020 into the period of the COVID crash (February to March 2020) and the remainder of the year, excluding the crash. Table 5.4 reports the results for each sub-period. Across all sub-periods, the term structure maintains a similar shape. Most importantly, the term structure consistently shows its distinct minimum between 10-minute and 30-minute return horizons. In addition, during periods of increased volatility – particularly during the 2020 crash and also in 2018 – return autocorrelations for short intervals become significantly

positive. These findings have two important implications. First, the overall shape of the term structure is robust, even during periods of crisis. Second, there is some variability in the term structure that may be linked to specific market conditions, which we investigate further in the next section.

Overall, we conclude that the term structure's shape is robust to various modifications. This suggests that reversals in intraday stock returns are a consistent feature across stocks of different sizes and across different time periods. Furthermore, we provide evidence that return autocorrelations at very high frequencies tend to become positive following periods of market closure and during times of high volatility. Given that substantial price discovery occurs during these periods, this may indicate that a relatively higher presence of informed traders contributes to higher return autocorrelations.

5.4.2 Links to Market Characteristics

5.4.2.1 Baseline Analysis

We now test our hypotheses regarding the relationship between the term structure of return autocorrelations and market characteristics. To examine how these characteristics influence return autocorrelations across different interval lengths, we estimate the following panel regression separately for each return interval q:

$$\begin{aligned}\widetilde{\rho(q)}_{i,t} =& \alpha + \beta_1 \widetilde{Volume}_{i,t} + \beta_2 \widetilde{Spread}_{i,t} + \beta_3 \widetilde{Retail}_{i,t} \\ &+ \beta_4 \widetilde{Impact}_{i,t-1} + \beta_5 \widetilde{NGE}_{i,t} + FE_t + \epsilon_{i,t},\end{aligned} \tag{5.11}$$

where α is a constant, FE_t denotes a time fixed effect, and the tildes indicate that the variables have been standardized. For each day, we standardize the independent variables by subtracting their cross-sectional means and scaling their standard deviations to one. This standardization allows us to immediately compare the effect sizes across different variables. The beta coefficients then represent the deviation from the average return autocorrelation due to a one-standard-deviation increase in the respective variable above its mean.[13] The intercepts represent the average return autocorrelations, as reported in the previous section.

Figure 5.3 illustrates the regression results based on Equation (5.11). For selected points along the term structure, the corresponding results are also reported in Table 5.5. We find that higher trading volume significantly increases return autocorrelations across most intraday return horizons. Similarly, the correlation between the overnight returns and subsequent daytime returns increases with higher volume. However, the correlation between daytime returns and subsequent overnight returns is not significantly altered and for return intervals of approximately

[13] We have also estimated the panel regressions without standardization and with additional firm-fixed effects, coming to the same conclusions.

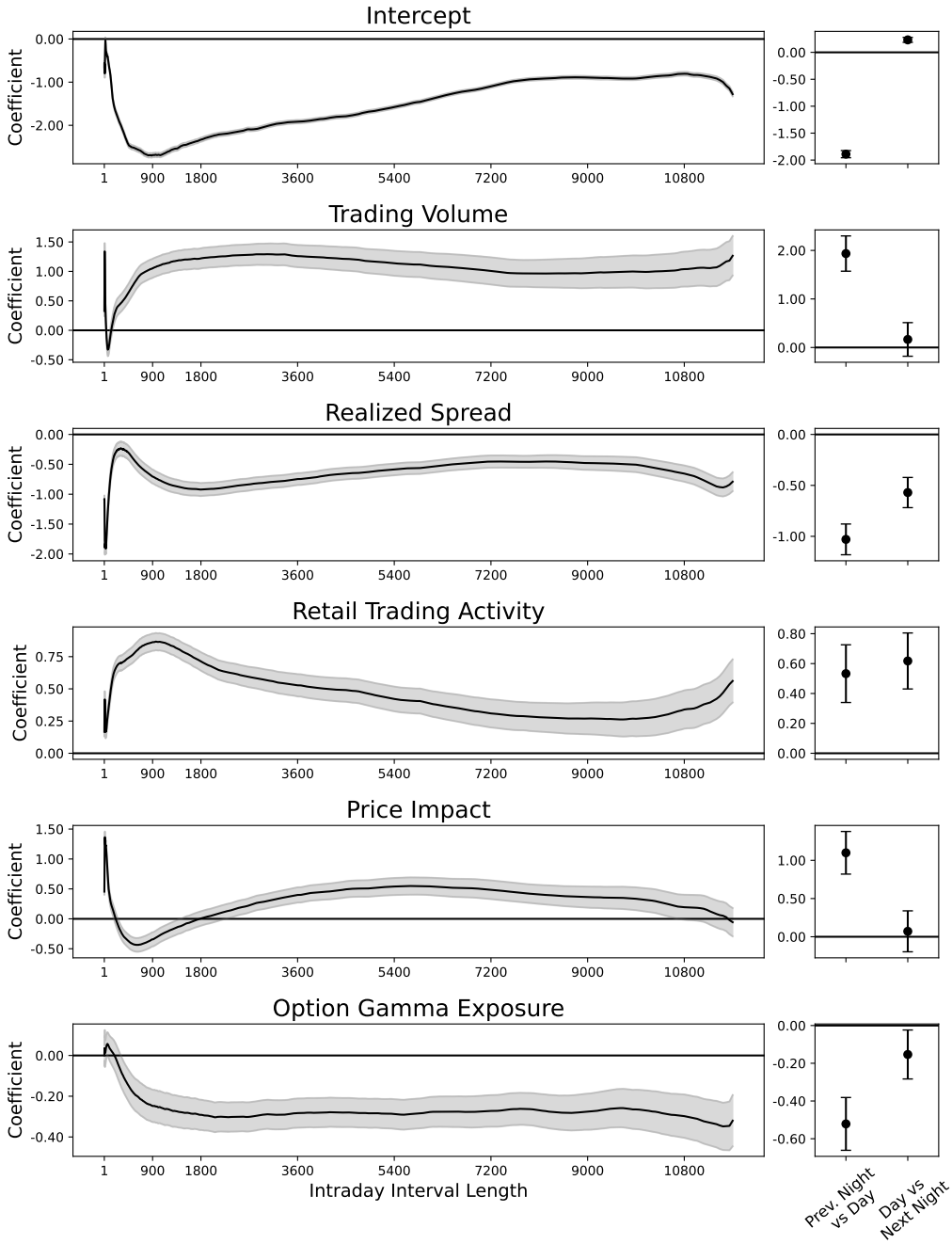

Figure 5.3. ***Links to Market Characteristics.*** *The figure shows the estimated coefficients for the regressions according to Equation (5.11). A separate regression is estimated for each interval q. The coefficients from the respective regressions are shown in separate graphs for each independent variable. All variables are winsorized at the 1% and 99% quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor 10^2. 95% confidence intervals are shown in gray and by whiskers. Inference is based on robust standard errors clustered by firm and day. The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

1 minute to 2 minutes the effect is significantly negative. Regarding the realized spread, we observe that lower spreads are associated with increased return autocorrelations across all return intervals, with the most pronounced effect observed for half-minute returns. Furthermore, a

higher share of retail trading activity leads to significantly higher return autocorrelations across all return intervals. Taken together, these findings strongly support Hypothesis 1: When market conditions make it easier for intermediaries to mean-revert their inventories, transitory price pressures diminish, and return autocorrelations become less negative. Moreover, a comparison of the average effect sizes across all return horizons reveals that trading volume (1.07%) and realized spreads (−0.63%) have a relatively larger impact on return autocorrelations than retail trading activity (0.46%).

We also find that when informational asymmetries are more pronounced – indicated by higher permanent price impacts – return autocorrelations tend to increase significantly for most return intervals. There is a significantly positive effect for return intervals between 1 second and 3 minutes, as well as for most return intervals longer than 30 minutes. In between, the effect turns slightly negative.[14] In addition, we find that higher permanent price impacts significantly increase the correlation between overnight returns and subsequent daytime returns. Overall, the predominantly positive effect of the permanent price impact on return autocorrelations supports our rationale that higher trading costs, due to more pronounced informational asymmetry, incentivize informed traders to execute their orders more gradually over time. This, in turn, increases return autocorrelations, consistent with Hypothesis 2.

Turning to the effect of option market makers' hedge adjustments, we observe significantly negative coefficients for all return intervals longer than 5 minutes. The effect size increases for longer return intervals until it stabilizes at around 30 minutes and beyond. This pattern suggests that hedge adjustments do indeed occur at medium frequencies but not at very high frequencies, likely due to transaction costs. In addition, the effect on the correlations between the overnight and subsequent daytime returns as well as between daytime and subsequent overnight returns is also significantly negative. Overall, our findings confirm that option market makers' hedge adjustments play a significant role in shaping return autocorrelations, consistent with Hypothesis 3. However, compared to other market characteristics, their effect size is relatively smaller, suggesting that while gamma hedging affects return dynamics, factors such as trading volume, spreads, and information asymmetry have a more dominant impact.

In regressions based on increasingly longer return horizons q, we observe a decline in the explained variance (R^2). This pattern arises because longer return horizons reduce the number of available observations at the stock-day level (see Equation 5.2). The smaller sample size increases the variance of the dependent variable, weakening the model fit. However, our primary focus is on the directional effects of market characteristics on average return autocorrelation. Since the estimated coefficients remain relatively stable, the decline in model fit does not impact our conclusions. For this reason, we show the results for the full term structure.

[14] A possible explanation for the temporarily negative effect is that that the measure of the permanent price impact picks up some transitory effects, which are associated with negative return autocorrelation.

	$\widehat{\rho(q)}$															
Variable	1	20	40	60	300	600	900	1800	3600	5400	7200	9000	10800	11640	$\langle N^-, D\rangle$	$\langle D, N^+\rangle$
α	-0.66^{***}	-0.03	-0.33^{***}	-0.40^{***}	-1.98^{***}	-2.55^{***}	-2.69^{***}	-2.33^{***}	-1.92^{***}	-1.56^{***}	-1.08^{***}	-0.90^{***}	-0.81^{***}	-1.28^{***}	-1.89^{***}	0.23^{***}
	(-27.1)	(-0.89)	(-11.2)	(-14.7)	(-75.3)	(-98.0)	(-104.2)	(-96.8)	(-95.6)	(-83.3)	(-63.5)	(-48.9)	(-36.0)	(-47.3)	(-56.0)	(9.92)
$Volume_{i,t}$	0.33^{***}	0.40^{***}	-0.10	-0.32^{***}	0.45^{***}	0.86^{***}	1.06^{***}	1.22^{***}	1.26^{***}	1.13^{***}	1.00^{***}	0.98^{***}	1.04^{***}	1.27^{***}	1.94^{***}	0.17
	(7.33)	(7.02)	(-1.78)	(-5.69)	(6.04)	(10.70)	(12.77)	(13.96)	(13.01)	(10.49)	(8.47)	(7.42)	(6.83)	(7.37)	(10.43)	(0.94)
$Spread_{i,t}$	-1.08^{***}	-1.86^{***}	-1.74^{***}	-1.36^{***}	-0.24^{***}	-0.48^{***}	-0.71^{***}	-0.92^{***}	-0.75^{***}	-0.58^{***}	-0.45^{***}	-0.48^{***}	-0.67^{***}	-0.79^{***}	-1.03^{***}	-0.57^{***}
	(-38.0)	(-39.9)	(-37.9)	(-29.1)	(-4.01)	(-7.98)	(-11.9)	(-16.6)	(-14.6)	(-11.5)	(-8.67)	(-8.18)	(-9.54)	(-9.74)	(-13.4)	(-7.54)
$Retail_{i,t}$	0.17^{***}	0.18^{***}	0.19^{***}	0.28^{***}	0.70^{***}	0.80^{***}	0.86^{***}	0.71^{***}	0.53^{***}	0.42^{***}	0.31^{***}	0.27^{***}	0.34^{***}	0.56^{***}	0.53^{***}	0.62^{***}
	(9.23)	(7.01)	(7.82)	(11.6)	(23.7)	(24.2)	(25.3)	(19.3)	(11.9)	(8.51)	(5.49)	(4.28)	(4.50)	(6.55)	(5.41)	(6.46)
$Impact_{i,t}$	0.45^{***}	1.22^{***}	1.09^{***}	0.73^{***}	-0.20^{***}	-0.43^{***}	-0.34^{***}	0.01	0.40^{***}	0.54^{***}	0.48^{***}	0.36^{***}	0.19	-0.06	1.10^{***}	0.07
	(16.8)	(31.6)	(27.2)	(17.5)	(-3.82)	(-7.46)	(-5.66)	(0.15)	(6.16)	(7.43)	(6.01)	(3.99)	(1.78)	(-0.47)	(7.72)	(0.52)
$NGE_{i,t-1}$	0.00	0.01	0.05	0.06	-0.07	-0.20^{***}	-0.25^{***}	-0.29^{***}	-0.28^{***}	-0.29^{***}	-0.27^{***}	-0.28^{***}	-0.30^{***}	-0.32^{***}	-0.52^{***}	-0.15^{*}
	(0.05)	(0.46)	(1.68)	(1.91)	(-1.86)	(-4.88)	(-6.13)	(-7.67)	(-7.73)	(-7.75)	(-6.84)	(-6.05)	(-5.52)	(-4.98)	(-7.30)	(-2.32)
FE_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs.	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$
R^2	7.14%	9.02%	5.44%	2.69%	0.64%	1.14%	1.22%	0.82%	0.34%	0.16%	0.08%	0.06%	0.06%	0.07%	0.12%	0.02%

Table 5.5. ***Links to Market Characteristics.*** *The table shows the estimated coefficients for the regression according to Equation (5.11). A separate regression is estimated for selected intervals q (seconds), including all sample stocks. All variables are winsorized at the 1% and 99% quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor 10^2. The last rows indicate time fixed effects, the number of observations, and the adjusted R^2. Inference is based on standard errors clustered by time t and firm i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

	$\widehat{\rho(q)}$														
	Small					Medium					Large				
Variable	60	900	3600	$\langle N^-, D\rangle$	$\langle D, N^+\rangle$	60	900	3600	$\langle N^-, D\rangle$	$\langle D, N^+\rangle$	60	900	3600	$\langle N^-, D\rangle$	$\langle D, N^+\rangle$
α	-0.16^{***}	-3.93^{***}	-2.88^{***}	-2.72^{***}	-0.10^{*}	-0.36^{***}	-2.42^{***}	-1.71^{***}	-1.80^{***}	0.59^{***}	-0.68^{***}	-1.72^{***}	-1.16^{***}	-1.15^{***}	0.20^{***}
	(-4.05)	(-89.7)	(-78.9)	(-55.6)	(-2.55)	(-7.92)	(-71.7)	(-61.3)	(-31.4)	(24.7)	(-19.3)	(-54.7)	(-39.6)	(-19.4)	(4.69)
$Volume_{i,t}$	-0.49^{***}	1.68^{***}	1.59^{***}	2.27^{***}	0.62^{***}	-0.19^{***}	1.11^{***}	1.17^{***}	1.76^{***}	0.49^{**}	-0.13	0.49^{***}	0.70^{***}	1.70^{***}	-0.22
	(-11.8)	(29.2)	(21.8)	(15.4)	(4.51)	(-4.20)	(18.1)	(13.2)	(8.95)	(2.65)	(-1.71)	(3.33)	(6.03)	(9.29)	(-1.31)
$Spread_{i,t}$	-1.65^{***}	-0.33^{***}	-0.57^{***}	-0.94^{***}	-0.54^{***}	-1.50^{***}	-0.58^{***}	-0.52^{***}	-0.52^{***}	-0.16	-1.58^{***}	-0.85^{***}	-0.62^{***}	-0.90^{***}	-0.09
	(-32.53)	(-5.27)	(-9.35)	(-9.14)	(-5.50)	(-19.5)	(-7.75)	(-7.60)	(-4.51)	(-1.62)	(-15.5)	(-4.26)	(-4.76)	(-6.68)	(-0.96)
$Retail_{i,t}$	0.30^{***}	1.22^{***}	0.83^{***}	0.59^{***}	0.72^{***}	0.31^{***}	0.57^{***}	0.35^{***}	0.40^{***}	0.42^{***}	0.27^{***}	0.36^{***}	0.03	0.03	0.71^{***}
	(8.99)	(27.03)	(14.10)	(4.71)	(5.95)	(9.18)	(13.65)	(6.60)	(3.64)	(3.92)	(8.02)	(6.29)	(0.54)	(0.24)	(6.40)
$Impact_{i,t}$	0.77^{***}	-0.53^{***}	0.36^{***}	0.84^{***}	0.10	0.58^{***}	-0.26^{***}	0.15^{*}	0.60^{***}	-0.11	0.74^{***}	0.01	0.09	0.70^{***}	0.22
	(21.2)	(-11.3)	(6.37)	(6.75)	(0.82)	(14.07)	(-5.16)	(2.51)	(4.46)	(-0.88)	(9.56)	(0.07)	(0.86)	(4.76)	(1.53)
$NGE_{i,t-1}$	0.08^{**}	0.07	-0.03	-0.03	0.06	0.05^{*}	-0.16^{***}	-0.17^{***}	-0.43^{***}	-0.04	0.02	-0.36^{***}	-0.41^{***}	-0.74^{***}	-0.28^{**}
	(2.71)	(1.72)	(-0.68)	(-0.36)	(0.85)	(2.08)	(-4.62)	(-4.38)	(-4.50)	(-0.46)	(0.45)	(-5.70)	(-7.08)	(-6.67)	(-2.70)
FE_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs.	$898K$	$898K$	$898K$	$898K$	$898K$	$900K$	$900K$	$900K$	$900K$	$900K$	$901K$	$901K$	$901K$	$901K$	$901K$
R^2	3.94%	1.95%	0.59%	0.23%	0.04%	3.40%	1.07%	0.30%	0.11%	0.02%	4.05%	0.51%	0.13%	0.08%	0.01%

Table 5.6. ***Links to Market Characteristics by Size.*** *The table shows the estimated coefficients for the regression according to Equation (5.11). A separate regression is estimated for selected intervals q (seconds) and three size groups formed according to terciles of market capitalization (Small, Medium, Large). All variables are winsorized at the 1% and 99% quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor 10^2. The last rows indicate time fixed effects, the number of observations, and the adjusted R^2. Inference is based on standard errors clustered by time t and firm i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

Next, we examine whether the observed patterns are driven by a specific size group, such as small stocks with larger frictions. For this purpose, we re-estimate the regressions according to Equation (5.11) separately for each of the three size groups. As before, we standardize the independent variables within each group. Table 5.6 reports the results for selected points along the term structure. We find that our previous results hold consistently across all size groups. The only notable exception is the effect of gamma exposure, which is mostly insignificant for small stocks. We attribute this finding to the generally lower levels of option gamma exposure in small stocks, with roughly 20% of them having zero gamma exposure on any given day.[15]

In summary, we provide strong evidence for links between the term structure of intraday return autocorrelations and the analyzed market characteristics, supporting our Hypotheses 1, 2, and 3.

5.4.2.2 Robustness

We now verify that our evidence on the links between return autocorrelations and market characteristics is robust. We start by modifying the daytime period to last from 10:00 to 15:30 and the overnight period to last from 15:30 to 10:00. Consequently, the shorter daytime period excludes trading activity that might be driven by the fact that exchanges open and close. Based on this modified framework, we re-calculate the return autocorrelations and then re-estimate the regressions according to Equation (5.11). The results are shown in Table 5.7. We detect the same patterns as before, indicating that the relationship between the variables is robust.

In our main analysis, the time lag between return autocorrelations (the dependent variable) and gamma exposure (an independent variable) supports a causal interpretation of the effects. However, contemporaneous relationships can introduce potential reverse causality, complicating the interpretation. Although our hypotheses provide a strong basis that reverse causality is unlikely to drive our results for trading volume, spread, retail trading activity, and permanent price impact, it is worth closer examination. For this reason, we replace the contemporaneous independent variables with their 1-day lagged counterparts and re-estimate our main model (5.11). Table 5.8 shows the results. They closely resemble our main results in Table 5.5, although the statistical significance of some variables decreases, and the explained variance declines. Since the effects remain detectable even with lagged variables, we conclude that the impact of the contemporaneous variables on return autocorrelations is robust. This moreover shows that the variables have predictive power. Overall, we conclude that our main results are robust.

[15] For comparison, fewer than 2% of stocks outside the small-size group have zero option gamma exposure per day.

	$\widehat{\rho(q)}$													
Variable	1	20	40	60	300	600	900	1800	3600	5400	7200	9000	$\langle N^-, D\rangle$	$\langle D, N^+\rangle$
α	-0.85^{***}	-0.15^{**}	-0.40^{***}	-0.46^{***}	-1.98^{***}	-2.54^{***}	-2.69^{***}	-2.33^{***}	-1.75^{***}	-1.34^{***}	-0.99^{***}	-0.77^{*}	-0.63^{***}	-0.09^{***}
	(-19.1)	(-2.77)	(-7.38)	(-7.99)	(-22.9)	(-24.3)	(-21.6)	(-15.1)	(-8.66)	(-5.38)	(-3.37)	(-2.19)	(-20.3)	(-4.30)
$Volume_{i,t}$	0.27^{***}	0.42^{***}	-0.11^{*}	-0.39^{***}	0.17^{*}	0.49^{***}	0.74^{***}	1.08^{***}	1.13^{***}	0.97^{***}	0.88^{***}	0.91^{***}	2.00^{***}	0.17
	(5.80)	(7.10)	(-2.04)	(-6.97)	(2.33)	(6.02)	(8.77)	(12.1)	(11.1)	(8.47)	(6.84)	(5.88)	(10.4)	(0.90)
$Spread_{i,t}$	-1.01^{***}	-1.74^{***}	-1.59^{***}	-1.23^{***}	-0.18^{**}	-0.42^{***}	-0.62^{***}	-0.78^{***}	-0.63^{***}	-0.46^{***}	-0.38^{***}	-0.38^{***}	-0.30^{***}	-0.86^{***}
	(-34.8)	(-36.7)	(-34.3)	(-26.2)	(-3.13)	(-7.09)	(-10.4)	(-13.9)	(-12.2)	(-8.74)	(-6.77)	(-5.56)	(-3.36)	(-10.2)
$Retail_{i,t}$	0.15^{***}	0.14^{***}	0.15^{***}	0.23^{***}	0.62^{***}	0.72^{***}	0.81^{***}	0.65^{***}	0.45^{***}	0.33^{***}	0.25^{***}	0.17^{*}	1.01^{***}	0.22^{*}
	(7.96)	(5.13)	(6.10)	(9.51)	(21.5)	(22.4)	(23.4)	(16.6)	(9.66)	(6.19)	(4.07)	(2.29)	(10.3)	(2.32)
$Impact_{i,t}$	0.52^{***}	1.19^{***}	1.02^{***}	0.70^{***}	-0.39^{***}	-0.65^{***}	-0.53^{***}	-0.13^{*}	0.32^{***}	0.50^{***}	0.47^{***}	0.41^{***}	0.79^{***}	-0.39^{**}
	(19.5)	(29.9)	(25.4)	(16.7)	(-7.39)	(-11.1)	(-8.57)	(-2.12)	(4.65)	(6.34)	(5.38)	(3.75)	(5.60)	(-2.83)
$NGE_{i,t-1}$	0.01	0.02	0.05	0.06	-0.03	-0.16^{***}	-0.21^{***}	-0.25^{***}	-0.26^{***}	-0.25^{***}	-0.25^{***}	-0.27^{***}	-0.50^{***}	-0.15^{*}
	(0.42)	(0.63)	(1.56)	(1.92)	(-0.78)	(-3.96)	(-5.15)	(-6.50)	(-7.02)	(-6.42)	(-5.87)	(-5.09)	(-7.01)	(-2.29)
FE_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs.	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$
R^2	6.19%	8.00%	4.64%	2.32%	0.42%	0.77%	0.83%	0.58%	0.22%	0.09%	0.05%	0.03%	0.09%	0.03%

Table 5.7. ***Links to Market Characteristics with Modified Specifications.*** *The table shows the estimated coefficients for the regression according to Equation (5.11). A separate regression is estimated for selected intervals q (seconds), including all sample stocks. In contrast to Table 5.5, the specifications of the day and night periods are modified: The day (night) period is shorted (extended) by shifting the start of the day period 30 minutes after the open and the end 30 minutes before the close. All variables are winsorized at the* 1% *and* 99% *quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor* 10^2*. The last rows indicate time fixed effects, the number of observations, and the adjusted* R^2*. Inference is based on standard errors clustered by time t and firm i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

	$\widehat{\rho(q)}$															
Variable	1	20	40	60	300	600	900	1800	3600	5400	7200	9000	10800	11640	$\langle N^-, D\rangle$	$\langle D, N^+\rangle$
α	-0.66^{***}	-0.03	-0.33^{***}	-0.40^{***}	-1.98^{***}	-2.55^{***}	-2.69^{***}	-2.33^{***}	-1.92^{***}	-1.56^{***}	-1.08^{***}	-0.90^{***}	-0.81^{***}	-1.28^{***}	-1.89^{***}	0.23^{***}
	(-26.7)	(-0.87)	(-11.1)	(-14.6)	(-75.6)	(-101)	(-109)	(-105)	(-111)	(-99.1)	(-77.8)	(-58.6)	(-40.7)	(-50.4)	(-66.2)	(9.96)
$Volume_{i,t-1}$	0.21^{***}	0.09	-0.41^{***}	-0.59^{***}	0.18^{*}	0.56^{***}	0.71^{***}	0.67^{***}	0.52^{***}	0.37^{***}	0.29^{*}	0.31^{*}	0.47^{**}	0.81^{***}	0.43^{*}	-0.04
	(4.68)	(1.68)	(-7.95)	(-11.06)	(2.57)	(7.46)	(9.27)	(8.36)	(5.78)	(3.57)	(2.52)	(2.45)	(3.21)	(4.94)	(2.40)	(-0.23)
$Spread_{i,t-1}$	-0.84^{***}	-1.24^{***}	-1.07^{***}	-0.88^{***}	-0.32^{***}	-0.55^{***}	-0.72^{***}	-0.82^{***}	-0.60^{***}	-0.43^{***}	-0.32^{***}	-0.35^{***}	-0.54^{***}	-0.69^{***}	-0.77^{***}	-0.56^{***}
	(-30.0)	(-26.4)	(-23.3)	(-18.9)	(-5.89)	(-10.0)	(-13.3)	(-15.9)	(-12.5)	(-8.97)	(-6.40)	(-6.15)	(-7.97)	(-8.93)	(-10.2)	(-7.42)
$Retail_{i,t-1}$	0.22^{***}	0.31^{***}	0.31^{***}	0.33^{***}	0.43^{***}	0.42^{***}	0.45^{***}	0.29^{***}	0.14^{***}	0.10^{*}	0.06	0.00	0.02	0.17^{*}	-0.02	0.50^{***}
	(12.0)	(12.3)	(13.2)	(14.1)	(15.8)	(14.7)	(14.8)	(8.71)	(3.36)	(2.22)	(1.08)	(0.01)	(0.21)	(2.07)	(-0.26)	(5.23)
$Impact_{i,t-1}$	0.10^{***}	0.27^{***}	0.09^{*}	-0.03	-0.28^{***}	-0.46^{***}	-0.42^{***}	-0.33^{***}	-0.13^{*}	-0.04	-0.04	-0.05	-0.04	-0.10	-0.02	-0.06
	(3.87)	(7.72)	(2.39)	(-0.77)	(-5.69)	(-8.73)	(-7.62)	(-5.94)	(-2.23)	(-0.59)	(-0.50)	(-0.59)	(-0.41)	(-0.87)	(-0.17)	(-0.49)
$NGE_{i,t-1}$	0.00	0.01	0.04	0.06^{*}	-0.01	-0.12^{**}	-0.16^{***}	-0.18^{***}	-0.16^{***}	-0.17^{***}	-0.16^{***}	-0.16^{***}	-0.18^{***}	-0.19^{**}	-0.28^{***}	-0.12
	(0.02)	(0.27)	(1.44)	(1.99)	(-0.35)	(-3.06)	(-4.12)	(-5.13)	(-4.63)	(-4.72)	(-4.10)	(-3.53)	(-3.30)	(-3.05)	(-4.11)	(-1.78)
FE_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Obs.	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$	$2700K$
R^2	4.78%	3.83%	1.78%	1.04%	0.35%	0.76%	0.81%	0.49%	0.14%	0.04%	0.02%	0.02%	0.03%	0.04%	0.03%	0.01%

Table 5.8. ***Links to Non-Contemporaneous Market Characteristics.*** *The table shows the estimated coefficients for the regression according to Equation (5.11). A separate regression is estimated for selected return intervals q (seconds), including all sample stocks. All variables are winsorized at the* 1% *and* 99% *quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor* 10^2*. The last rows indicate time fixed effects, the number of observations, and the adjusted* R^2*. Inference is based on standard errors clustered by time t and firm i. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.*

5.5 Conclusion

Intraday return autocorrelations have not yet been studied widely across various return horizons. Given that multiple and opposing forces affect return autocorrelations, their relative importance could vary depending on the return horizon. As a consequence, we expect that the degree of autocorrelation depends on the return horizon. We address this gap by constructing and analyzing a term structure of intraday return autocorrelations.

Our results show that average return autocorrelations are mostly negative, and that the degree of autocorrelation depends indeed on the return horizon. On 15-minute horizons, return reversals are most pronounced. On sub-minute horizons, return continuations occur in relatively larger stocks, during periods of market stress, and in the first half hour of trading.

Furthermore, we draw on the literature and derive and test three hypotheses that link intraday return autocorrelations to specific sources of market friction and trading needs that depend systematically on past returns. We provide evidence that return autocorrelations depend on the ease with which intermediaries can mean-revert their inventories, the degree of informational asymmetry, and hedge adjustments of option market makers due to gamma exposure. Finally, despite these distinct and robust patterns in the term structure of return autocorrelations, it is noteworthy that return autocorrelations deviate only modestly from zero. This means deviations from weak-form efficiency are relatively minor after all.

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Authorship Contribution

Essay 1: **Feedback Trading: The Intraday Case of Retail Derivatives**
Published in Journal of Futures Markets 44, 1487–1507
(`https://doi.org/10.1002/fut.22536`)
Rainer Baule: Conceptualization, Methodology, Writing – review & editing.
Bart Frijns: Methodology, Resources, Writing – review & editing.
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Essay 2: **Shorting in the Dark: The Dual Role of Short Sales in Off-Exchange Trading**
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Essay 3: **Interday Cross-Sectional Momentum: Global Evidence and Determinants**
Forthcoming in Finance
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Eidesstattliche Erklärung

Hiermit versichere ich an Eides statt, dass ich die Dissertation selbstständig und ohne Inanspruchnahme fremder Hilfe angefertigt habe. Ich habe dabei nur die angegebenen Quellen und Hilfsmittel verwendet und die aus diesen wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht. Die Hilfe einer Promotionsberaterin/eines Promotionsberaters habe ich nicht in Anspruch genommen. Die Arbeit hat in gleicher oder ähnlicher Form noch keiner anderen Prüfungsbehörde vorgelegen. Ich erkläre mich damit einverstanden, dass die Arbeit mit Hilfe eines Plagiatserkennungsdienstes auf enthaltene Plagiate überprüft wird.

Mai 2025 Sebastian Schlie