Interday Cross-Sectional Momentum: Global Evidence and Determinants

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Abstract

Using a novel set of international high-frequency data, we examine whether half-hour returns continue to predict half-hour returns on subsequent days in global stock markets at the firm level, and how market characteristics determine the strength of this "interday momentum" pattern. Our results show that the pattern is still present in the U.S., albeit weaker than in previous studies, and that it also exists across all novel markets of our sample. The pattern is most pronounced during the last half-hour interval of a trading day. Interday momentum tends to decline for high-volatility stocks, and after a more pronounced absolute overnight return. The strategic timing of trades can save international investors transaction costs of economically significant size.

JEL Classification: D4, D8, D82, G15

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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 (see, e.g., Rouwenhorst, 1998; Griffin et al., 2003; Asness et al., 2013). However, little is known about whether this pattern is 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 subsequent days.[1] They find that the predictability is most pronounced during the first and the last half hour of a trading day. This may be due to the common usage of strategies, which execute an order piece-wise in proportion to the then present U-shape of diurnal trading volume (Białkowski et al., 2008). Murphy and Thirumalai (2017) confirm the existence of this interday cross-sectional momentum effect for the Indian stock market, and show that it is indeed partly explained by institutional traders who execute large orders over multiple days in order to minimize execution costs.[2] Similar systematic price pressure and therefore momentum can result from autocorrelated fund inflows and outflows, as well as autocorrelation in repetitively scheduled trading of market participants over subsequent days (Heston et al., 2010).

The empirical evidence of interday cross-sectional momentum is limited to the above studies.[3] This limitation arises from the scarcity of high-frequency data sets that cover multiple markets and extended time periods. The current state of the literature therefore poses a

[1]More generally, Lou et al. (2019) look at the overnight return and the aggregate intraday return, and find that past intraday (overnight) returns are positively related to future intraday (overnight) returns in the U.S. cross-section.

[2]As in Heston et al. (2010), we define *interday cross-sectional momentum* as the positive relationship between a given half-hour return on day t and the same half-hour return on previous days $t-1$, $t-2\ldots$ Murphy and Thirumalai (2017) term this pattern *micro momentum*. In contrast, *intraday (time series) momentum*, as in Gao et al. (2018) and Li et al. (2022) among others, describes the positive relation between the overnight, and first half-hour return on day t and the return in the last half-hour on the same day t.

[3]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) study the data from 2005 to 2006 for India. To the best of our knowledge, these are the only studies that focus on the interday cross-sectional momentum.

particular challenge in addressing the question of whether the interday momentum pattern holds across other markets and whether it persists over time. Inter-market variability could arise from heterogeneity in market size, trading mechanisms, and investor behaviour. Time-variability could be induced through changes in the market structure[4] and competition among traders to exploit the momentum effect (Admati and Paul, 1991; McLean and Pontiff, 2016; Bessembinder et al., 2016). For other return patterns, there is a growing literature that documents variability with regard to these two dimensions (see, e.g., Kaplanski, 2023, Rosa, 2022, Jacobs and Müller, 2020, Hameed and Kusnadi, 2002).

In this paper, we extend the work of Heston et al. (2010, 2011) and Murphy and Thirumalai (2017) by investigating whether interday cross-sectional momentum is a global phenomenon that is (still) present in international stock markets. We build our analysis on a high-frequency data sample, covering nine stock markets across North America, Europe, Asia and Australia. Both our sample period and eight of our sample markets have not been studied before. Using univariate panel regressions, we provide empirical evidence that interday momentum is still present in the U.S., and that it also exists in the novel markets of our sample. Regarding the diurnal distribution of its strength, 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 might be related to favorable conditions for repetitive trades: The intraday price discovery is almost completed, the liquidity is high, and the volatility is low. 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 interday momentum 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. In other words, investors across markets tend to behave similarly towards the end of the trading day.

[4]Major changes in the market structure include the dissemination of algorithmic traders (Weller, 2018; O'Hara et al., 2014; Hendershott and Riordan, 2013; Hendershott et al., 2011), retail traders (Eaton et al., 2022; Welch, 2022; Ozik et al., 2021), and a shift in trading volume towards the close (Bogousslavsky and Muravyev, 2023; Raillon, 2020; Johann et al., 2019).

Having established that interday momentum in the last half hour is a global phenomenon, we examine possible determinants of its strength. We find some evidence that interday momentum is stronger for firms with less volatile stock returns. This relation might be explained by the interaction of positive feedback traders and rational, risk-averse traders in the model of Sentana and Wadhwani (1992). Positive feedback traders buy (sell) after prices have risen (fallen). This behaviour aligns with common strategies such as trend-chasing, and stop-loss selling. With higher volatility, rational traders allow feedback traders greater influence until they step in. The heightened impact of feedback traders fosters intraday overreactions. If this overreaction is corrected on the subsequent day, daily return autocorrelation, and consequently interday momentum, diminishes. An increase in volatility can therefore create price pressure that counteracts the interday momentum effect. Apart from volatility, we find no consistent and significant evidence that the interday momentum effect is moderated by liquidity, high-frequency price efficiency, or firm size. Interday momentum is therefore not limited to a few hard-to-trade niche stocks, but is a widespread phenomenon.

We also examine the relationship between overnight returns and interday momentum in the last half hour. Our results show that a more pronounced absolute overnight return tends to reduce the interday momentum effect. This moderation effect is statistically significant in five out of eight markets. We attribute this result to two trading motives at the end of the day: The need for market makers to reduce (after buying) or increase (after selling) their holdings after providing liquidity in the morning (Bogousslavsky, 2016), and late-informed traders trading on overnight news (Gao et al., 2018). Both trading motives connect the trading activity in the morning with the trading activity in the last half hour. They suggest that the overnight returns can cause price pressure in the last half hour. This price pressure is unrelated to yesterday's returns and can therefore lessen interday momentum. Finally, we show that both the interday momentum effect and the moderation effect of the absolute overnight returns are robust. They persist after additionally controlling for the directional overnight return, the first half-hour return and the penultimate half-hour return.[5]

The interday momentum pattern is economically significant. To demonstrate this, we take a practitioner perspective and construct the long-short portfolios in the sense of Jegadeesh

[5] A comprehensive review of the literature on intraday momentum is provided in section 5.1.

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. 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 demonstrates that this is possible across global markets.

Our paper contributes to the literature in several ways. First, our paper extends the growing literature on intraday return patterns, with the first analysis of cross-sectional interday momentum 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. Furthermore, we relate interday momentum to market characteristics, and trading motives related to overnight returns. 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 2 presents the data and details on the trading mechanism per market. Section 3 defines variables and presents descriptive statistics. Section 4 provides evidence of the pervasiveness of cross-sectional interday momentum. Section 5 proposes hypotheses, that link interday momentum with market characteristics, and subsequently tests them. Section 6 examines the economic significance of interday momentum. Section 7 concludes.

2 Data and Trading Mechanisms

2.1 Data

We collect 1-minutely transaction price and volume data for listed firms that constitute the benchmark stock indices of 15 countries.[6] The countries are selected according to market

[6]The transaction data are aggregated over 1-minute intervals. For each time-stamped interval, they 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 has been used in Li et al. (2022).

capitalization and data availability. The data is from Refinitiv and covers August 2021 to Mai 2023. Additionally, we retrieve the official daily opening and closing auction prices from Refinitiv 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.

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

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 European countries and treat Europe as one.[7] Table 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.

[Insert Table 1 Here]

2.2 Trading Mechanisms

The trading mechanisms of the markets in our international sample are diverse. As reported in Table 1, differences exist with regard to whether (i) a market operates purely under an order driven or designated market maker (specialist) system,[8] (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 differ-

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

[8] For discussions of the two system, see, e. g., Venkataraman and Waisburd (2007); Menkveld and Wang (2013); Theissen and Westheide (2020); Bellia et al. (2022); Theissen and Westheide (2023).

ences 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.[9] 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.

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.[10] For these intervals, we calculate simple returns. More specifically, the return on firm i, on day t within interval j is

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

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.[11] Figure 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, and overnight (ON).

[Insert Figure 1 Here]

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

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

[10] For each market, we focus on the regular trading hours as given in Table 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.

[11] Using auction prices appears adequate, as they usually concentrate significant trading volume (Bogousslavsky and Muravyev, 2023; Johann et al., 2019). 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-minutely data during the regular trading hours, coming to similar results.

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 $Spread_{i,t}$. Finally, we use the measure of Amihud (2002) as a proxy for the price impact of trading 1 Mio. USD within an interval, defined as

$$PriceImpact_{i,t,j} = \frac{\left| r_{i,t,j} \right| \cdot 10^6}{Volume_{i,t,j}}. \tag{2}$$

To measure price inefficiency, we focus on high-frequency return autocorrelation. In our transaction-based data set, this kind of predictability can result from the bid-ask bounce effect.[12] We define $Inefficiency_{i,t,j}$ as the absolute value of the return coefficient in an AR(1) process fitted to the 1-minute returns within an interval. 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 institutional activity through indexing. Finally, we measure a firm's volatility by the standard deviation of daily close-to-close returns within the sample period as $Volatility_i$.

For each market, Table 2 provides descriptive statistics of the above variables for different times of the day. There is no consistent pattern of intraday seasonality in the sign of returns. However, in all markets, the overnight and first half-hour returns feature substantially higher volatility compared to returns during the remainder of the day. This period also concentrates between 39% (Europe) and 65% (Japan) of the daily price discovery, as measured for a given interval by the average ratio of the return in that interval over the daily return. As important news (e.g., earning announcements) are often released overnight, price discovery in the morning increases and thus elevates volatility (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%).[13] 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

[12]High-frequency mid-quote return autocorrelation can also result from autocorrelation in order imbalances (Chordia et al., 2005).

[13]Our U.S. sample covers trading activity on the NYSE and NASDAQ. The market share in terms of trading volume across all venues is roughly 30% for respectively listed firms (Jurich, 2021). Accounting for trading volume on other venues should therefore slightly decrease the (relative) activity peak at the end of the trading day. However, as the exchanges lead in terms of price discovery (Hatheway et al., 2017), we expect no impact on our analysis of return patterns.

observed in several markets (Bogousslavsky and Muravyev, 2023; Raillon, 2020; Johann et al., 2019). 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. In terms of market efficiency over the course of a day, we observe that high frequency autocorrelation is similar in Europe, Canada and the U.S., while it experiences a slight increase in the other markets. The average size of firms per market in our sample ranges between 7 bn. USD (Korea) and 75 bn. USD (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. The latter is in the focus of this paper to explain variation in interday momentum.

[Insert Table 2 Here]

4 Interday Cross-Sectional Momentum

4.1 Baseline Model and Results

In this section, we investigate whether the cross-sectional interday momentum pattern still exists in the U.S. market, and whether it is also present in other markets. To do so, we analyze the relation between the half-hour stock returns on day t in interval j and those lagged by k days. As Murphy and Thirumalai (2017), we conduct the following univariate panel regression for each market in our sample

$$r_{i,t,j} = \beta_k \cdot r_{i,t-k,j} + FE_{t,j} + \epsilon_{i,t,j}, \tag{3}$$

where $r_{i,t,j}$ is the return on firm i, day t, and interval j, and $FE_{t,j}$ is a time-fixed effect that captures the overall market move on day t within interval j. We estimate model (3) for each market for the daily lags $k = 1, \ldots, 5$ (i.e., one trading week). To address concerns about the impact of outliers, we winsorize returns at the 1% level each month in our main results, following Heston et al. (2010).

Table 3 presents the results per market for our baseline model. As dependent variables, we consider returns for the first half-hour intervals (FH), the middle half-hour intervals (MH), and the last half-hour intervals (LH).

Our 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 further lags are insignificant. This result differs dramatically from Heston et al. (2010) who find that the momentum pattern is significantly positive in the first half hour for multiples of daily lags.

[Insert Table 3 Here]

In the middle half-hour intervals (Columns *MH*), we observe the interday momentum pattern on the one-day lag in the U.S., Australia, Korea, and Taiwan. For further lags, significance tends to decline. In Hong Kong, the coefficient of the two-day lag is significantly positive, while the one-day lag is not. In China, there is a significant one-day lag reversal. The respective coefficient differs significantly from the average momentum across all markets. This finding is consistent with the expected impact of the unique $T + 1$ rule in China: as investors cannot close the positions that they have opened on the same day, they close them on the next day if they are short-term oriented. They thereby create one-day lag return reversals instead of continuations.

Finally, our empirical results show that the last half-hour momentum is widely present and can last up to five trading days for most of the markets in our sample (Columns *LH*). However, the U.S. market is one exception with only three significant lags. Again, compared to Heston et al. (2010), our results suggest a weakening last half-hour momentum for the U.S. market.[14] The most pronounced interday momentum in the last half hour is consistent with previous results and may be boosted by the trading activity of index funds (Heston et al., 2010), and the increased concentration of trading volume near the close (Bogousslavsky and Muravyev, 2023; Raillon, 2020; Johann et al., 2019).

[14]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 6 (Table IA6). These results suggest that the size of the effect declined by about 75% for the first lag.

Overall, our results suggest an increase in market efficiency, such that predictability is sustained primarily in the last half hour and only to a lesser extent. This is consistent with the hypothesis that liquidity providers compete to provide liquidity to predictable trades, thereby decreasing the temporary price impact of trades and return predictability (Admati and Paul, 1991; Bessembinder et al., 2016; Murphy and Thirumalai, 2017). Similar tendencies can be observed in other intraday return patterns (Rosa, 2022; Hossain et al., 2021; Huang et al., 2023).

Up to now, our analysis focuses on the existence of momentum between the same intraday interval on different trading days. To answer the question of how the momentum pattern differs between daily and non-daily lags, we re-estimate the model (3), covering all half-hour intervals of the previous 10 trading days.[15] Figure 2 shows the estimated coefficients for the last half hour and confirms that the coefficients of the same interval on previous days are more pronounced than those of other intervals. For the first half-hour, we cannot see a clear pattern, while for the middle half-hour intervals, multiples of one-day lags are more pronounced. Consistent with the literature (Heston et al., 2010; Murphy and Thirumalai, 2017), all markets feature significant mean-reversion – relative to the market – for the first lag. This may result from liquidity imbalances, overreactions or the bid-ask bounce.

[Insert Figure 2 Here]

4.2 Robustness

We conduct robustness checks by re-estimate model (3) with some modifications. To start, we conduct (i) Fama-MacBeth regressions instead of the panel regression approach, (ii) regressions only with prices from continuous trading omitting the official opening and closing prices, and (iii) regressions based on raw returns. In all cases, we obtain similar results. For the sake of brevity, we do not tabulate them here.[16]

[15] Note that the regular trading hours, and therefore the number of daily half-hour intervals, differ across exchanges. Consequently, the number of intervals that constitutes 10 trading days varies.

[16] The results are tabulated in the appendix, respectively in the Tables IA1, IA2, IA3, IA4, and IA5.

Next, we include control variables for changes in intraday market characteristics that might explain the momentum pattern. We control for k-day lagged changes in the logarithm of trading volume ($\Delta Volume_{i,t-k,j}$), volatility ($\Delta Volatility_{i,t-k,j}$), price impact ($\Delta PriceImpact_{i,t-k,j}$), and inefficiency ($\Delta Inefficiency_{i,t-k,j}$).[17] To rule out that the 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:

$$r_{i,t,j} = \beta_k \cdot r_{i,t-k,j} + Ctrl_{i,t-k,j} + FE_{t,j} + FE_i + \epsilon_{i,t,j}, \tag{4}$$

where $Ctrl_{i,t-k,j}$ summarizes the control variables and the other variables are as in (3). Table 4 reports the estimation results for model (4). The results show that, after including various control variables, the conclusions remain unchanged. Furthermore, the average firm-level return in an interval cannot explain the momentum pattern, though it reduces significance slightly.

[Insert Table 4 Here]

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 fact that it is still significant in the last half-hour could be associated with favorable conditions for repetitive traders: The intraday price discovery is almost completed, the availability of liquidity, in the form of turnover and depth is high (Lee et al., 1993), and volatility is low. This suggests that large trades in the last half-hour have a small price impact (compared to the first half-hour), making trading then attractive.

[17] Variables are calculated based on local currency. Changes are defined as the first order differences between the current value of the variable and its one interval lagged value.

5 Determinants

In this section, we examine possible determinants of the strength of interday momentum. We propose five hypotheses, that link interday cross-sectional momentum in the last half hour with trading motives related to market characteristics and overnight returns, and subsequently test them. We focus on the last half hour since this is the interval where the pattern is strongest across all sample markets.

5.1 Hypotheses Development

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). Put differently, the less liquid a security is, the more difficult it is to convert from or to it. Considering costs and price impact, traders that demand liquidity could be incentiviced to spread the execution of large orders over time the less liquid the security. Instead of causing one large liquidity shock from a single trade, this behaviour would then cause repetitive but smaller liquidity shocks in the same direction over time, and thus amplify interday momentum.

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

Theory and empirical evidence suggest that traders compete to exploit predictable trades, thereby decreasing their temporary price impact and return predictability (Admati and Paul, 1991; Bessembinder et al., 2016; Murphy and Thirumalai, 2017). This makes prices more efficient, while predictability based on historical returns deteriorates. Consequently, the more efficient the market is, the less pronounced the momentum pattern could be.

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

The empirical literature finds that the level of volatility influences return autocorrelations. While an increase in volatility tends to elevate return autocorrelation on different intraday frequencies (Rosa, 2022; Gao et al., 2019; Bianco and Renò, 2006), it tends to decrease the autocorrelation on the daily frequency (McKenzie and Kim, 2007; McKenzie and Faff, 2003; Säfvenblad, 2000; Sentana and Wadhwani, 1992; LeBaron, 1992). Theoretically, the switch in the sign of the effect of volatility can be resolved by trading models with both positive feedback traders and rational risk-averse traders (Sentana and Wadhwani, 1992). Positive feedback trading includes common strategies such as trend-chasing, stop-loss selling, herding, and dynamic portfolio insurance. It requires to buy (sell) after prices have risen (fallen). When volatility increases, rational traders will allow feedback traders to have relatively more impact on the price until they step in. Intuitively, this increases return autocorrelation and may lead to overreactions on the intraday level. Once these overreactions are resolved later, daily return autocorrelation decreases. We therefore expect that the interday momentum is inversely related to volatility.

Hypothesis 3. *Interday cross-sectional momentum is stronger for less volatile securities.*

Size, as measured by the market value of a firm, is positively related to liquidity (Amihud, 2002). If size would only be a proxy for liquidity, we would expect interday momentum to decline with size (Hypothesis 1). However, size is also a proxy for indexing. This is notable, as our sample consists exclusively of firms that are constituents of a major index in their respective country. Mutual funds that replicate or benchmark these indices typically invest or divest large inflows or outflows on a daily basis (Heston et al., 2010). As these flows are price-insensitive and typically autocorrelated, they should amplify interday momentum. Furthermore, as the indices weight constituents by their market value, these flows and therefore momentum could increase with firm size. Heston et al. (2010) find that interday momentum in the U.S. cross-section increases in the last half hour between medium and large firms, but declines in the first half hour. We therefore have two competing hypothesis for size.

Hypothesis 4a. *Interday cross-sectional momentum is stronger for securities that have a small market value.*

Hypothesis 4b. *Interday cross-sectional momentum is stronger for securities that have a large market value.*

An important function of financial markets is to facilitate price discovery. Outside of the regular trading hours, new information are accumulated. This includes important news such as earning announcements. At the open, these overnight news are incorporated into prices. This process may decrease interday momentum via two channels: First, incorporating overnight news into prices may cause a transient liquidity shock at the open. 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 – unrelated to interday momentum. Across the trading times of these liquidity providers, price pressure can create momentum in returns. This setting is subject to the theoretical model of Bogousslavsky (2016). Given the diurnal U-shape of trading volume and the narrowing bid-ask spread towards the end of day, liquidity providers may choose to close their excess positions at the end of the day. As such, overnight shocks may disrupt interday momentum at the end of the day. Second, there may be late informed traders (Gao et al., 2018). These traders want to trade on the overnight information, but do not want to or do not manage to trade immediately at the open. Given the diurnal shape of liquidity, these traders may choose to trade near the close. Again, this may create a new liquidity shock in the same direction[18]. If the above conjectures hold, then the magnitude of overnight returns should decrease interday momentum at the close.

Hypothesis 5. *Interday cross-sectional momentum is less pronounced when overnight returns are large.*

5.2 Market Characteristics

We now investigate how the market characteristics liquidity, efficiency, volatility, and size affect the interday momentum effect. To this end, we use a two-step regression approach.

[18]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. market. This market-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 also 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 (Huang et al., 2023; Rosa, 2022; Hossain et al., 2021). 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. None of the two account for interday momentum.

In the first step, we obtain an interday momentum coefficient for each firm in our sample by re-estimating the time-series version of model (3) as:[19]

$$\tilde{r}_{i,t,LH} = \alpha_i + \beta_i^{MOM} \cdot \tilde{r}_{i,t-1,LH} + \epsilon_{i,t,LH}. \tag{5}$$

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, and 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 5 presents descriptive statistics for the estimated 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.[20] We find that the percentage of positive momentum coefficients ranges between 61% (Europe) and 92% (Taiwan). Moreover, between 24% (U.S.) and 56% (Taiwan) of the firms per market feature significantly positive momentum at the 10% level. Overall, the interday momentum effect is also widely present at the firm level.

[Insert Table 5 Here]

In the second step, we attempt to identify the relationship between the interday momentum proxies β_i^{MOM} and firms' characteristics. We estimate the following cross-sectional regression for all firms in our sample:

$$\begin{aligned} \widehat{\beta_i^{MOM}} = \alpha &+ \beta_1 \cdot Illiqudity_i + \beta_2 \cdot Inefficiency_i \\ &+ \beta_3 \cdot Size_i + \beta_4 \cdot Volatility_i + FE_m + \epsilon_i. \end{aligned} \tag{6}$$

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

[20]The closest match among the tabulated panel data models is model (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) 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.

The independent variable α is a constant that captures the average momentum, and the other variables measure the firms' liquidity ($Illiqudity_i$), price efficiency ($Inefficiency_i$), size ($Size_i$), and volatility ($Volatility_i$).[21] To account for market-level effects, we include a fixed effect per market FE_m, and to ease comparability we normalize the independent variables at the market level.[22] 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.

The results are presented in Table 6. On the pool level, we find that the coefficient for volatility is significantly negative in accordance with our Hypothesis 3. On the market level however, the evidence is weaker, with significantly negative coefficients in only four markets. The coefficients for illiquidity, inefficiency and size are almost entirely insignificant. There is therefore no support for the Hypotheses 1, 2, 4a, and 4b.

[Insert Table 6 Here]

To summarize, we find that interday momentum in the last half hour is inversely related to volatility in some markets. However, it is largely independent of illiquidity, inefficiency and size. Interday momentum is therefore not limited to hard-to-trade niche stocks, but is a widespread phenomenon.

5.3 Overnight Returns

We now test our hypothesis 5 regarding the impact of overnight returns on the interday momentum pattern. We expect that absolute overnight returns negatively affect interday momentum during the last half-hour trading interval. The larger the absolute shock, the lower the interday momentum on that day. The rational is that the overnight return itself affects the last half-hour return, possibly due to infrequent (intraday) rebalancing

[21] $Illiquidity_i$ 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 variables $Spread_i$, $Volume_i$, $PriceImpact_i$, $Size_i$, $Volatility_i$ are constructed by averaging the respective observations over time.

[22] Variables are normalized on the market level by subtracting their means and scaling their standard deviations to one. The conclusions remain qualitatively similar without normalization.

(Bogousslavsky, 2016) and late informed trading (Gao et al., 2018). This (positive) relation is referred to as intraday momentum in the literatrue (see, e.g., Gao et al. (2018)). To formally test this, we estimate the following model:

$$
\begin{aligned}
r_{i,t,LH} =& \beta_1 \cdot r_{i,t-1,LH} + \beta_2 \cdot r_{i,t-1,LH} \cdot \left|r_{i,t,ONFH}\right| + \beta_3 \cdot \left|r_{i,t,ONFH}\right| \\
&+ \beta_4 \cdot r_{i,t,ON} + \beta_5 \cdot r_{i,t,FH} + \beta_6 \cdot r_{i,t,MH_{Last}} + FE_{t,LH} + FE_i + \epsilon_{i,t,LH}.
\end{aligned}
\tag{7}
$$

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 $\left|r_{i,t,ONFH}\right|$. 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 fact that it may take up to 30 minutes to fully incorporate the overnight news, and assures consistency with the intraday momentum literature.[23] We additionally control for direct effects of the absolute return ($\left|r_{i,t,ONFH}\right|$), as well as direct effects of the signed overnight ($\cdot r_{i,t,ON}$) and first-half hour ($r_{i,t,FH}$) return. Moreover, we control for the effect of 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. Finally, we control for time and firm specific effects.

Table 7 presents the results for model (7) per market.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 $r_{i,t-1,LH} \cdot \left|r_{i,t,ONFH}\right|$ is negative in all markets and significantly negative in 5 markets (China, Hong Kong, Japan, Korea, Taiwan). The results suggest that overnight shocks dampen the price impact of repetitive traders, in line with Hypothesis 5. Although, this overnight induced effect is not present in all markets. 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 (China and Hong Kong) and the first half-hour returns (Australia, Japan, Korea, and Taiwan). For Europe and Canada, we find no significant intraday momentum. In the U.S., the last half-hour return depends negatively on

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

the overnight and first half-hour return. This is inconsistent with the above theory, but consistent with the findings of Komarov (2017). Finally, 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.

Overall, we conclude that overnight shocks can cause interday momentum to decline. Furthermore, interday momentum is a distinct feature that is neither an artifact of intraday momentum nor short-run mean-reversion.

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 investigate this, 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 3. We observe that decile portfolio returns tend to increase approximately linear with past returns in all markets.

[Insert Figure 3 Here]

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 same 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).

The average long-short portfolio returns along with descriptive statistics are shown in Panel A of Table 8.[24] 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 16.2 basis points (Taiwan).[25] They are positive on 54% to 75% of the days. However, 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 full spread in order to create and close it.[26] We find that between 1.84% (Australia) and 38.32% (China) of the quoted spread are earned by the strategy. This suggests that the pattern cannot be exploited by actively consuming liquidity, which is consistent with previous results for the U.S. (Heston et al., 2010). However, the strategic timing of trades can significantly reduce transaction costs.

The results in Section 5 show that interday momentum tends to be more pronounced when overnight returns are low and that the returns in the last half hour are inversely related to the returns 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 IA6 shows the results for the threshold strategy in Panel B. The filters tend to increase the average returns, such that 3.82% (Australia) to 99.49% (China) of the quoted spread are earned. However, the threshold strategy remains unable to earn the full bid-ask spread.

This could be a reason why the pattern is so persistent and not completely arbitraged (Gromb and Vayanos, 2010). However, combined with other trading motives the pattern

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

[25]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.

[26]This is a rather conservative assumption, as many trades happen inside of the spread.

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

may still be of practical relevance to reduce transaction costs, e.g. to decide when to trade and whether to execute an order actively or passively.

[Insert Table 8 Here]

7 Conclusion

The interday cross-sectional momentum has not yet been analyzed extensively across time periods and markets (Heston et al., 2010, 2011; Murphy and Thirumalai, 2017). Our paper attempts to fill this gap by providing new evidence from international financial markets. We show that interday momentum is present in all sample markets, and most pronounced during the last half hour of a trading day. Interday momentum is therefore a cross-market phenomenon. Compared to previous U.S. evidence, the pattern is substantially weaker in our sample period but still very pervasive and robust. This suggests that markets have become more efficient over time.

Furthermore, our study enhances the understanding of interday momentum patterns by investigating possible determinants of its strength. In the last half-hour the pattern tends to decline for high-volatility stocks, and after a more pronounced overnight return. These findings are consistent with theory (Gao et al., 2018; Bogousslavsky, 2016; Sentana and Wadhwani, 1992).

Finally, we examine if the interday momentum pattern could be exploited economically. The results based on our long-short portfolio strategy show that these strategies 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 can save investors an economically significant amount of transaction costs.

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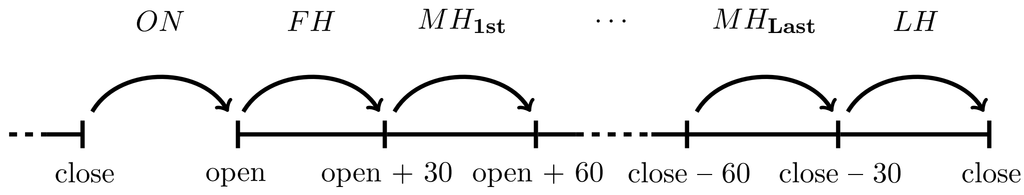
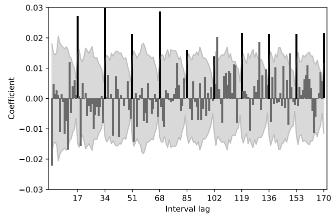
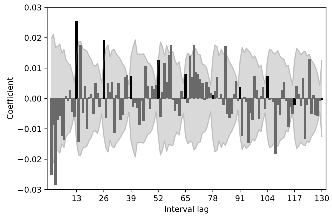


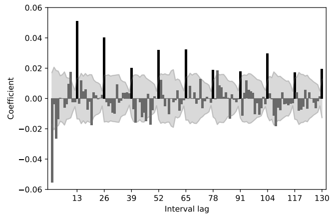
Figure 1: **Partitioning of a Trading Day.** The figure shows the points in time used to partition the trading day into half-hour intervals. We define the overnight interval (ON), the first half-hour interval (FH), the middle half-hour intervals (MH), and the last half-hour interval (LH).



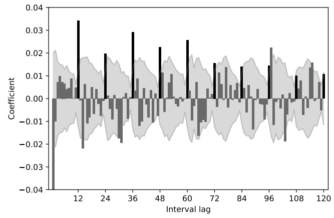
(a) **Europe**



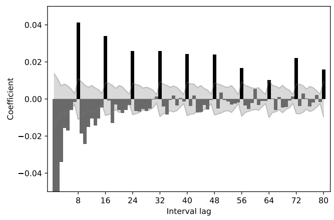
(b) **USA**



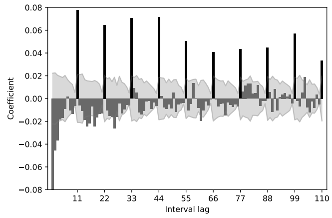
(c) **Canada**



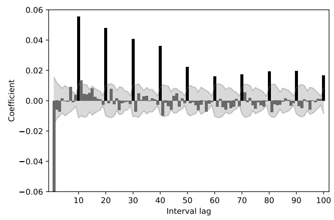
(d) **Australia**



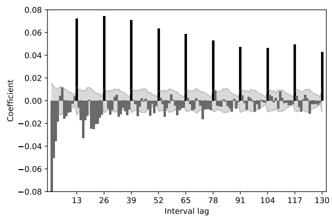
(e) **China**



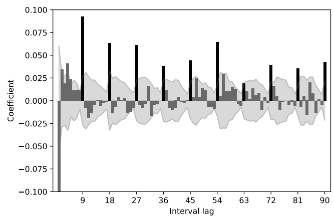
(f) **Hong Kong**



(g) **Japan**

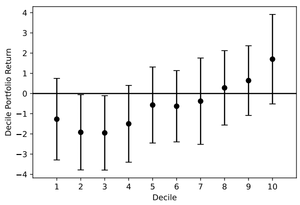


(h) **Korea**

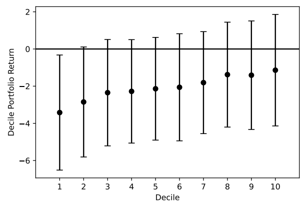


(i) **Taiwan**

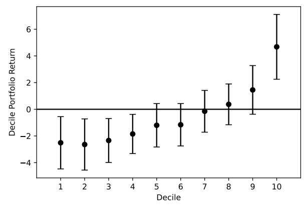
Figure 2: **Coefficients for the last Half-Hour Returns.** The estimation results for the panel regressions according to model (3) per market are shown in separate panels. In all regressions, only returns of the last half-hour interval (LH) per day are included as the dependent variable. The x-axis indicates the half-hour interval lag for the explanatory returns. For each market, Table 1 shows the number of daily half-hour intervals. The y-axis indicates the value for the coefficient of the lagged returns. For each country and lag, a separate panel regression is estimated. For each of these regressions, the estimated coefficient is represented by a bar. Bars that represent lags of multiples of one trading day, are shaded black. 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 Mai 2023.



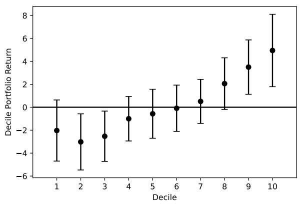
(a) **Europe**



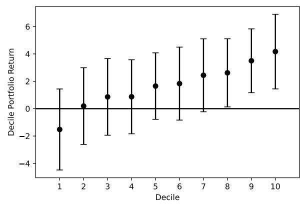
(b) **USA**



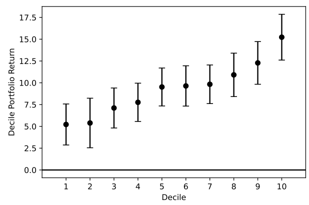
(c) **Canada**



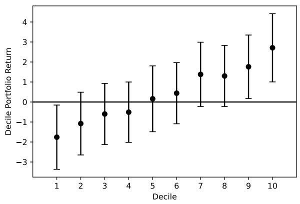
(d) **Australia**



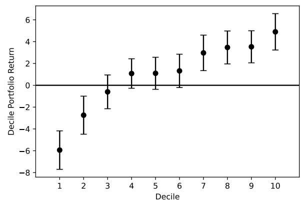
(e) **China**



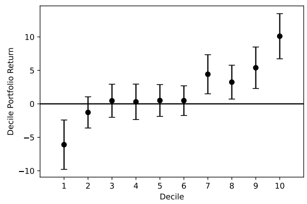
(f) **Hong Kong**



(g) **Japan**



(h) **Korea**



(i) **Taiwan**

Figure 3: **Average Decile Portfolio Returns in the last Half Hour.** 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, average decile portfolio returns of a given market are represented by dots. The whiskers span 95% confidence intervals. Inference is robust to heteroscedasticity and autocorrelation. Returns are given in basis points. The sample period is August 2021 to Mai 2023.

Table 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 the countries Austria, Belgium, France, Germany, Netherlands, Portugal, and Spain. The sample period is August 2021 to Mai 2023.

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 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 Mai 2023.

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.	Kurt.	Daily [%]	Mean	Med.	Std.	Kurt.	Mean	Med.	Std.	Kurt.	Mean	Med.	Std.	Kurt.	Mean	Med.	Std.	Kurt.
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	28	8	153.20	20.66	576	67	0.18	0.15	0.15	5								
	MH	1,361,235	0.00	-0.05	39	13	4	2.15	0.94	4	184	3	132.17	19.26	467	115	0.20	0.16	0.22	13								
	LH	90,749	-0.58	-1.16	36	8	5	24.08	13.83	31	13	39	39.00	1.67	261	100	0.19	0.16	0.15	5	33	16	49	19	11	6	16	34
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	87	12	184.76	75.36	262	8	0.19	0.16	0.14	4								
	MH	1,166,253	0.03	-0.28	49	14	4	1.11	0.37	2	133	4	165.60	55.74	258	8	0.20	0.17	0.20	13								
	LH	106,023	-0.56	-1.62	39	7	4	14.45	2.19	47	61	32	38.87	9.53	87	38	0.19	0.17	0.14	4	11	3	20	22	74	62	54	11
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	146	9	17.43	9.62	20	6	0.17	0.15	0.12	3								
	MH	2,532,002	0.13	0.36	41	21	4	4.69	1.89	16	336	3	18.73	10.48	21	5	0.16	0.14	0.12	3								
	LH	230,182	-2.09	-2.06	29	8	6	69.86	37.19	126	71	56	1.24	0.68	3	212	0.16	0.14	0.11	3	74	31	188	96	3	2	3	7
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	43	12	332.47	84.22	669	18	0.22	0.19	0.16	4								
	MH	911,660	0.01	-0.27	46	23	4	0.84	0.30	2	49	5	234.74	49.37	542	29	0.27	0.25	0.19	5								
	LH	91,166	0.24	-0.76	61	12	9	6.12	2.09	13	31	34	105.80	12.61	358	55	0.30	0.29	0.18	3	8	2	21	47	170	128	144	8
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	28	25	6.49	3.94	7	6	0.19	0.17	0.14	3								
	MH	790,176	-0.16	-3.59	67	11	8	13.85	7.33	20	47	8	7.11	4.27	8	5	0.23	0.20	0.16	3								
	LH	131,696	1.70	0.34	37	11	5	16.42	9.70	20	23	13	4.01	2.33	5	12	0.25	0.24	0.17	2	26	14	43	56	8	5	8	5
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	23	15	23.78	12.72	28	5	0.20	0.18	0.14	3								
	MH	272,151	-0.58	-0.91	56	9	4	6.88	2.66	14	40	5	20.46	9.50	27	6	0.26	0.24	0.17	2								
	LH	30,239	9.35	7.99	37	5	3	21.26	10.10	35	19	25	4.72	2.43	7	12	0.29	0.28	0.17	2	57	26	75	13	15	13	8	4
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	32	20	18.16	8.07	24	7	0.18	0.15	0.13	3								
	MH	804,480	-0.03	-0.02	35	16	4	3.95	1.63	8	81	5	21.62	9.35	28	5	0.21	0.18	0.15	3								
	LH	100,560	0.40	0.40	24	7	4	18.43	10.93	23	16	34	4.08	1.51	9	50	0.25	0.23	0.17	3	17	8	28	36	20	17	11	4
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	78	18	140.58	53.88	219	11	0.23	0.21	0.15	3								
	MH	965,701	-0.42	-0.78	49	24	4	1.56	0.45	5	161	5	128.08	43.49	213	11	0.35	0.36	0.17	2								
	LH	87,791	0.93	0.09	42	9	5	3.18	0.94	10	99	13	86.37	23.30	172	19	0.36	0.36	0.18	2	7	2	26	161	22	18	11	5
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	21	30.81	15.50	40	8	0.23	0.21	0.16	3								
	MH	151,347	0.01	-0.53	42	9	5	4.15	1.21	10	39	6	30.77	13.62	44	8	0.34	0.35	0.18	2								
	LH	21,621	1.75	0.46	41	5	12	11.31	4.03	25	27	23	13.32	6.08	22	15	0.36	0.37	0.18	2	19	5	66	46	22	18	11	4

Table 3: **Baseline Model.** The table shows the estimation results for the panel regressions according to model (3). Each cell represents a separate regression. The second row indicates whether the first half-hour intervals (FH), the middle half-hour intervals (MH), or the last half-hour intervals (LH) are included as dependent variables in the regressions. 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 Mai 2023.

	Returns														
	First half-hour intervals (FH)					Middle half-hour intervals (MH)					Last half-hour intervals (LH)				
Market (m)	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***	1.6*
	(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**	3.2***	3.22***
	(-0.64)	(1.38)	(0.27)	(1.05)	(0.42)	(1.86)	(0.38)	(1.01)	(1.27)	(1.78)	(7.42)	(5.1)	(3.23)	(4.53)	(4.42)
USA	2.23*	1.07	-1.43	0.73	-1.5	0.85*	0.2	-0.2	0.67*	0.41	2.54***	1.91**	0.75	1.28*	0.8
	(2.02)	(1.09)	(-1.59)	(0.75)	(-1.53)	(2.49)	(0.6)	(-0.61)	(2.01)	(1.24)	(3.5)	(3.05)	(1.04)	(2.0)	(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)	(4.6)	(4.57)	(1.66)	(1.57)	(2.24)	(5.59)	(3.1)	(4.39)	(3.8)	(4.05)
China	-0.78	-1.14	-1.91*	-0.52	0.46	-1.36***	0.3	0.15	0.55	-0.06	4.1***	3.4***	2.57***	2.58***	2.42***
	(-0.85)	(-1.3)	(-2.2)	(-0.6)	(0.53)	(-3.6)	(0.81)	(0.4)	(1.5)	(-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	0.6	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)	(6.2)	(6.99)	(7.5)	(5.61)
Japan	-0.89	-0.55	0.76	-0.1	0.2	0.36	-0.15	0.12	-0.13	-0.06	5.54***	4.78***	4.05***	3.59***	2.23***
	(-1.11)	(-0.75)	(1.0)	(-0.16)	(0.28)	(1.31)	(-0.53)	(0.44)	(-0.49)	(-0.23)	(9.7)	(9.36)	(7.59)	(8.01)	(5.03)
Korea	-1.92*	-0.41	2.27**	0.6	1.13	0.6**	0.7***	0.59***	0.47**	0.23	7.22***	7.46***	7.1***	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	-0.0	0.58	0.03	1.86***	1.42**	1.16*	0.81	1.39***	9.23***	6.32***	6.12***	3.79**	4.4***
	(-0.77)	(-0.7)	(-0.0)	(0.62)	(0.03)	(4.12)	(2.66)	(2.36)	(1.83)	(3.86)	(6.73)	(3.81)	(5.4)	(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
$\Delta Volume_{i,t-k,j}$	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: **Baseline Model with Controls.** The table shows the estimation results for the panel regressions according to model (4). Each cell represents a separate regression. The second row indicates whether the first half-hour intervals (FH), the middle half-hour intervals (MH), or the last half-hour intervals (LH) are included as dependent variables in the regressions. 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 Mai 2023.

	Returns														
	First half-hour intervals (FH)					Middle half-hour intervals (MH)					Last half-hour intervals (LH)				
Market (m)	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**	0.5	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	0.3	-0.32	0.62	0.09	0.29	0.4	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	0.4	2.08**	1.47*	0.22	0.8	0.3
	(1.67)	(0.7)	(-2.01)	(0.36)	(-1.94)	(2.42)	(0.53)	(-0.68)	(1.94)	(1.19)	(2.85)	(2.32)	(0.3)	(1.24)	(0.46)
Australia	0.65	1.34*	-0.1	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)	(4.4)	(1.46)	(1.32)	(2.05)	(4.46)	(1.98)	(3.46)	(2.56)	(3.12)
China	-1.54	-1.49	-2.2*	-1.07	0.12	-1.3***	0.21	0.11	0.5	-0.08	3.2***	2.46***	1.58***	1.63***	1.6***
	(-1.62)	(-1.66)	(-2.5)	(-1.21)	(0.14)	(-3.4)	(0.56)	(0.29)	(1.35)	(-0.23)	(5.63)	(5.29)	(3.66)	(3.4)	(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)	(1.1)	(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***	4.0***	3.27***	2.81***	1.44**
	(-1.62)	(-1.33)	(0.5)	(-0.82)	(-0.3)	(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	1.8*	0.11	0.66	0.61**	0.63***	0.55**	0.4*	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)	(0.9)	(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	1.2***	8.43***	5.3**	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
$\Delta Volume_{i,t-k,j}$	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 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 (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.

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	3.85	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 6: **Market Characteristics.** The table shows the estimation results for the regressions according to model (6). The regressions are based on momentum coefficients per firm, calculated from last half-hour interval (LH) returns according to (5). Firm momentum coefficients are used as independent 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 and show the number of firms included in the regressions. 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 Mai 2023.

	Firm Momentum Coefficients									
		Market Level								
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)
$Illiquidity_i$	-0.0	0.68	-1.05	-0.28	-1.5	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	-0.7	0.83	-0.49	-1.04	-0.4
	(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)	(0.8)	(-0.21)
$Volatility_i$	-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)
FE_m	Yes	No	No	No	No	No	No	No	No	No
# Firms	2076	201	249	515	213	342	77	229	200	50

Table 7: **Overnight Returns.** The table shows the estimation results for the panel regressions according to model (7). 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. 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 Mai 2023.

	Returns in the last half-hour intervals (LH)									
Variables	Pooled	Europe	Canada	USA	Australia	China	Hong Kong	Japan	Korea	Taiwan
$r_{i,t-1,LH}$	4.56***	3.02***	4.86***	2.8***	3.89***	4.61***	7.39***	5.99***	7.12***	10.99***
	(14.06)	(3.7)	(6.08)	(3.33)	(4.59)	(7.54)	(6.75)	(7.95)	(9.75)	(7.12)
$\lvert r_{i,t,ONFH}\rvert$	-0.06	0.04	-0.15	-0.22	-0.07	-0.11	0.3	-0.37*	0.05	0.77
	(-0.68)	(0.11)	(-0.54)	(-0.97)	(-0.2)	(-0.7)	(0.92)	(-2.29)	(0.25)	(1.69)
$r_{i,t-1,LH} \cdot \lvert r_{i,t,ONFH}\rvert$	-78.95***	-112.26	-55.81	-62.43	-61.5	-85.46***	-128.95**	-116.32**	-92.53*	-198.93*
	(-4.46)	(-1.5)	(-1.33)	(-1.29)	(-1.37)	(-3.37)	(-2.59)	(-2.66)	(-2.43)	(-2.54)
$r_{i,t,ON}$	0.1	-0.23	-0.22	-0.7*	0.62	0.73**	1.4**	0.4	0.11	-0.31
	(0.73)	(-0.55)	(-0.53)	(-2.09)	(1.59)	(2.9)	(2.75)	(1.92)	(0.37)	(-0.49)
$r_{i,t,FH}$	0.04	0.18	-0.16	-0.58*	0.76*	-0.04	-0.27	0.51**	0.72***	1.57**
	(0.43)	(0.49)	(-0.6)	(-2.2)	(2.12)	(-0.26)	(-0.94)	(2.6)	(3.55)	(3.23)
$r_{i,t,MH_{Last}}$	-10.03***	-2.21*	-5.54***	-2.27*	-12.82***	-12.37***	-15.25***	-8.61***	-20.68***	-15.38***
	(-26.15)	(-2.44)	(-6.25)	(-2.25)	(-12.5)	(-17.79)	(-13.75)	(-10.93)	(-27.0)	(-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

Table 8: **Decile Portfolio Spread Returns.** The table shows descriptive statistics for the average decile portfolio spread return per market. The holding periods are the last half-hour intervals (LH). The formation periods are the last half-hour intervals 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 percentage proportion of the quoted spread that is earned by the decile spread portfolio ($\frac{\textbf{Mean}}{\textbf{Spread}}$), the standard deviation (Std.), the skewness (Skew), the kurtosis (Kurt.), and the percentage of days with positive returns (> 0) 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 Mai 2023.

	Decile Portfolio Spread Return					
Market	Mean	$\frac{\textbf{Mean}}{\textbf{Spread}}$	Std.	Skew	Kurt.	> 0
Panel A: Baseline Strategy						
Europe	2.97**	10.78	18.10	0.03	3.98	57
Canada	7.19***	4.09	19.04	0.19	3.81	65
USA	2.28**	29.75	16.04	0.75	5.59	54
Australia	6.98***	1.84	30.74	-0.01	4.55	59
China	5.69***	38.32	14.95	0.23	5.31	67
Hong Kong	10.02***	30.79	25.45	0.14	3.80	66
Japan	4.46***	9.44	9.82	0.08	3.61	69
Korea	10.84***	22.81	17.45	0.35	4.57	75
Taiwan	16.2***	32.95	43.48	1.14	7.65	66
Panel B: Threshold Strategy						
Europe	3.49**	16.46	22.47	1.65	26.61	55
Canada	5.97***	3.87	20.06	1.22	13.64	62
USA	2.95***	47.40	17.18	0.90	12.65	57
Australia	13.94***	4.61	38.97	1.50	33.88	70
China	13.86***	99.21	18.92	0.44	6.75	80
Hong Kong	16.48***	53.98	29.67	0.74	10.08	76
Japan	6.47***	15.96	12.66	-0.60	8.68	75
Korea	23.6***	54.23	23.05	0.36	6.05	88
Taiwan	21.92***	48.13	47.69	0.28	14.70	73

Interday Cross-Sectional Momentum: Global Evidence and Determinants

Internet Appendix

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Table IA1: **Regression Results for the Baseline Model with Raw Returns.** The table shows the estimation results for the panel regressions according to model (3). Each cell represents a separate regression. The first row indicates that raw returns are used. The second row indicates whether all half-hour intervals (All), only the first half-hour intervals (FH), or only the last half-hour intervals (LH) are included as dependent variables in the regressions. The third row indicates the lag k for explanatory variables. For each market m, Table 1 shows the number of daily half-hour intervals. 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 Mai 2023.

	Returns														
	First half-hour intervals (FH)					Middle half-hour intervals (MH)					Last half-hour intervals (LH)				
Market (m)	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	1.5	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
	(1.3)	(2.26)	(1.14)	(4.09)	(1.21)	(0.9)	(1.12)	(0.66)	(1.42)	(-1.98)	(2.39)	(4.2)	(2.96)	(3.55)	(1.43)
Canada	-1.14	1.2	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)	(3.1)	(4.27)	(3.7)
USA	2.05	0.96	-1.36	0.6	-1.98*	0.56	-0.3	0.07	0.31	0.16	1.84*	1.99*	1.01	1.63	0.58
	(1.89)	(1.0)	(-1.56)	(0.63)	(-2.06)	(1.15)	(-0.74)	(0.14)	(0.75)	(0.46)	(1.98)	(2.5)	(1.31)	(1.81)	(0.88)
Australia	1.29	1.93**	0.58	1.61*	1.87**	1.0***	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	-1.4***	0.3	0.14	0.47	-0.09	3.43***	2.97***	2.39***	2.55***	1.93***
	(-0.45)	(-1.4)	(-2.18)	(-0.53)	(0.64)	(-3.72)	(0.8)	(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	0.4	-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)	(6.5)	(6.21)	(4.54)
Japan	-1.66	-0.23	0.41	-0.21	0.3	0.28	-0.17	-0.34	-0.31	-0.1	4.67***	4.14***	3.71***	3.31***	1.85***
	(-1.56)	(-0.27)	(0.5)	(-0.33)	(0.39)	(0.92)	(-0.61)	(-0.79)	(-1.09)	(-0.38)	(6.59)	(8.0)	(6.69)	(7.21)	(3.75)
Korea	-2.01**	-0.19	1.91*	0.41	0.81	0.49*	0.65**	0.52**	0.4*	0.13	6.22***	6.33***	5.7***	6.17***	4.94***
	(-2.6)	(-0.28)	(2.48)	(0.6)	(1.13)	(2.5)	(3.06)	(2.96)	(2.2)	(0.65)	(8.73)	(8.12)	(6.63)	(10.92)	(9.67)
Taiwan	-0.83	-0.64	-0.2	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)	(3.2)	(6.59)	(2.7)	(3.34)	(2.8)	(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
$\Delta Volume_{i,t-k,j}$	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 IA2: **Fama-MacBeth-Regression Results for the Baseline Model with Raw Returns.** The table shows the estimation results for the Fama-MacBeth version of the model (3). Each cell represents a separate regression. The first row indicates that raw returns are used. The second row indicates whether all half-hour intervals (All), only the first half-hour intervals (FH), or only the last half-hour intervals (LH) are included as dependent variables in the regressions. The third row indicates the lag k for explanatory variables. For each market m, Table 1 shows the number of daily half-hour intervals. 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 Mai 2023.

	Returns														
	First half-hour intervals (FH)					Middle half-hour intervals (MH)					Last half-hour intervals (LH)				
Market (m)	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)	(1.2)	(0.95)	(2.38)	(-1.24)	(4.4)	(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***	2.3***	2.81***	2.64***
	(-0.34)	(1.55)	(1.57)	(1.0)	(1.55)	(1.24)	(-0.14)	(0.56)	(1.3)	(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	2.0**	1.92***	0.76	1.43*	0.71
	(2.51)	(1.17)	(-1.47)	(0.6)	(-1.04)	(1.94)	(-0.14)	(-0.13)	(2.06)	(0.27)	(2.83)	(3.72)	(1.3)	(2.37)	(1.13)
Australia	1.07	1.94**	0.49	1.6**	2.1**	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)	(1.2)	(1.59)	(0.87)	(0.94)	(1.51)	(5.27)	(3.46)	(5.03)	(3.92)	(4.2)
China	-0.43	-1.56*	-1.67*	-0.53	0.5	-0.81**	0.03	0.15	0.33	0.06	4.16***	3.69***	2.79***	2.5***	1.94***
	(-0.47)	(-2.17)	(-2.19)	(-0.6)	(0.59)	(-2.71)	(0.09)	(0.5)	(1.26)	(0.22)	(8.78)	(9.43)	(6.24)	(5.01)	(3.84)
Hong Kong	1.8	2.24*	0.84	1.21	0.9	0.42	0.84*	0.22	0.4	0.4	8.22***	7.74***	6.98***	7.55***	5.63***
	(1.6)	(2.07)	(0.76)	(1.03)	(0.85)	(1.28)	(2.43)	(0.64)	(1.2)	(1.15)	(10.44)	(9.93)	(8.3)	(8.42)	(7.32)
Japan	-1.05	0.15	0.31	-0.27	0.41	0.57*	-0.39	0.22	-0.05	-0.2	5.64***	4.65***	4.26***	3.66***	2.14***
	(-1.4)	(0.2)	(0.43)	(-0.41)	(0.58)	(2.44)	(-1.67)	(0.99)	(-0.25)	(-0.9)	(11.0)	(9.43)	(9.63)	(7.6)	(4.6)
Korea	-2.22**	0.16	1.46*	0.24	0.83	0.37*	0.6***	0.62***	0.3*	0.23	7.3***	7.41***	6.9***	6.7***	5.72***
	(-3.13)	(0.25)	(2.1)	(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***	6.8***	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)	(5.0)	(4.28)
$FE_{t,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta Volume_{i,t-k,j}$	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 IA3: **Fama-MacBeth-Regression Results for the Baseline Model with Winsorized Returns.** The table shows the estimation results for the Fama-MacBeth version of the model (3). Each cell represents a separate regression. The first row indicates that raw returns are used. The second row indicates whether all half-hour intervals (All), only the first half-hour intervals (FH), or only the last half-hour intervals (LH) are included as dependent variables in the regressions. The third row indicates the lag k for explanatory variables. For each market m, Table 1 shows the number of daily half-hour intervals. 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 Mai 2023.

	Returns														
	First half-hour intervals (FH)					Middle half-hour intervals (MH)					Last half-hour intervals (LH)				
Market (m)	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	3.1***	3.39***	2.17***	3.0***	1.72**
	(3.72)	(3.55)	(3.3)	(4.02)	(3.12)	(2.49)	(1.7)	(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)	(6.1)	(3.43)	(5.48)	(4.32)
USA	2.4*	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)	(-0.5)	(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***
	(2.1)	(3.3)	(0.76)	(3.53)	(3.9)	(1.2)	(1.99)	(0.43)	(1.33)	(1.47)	(6.76)	(4.36)	(6.58)	(5.02)	(5.41)
China	-0.6	-1.46*	-1.72*	-0.57	0.32	-0.88**	0.04	0.12	0.47	0.01	4.3***	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)	(6.2)	(5.55)
Hong Kong	1.72	1.94	0.41	1.26	0.82	0.6*	0.83**	0.23	0.53	0.49	8.49***	7.74***	7.17***	7.58***	5.76***
	(1.61)	(1.9)	(0.42)	(1.25)	(0.8)	(1.98)	(2.6)	(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)	(-0.8)	(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	-0.2	0.73	0.05	1.71***	1.07**	1.38***	0.94**	1.25**	10.0***	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
$\Delta Volume_{i,t-k,j}$	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 IA4: **Regression Results for the Baseline Model with Raw Returns from Continuous Trading.** The table shows the estimation results for the panel regressions according to model (3). Each cell represents a separate regression. The first row indicates that raw returns are used. The second row indicates whether all half-hour intervals (All), only the first half-hour intervals (FH), or only the last half-hour intervals (LH) are included as dependent variables in the regressions. The third row indicates the lag k for explanatory variables. For each market m, Table 1 shows the number of daily half-hour intervals. 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 Mai 2023.

	Returns														
	First half-hour intervals (FH)					Middle half-hour intervals (MH)					Last half-hour intervals (LH)				
Market (m)	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	1.5	2.27*	1.18	3.25***	1.15	0.24	0.29	0.17	0.35	-0.51*	-1.07	0.44	0.05	0.6	-0.3
	(1.31)	(2.3)	(1.2)	(4.09)	(1.21)	(0.9)	(1.12)	(0.66)	(1.42)	(-1.98)	(-1.34)	(0.6)	(0.07)	(0.83)	(-0.41)
Canada	-1.14	1.2	0.23	0.77	0.65	0.56	-0.14	0.29	0.43	0.51	4.01***	2.56**	1.75*	2.45***	2.3**
	(-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	-0.3	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*	2.2***	1.0***	1.02***	0.45	0.18	0.54*	2.54**	-0.84	0.71	-0.98	0.75
	(1.44)	(2.9)	(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	-1.3	-1.93*	-0.37	0.55	-1.4***	0.3	0.14	0.47	-0.09	3.0***	2.49***	1.86***	2.2***	1.69***
	(-0.48)	(-1.46)	(-2.23)	(-0.41)	(0.62)	(-3.72)	(0.8)	(0.35)	(1.29)	(-0.26)	(4.77)	(5.13)	(3.8)	(4.04)	(3.42)
Hong Kong	1.15	1.12	1.96	1.28	-0.04	-0.46	0.87	-0.23	0.4	-0.26	1.56	2.03*	2.82***	4.39***	2.16**
	(0.9)	(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	0.3	0.28	-0.17	-0.34	-0.31	-0.1	4.56***	4.3***	3.84***	3.16***	1.49**
	(-1.56)	(-0.27)	(0.5)	(-0.33)	(0.39)	(0.92)	(-0.61)	(-0.79)	(-1.09)	(-0.38)	(5.75)	(8.02)	(6.73)	(6.4)	(2.94)
Korea	-2.3**	-0.5	1.72*	0.33	0.72	0.49*	0.65**	0.52**	0.4*	0.13	4.61***	4.44***	4.03***	3.78***	3.22***
	(-2.95)	(-0.68)	(2.18)	(0.47)	(0.98)	(2.5)	(3.06)	(2.96)	(2.2)	(0.65)	(6.43)	(7.84)	(4.92)	(7.0)	(5.86)
Taiwan	-0.83	-0.64	-0.2	0.52	-0.16	1.57***	1.24*	0.93	0.58	1.15**	5.38***	1.12	2.25	0.9	1.65
	(-0.61)	(-0.56)	(-0.19)	(0.57)	(-0.18)	(3.39)	(2.27)	(1.87)	(1.22)	(3.2)	(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
$\Delta Volume_{i,t-k,j}$	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 IA5: **Regression Results for the Baseline Model with Winsorized Returns from Continuous Trading.** The table shows the estimation results for the panel regressions according to model (3). Each cell represents a separate regression. The first row indicates that winsorized returns are used. The second row indicates whether all half-hour intervals (All), only the first half-hour intervals (FH), or only the last half-hour intervals (LH) are included as dependent variables in the regressions. The third row indicates the lag k for explanatory variables. For each market m, Table 1 shows the number of daily half-hour intervals. 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 Mai 2023.

	Returns														
	First half-hour intervals (FH)					Middle half-hour intervals (MH)					Last half-hour intervals (LH)				
Market (m)	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)	(5.7)	(3.98)	(2.52)	(3.65)	(3.66)
USA	2.24*	1.05	-1.44	0.75	-1.54	0.85*	0.2	-0.2	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)	(0.6)	(-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)	(3.2)	(1.35)	(2.9)	(4.05)	(4.6)	(4.57)	(1.66)	(1.57)	(2.24)	(2.88)	(0.19)	(1.91)	(-0.5)	(1.73)
China	-0.81	-1.2	-1.97*	-0.42	0.44	-1.36***	0.3	0.15	0.55	-0.06	3.62***	2.79***	2.14***	2.12***	2.22***
	(-0.86)	(-1.34)	(-2.26)	(-0.48)	(0.5)	(-3.6)	(0.81)	(0.4)	(1.5)	(-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	0.6	0.13	1.91*	2.21**	3.0***	4.25***	2.71***
	(0.6)	(0.98)	(0.61)	(1.0)	(0.21)	(-0.01)	(2.01)	(-0.18)	(1.22)	(0.28)	(2.3)	(2.62)	(4.22)	(5.64)	(3.75)
Japan	-0.89	-0.55	0.76	-0.1	0.2	0.36	-0.15	0.12	-0.13	-0.06	5.61***	4.94***	4.07***	3.45***	1.89***
	(-1.11)	(-0.75)	(1.0)	(-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	0.6**	0.7***	0.59***	0.47**	0.23	5.63***	4.94***	4.88***	4.08***	3.72***
	(-2.91)	(-1.0)	(2.72)	(0.74)	(1.47)	(3.06)	(3.71)	(3.36)	(2.74)	(1.18)	(9.41)	(9.74)	(9.0)	(8.8)	(8.02)
Taiwan	-1.03	-0.83	0.0	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)	(-0.7)	(0.0)	(0.62)	(0.03)	(4.12)	(2.66)	(2.36)	(1.83)	(3.86)	(4.54)	(1.99)	(2.52)	(0.63)	(1.4)
$FE_{t,j}$	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
$\Delta Volume_{i,t-k,j}$	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 IA6: **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 as basis points per half-hour without accounting for any costs. The second row indicates whether the first half-hour intervals (FH), the middle half-hour intervals (MH), or the last half-hour intervals (LH) are used in the formation and holding period. 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 return per 30 minutes 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 Mai 2023.

	Average Decile Portfolio Spread Returns														
	First half-hour intervals (FH)					Middle half-hour intervals (MH)					Last half-hour intervals (LH)				
Market (m)	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**	4.2***	2.69**	3.59***	1.76*
	(3.02)	(1.97)	(2.01)	(3.61)	(2.9)	(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	1.7	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)	(3.3)	(3.84)
USA	7.27*	4.38	-4.56*	3.21	-3.56	0.55	0.1	-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***	1.2***	0.6	0.33	0.77*	6.98***	4.85***	6.4***	4.65***	4.51***
	(1.38)	(2.96)	(-0.02)	(2.63)	(2.89)	(4.24)	(4.0)	(1.92)	(1.01)	(2.56)	(4.68)	(3.42)	(4.26)	(3.4)	(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***
	(-1.0)	(-1.18)	(-1.81)	(-0.7)	(0.46)	(-3.09)	(0.44)	(0.69)	(0.89)	(-0.12)	(7.18)	(6.64)	(6.85)	(5.43)	(3.9)
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***	5.3***
	(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	0.4	-0.27	0.11	-0.33	-0.12	4.46***	3.68***	3.28***	2.86***	1.56***
	(-1.03)	(0.03)	(0.3)	(-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	-11.1**	0.73	7.5**	1.2	3.01	0.66*	1.2***	0.85**	0.62*	0.48	10.84***	10.52***	10.46***	10.31***	8.83***
	(-3.22)	(0.2)	(2.64)	(0.29)	(0.9)	(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*	16.2***	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)	(6.8)	(4.65)	(5.34)	(3.27)	(4.07)