Intraday time series momentum: Global evidence and links to market characteristics ⋆

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Abstract

We examine intraday time series momentum (ITSM) in an international setting by employing high-frequency data of 16 developed markets. We show that ITSM is economically sizable and statistically significant both in- and out-of-sample in most countries. Based on theories of investor behavior, we propose and test four hypotheses to reveal the source of ITSM profitability. We document both in the cross-section and time series dimension that ITSM is stronger when liquidity is low, volatility is high, and new information is discrete. Overall, our results suggest that the ITSM is driven by both market microstructure and behavioral factors.

Keywords: high-frequency trading, intraday, international markets, momentum, market characteristics

JEL classification: G11, G14, G15, G17

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1. Introduction

In the asset return predictability literature, momentum is a well-known phenomenon in financial markets and suggests that assets that perform well in the past will continue to perform well in the future. Since the seminal work by Jegadeesh and Titman (1993), the effect has been well established and attracted significant interest from both academics and practitioners. For example, Chan et al. (1996), Hong and Stein (1999), Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001), George and Hwang (2004), Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) examine momentum in the cross-section of U.S. stock returns both empirically and theoretically, while Griffin et al. (2003), Liu et al. (2011), Fama and French (2012), Menkhoff et al. (2012) and Asness et al. (2013) provide international evidence in a broader collection of asset classes. Moreover, Moskowitz et al. (2012) reveal a momentum effect in the time series of asset returns, which has also been extensively studied in a variety of asset classes and factors both inside and outside of the U.S. (Moskowitz et al., 2012; Goyal and Wahal, 2015; He and Li, 2015; Georgopoulou and Wang, 2016; Kim et al., 2016; Hurst et al., 2017; Lim et al., 2018; Gupta and Kelly, 2019; Ham et al., 2019; Huang et al., 2020).

While most forms of momentum are studied at monthly, weekly, or daily frequencies, the rise of technology has led to a substantial increase in high-frequency trading (HFT). As noted by Malceniece et al. (2019), the scale of HFT activity varies depending on the market and how broadly HFT is defined, but there is no doubt that HFT accounts for a large share of trading volume in most developed markets. The impact of HFT has changed the way traders trade, the way markets are structured, and how liquidity and price discovery arise (O'Hara, 2015). Therefore HFT has had a fundamental impact on markets, which has led many academics to start examining the trading behavior of financial markets at a much higher frequency (Hagströmer and Nordén, 2013; Hendershott and Riordan, 2013; Brogaard et al., 2014; Chaboud et al., 2014).

In this paper, we provide a cross-country study on intraday momentum based on the work of Gao et al. (2018). These authors provide strong evidence of intraday time series momentum (ITSM) where the first half-hour return of the trading day significantly predicts the last half-hour return in a selection of U.S. exchange-traded funds (ETFs) that track the U.S.

market, various U.S. sectors, and emerging markets. We provide a global study on ITSM by employing international indices to determine the statistical and economic power of ITSM around the globe. We first show that ITSM is economically sizable and statistically significant in international stock markets. Then, we examine the potential sources of ITSM by testing four hypotheses proposed both in the market microstructure and behavioral academic literature. We find significant relationships between ITSM and market characteristics, such as the market liquidity, volatility, information discreteness, and the degree of individualism.

Our research proceeds in four steps. First, we confirm the in-sample statistical significance of the intraday momentum effect across the global markets. Specifically, we follow the standard predictive regression approach in Gao et al. (2018) and regress the last half-hour return against the first half-hour return on each of the 16 developed markets in our sample, respectively. As in Gao et al. (2018), our first half-hour return includes overnight information and is computed using prices at the previous day's close and 30 minutes after current day's open. Our results reveal significant predictability of the first half-hour return on the last half-hour return in 12 out of 16 markets. When all 16 markets are pooled, we find a positive and statistically significant relationship between the first and the last half-hour returns, which is also confirmed in various market conditions. We find statistical significance in all sub-periods, but the magnitudes of the predictive slopes are larger during the financial crisis and economic recession periods, consistent with Gao et al. (2018).

Second, we perform a thorough out-of-sample (OOS) evaluation, of which the results suggest significant OOS forecasting power (of the first half-hour return on the last half-hour return) in most countries. For instance, 11 out of 16 countries have a positive OOS R^2 (Campbell and Thompson, 2008), all of which are supported by the equal predictive accuracy test of Clark and West (2007). Through the encompassing test of Clark and McCracken (2001), we also confirm that the first half-hour return conveys incremental information relative to the historical mean in 12 out of 16 countries. We also show that this out-of-sample predictability can be translated into economic gains. A simple trading strategy based on ITSM produces a significant positive return in 13 markets and beats the passive buy-and-hold benchmark in terms of Sharpe ratio in 12 markets.

Third, we propose four hypotheses based on theories of market microstructure and behavioral bias of investors. Gao et al. (2018) assert that the ITSM effect originates from the overnight information accumulation and suggest two possible explanations. The first explanation is the infrequent trading behavior of investors that has been documented both empirically and theoretically (Rakowski and Wang, 2009; Duffie, 2010; Heston et al., 2010; Bogousslavsky, 2016). The model by Bogousslavsky (2016) suggests that infrequent traders who absorb a liquidity shock by taking a sub-optimal position will have the intention to unload the sub-optimal position at the next active period, causing another liquidity shock that is in the same direction as the original one. Based on this model, we hypothesize that ITSM is associated with market liquidity provision. The rationale is that when the market is illiquid (liquid), both the original and the second liquidity shocks should have larger (smaller) market impact causing stronger (weaker) price movements in the same direction. The second explanation given by Gao et al. (2018) is the existence of traders who are slow in receiving or processing information. We relate this explanation to the overconfidence, particularly self-attribution bias of the investor (Chan et al., 1996; Barberis et al., 1998; Daniel et al., 1998, 2001) and introduce three hypotheses accordingly. Both Daniel and Titman (1999) and Zhang (2006) suggest that investor overconfidence bias can explain the conventional momentum effect and this bias is more pronounced when new information becomes vague. To put it simply, when the market is uncertain about the effect of new information, market participants tend to trade based on their own beliefs, resulting in a larger market volatility. Therefore, we capture the ambiguity of information via the intraday volatility and hypothesize that ITSM is stronger when markets are more volatile.

In addition to the market perception of new information, Da et al. (2014) propose the "frog-in-the-pan" hypothesis, highlighting the vital role of the information arrival process. In their hypothesis, investors under-react to information that arrives gradually to the market and over-react to information that comes as a surprise. Thus, our third hypothesis is that ITSM is stronger when the overnight information is digested smoothly and weaker when the market reacts swiftly with strong emotion. Finally, Chui et al. (2010) show that the conventional momentum is stronger in countries with high individualistic cultures. Our last hypothesis addresses this cultural effect and states that ITSM is related to individualism.

Fourth, we test these hypotheses in both the cross-section and time series of country equity market indices. Through our Fama and MacBeth (1973) cross-sectional regression analysis, we find that ITSM is largely supported by our hypotheses related to liquidity, information arrival process, and cultural characteristics. The average ITSM return of our strategies based on the liquidity, information arrival process, and individualism characteristics is equal to 1.19%, 1.92%, and 0.89% per annum, respectively. Our time series sorting analysis shows that ITSM is more pronounced in periods when liquidity provision is low, when information arrives continuously, and when information uncertainty is high. Overall, our results suggest that the ITSM is driven by both market microstructure and behavioral factors.

Our paper is also related to the recent academic studies addressing intraday return predictability and financial market microstructure. For example, Lou et al. (2019) relate firm-level intraday momentum and overnight reversal to investor heterogeneity. Xu (2017) uses intraday predictability for long-term portfolio construction while Fishe et al. (2019) study the relationship between anticipatory traders and high-frequency momentum trading. Elaut et al. (2018) investigate intraday momentum in the RUB–USD FX market. While these studies mainly focus on the cross-sectional predictability of U.S. stocks, commodity futures, or FX, our work adds to the literature on the time series of international stock return intraday predictability.

The rest of the paper is organized as follows. We describe the data in Section 2. In Section 3, we examine the pervasiveness of intraday time series momentum around the world both statistically and economically. We develop the hypotheses that relate ITSM to market characteristics in Section 4. In Section 5, we discuss hypothesis testing results. We conclude in Section 6.

2. Data and intraday returns

2.1. Data

We collect 1-minute data from the Thomson Reuters Tick History (TRTH) database and restrict our analysis to stock indices of the developed markets classified by the MSCI due to liquidity concerns.[1] We use as long a sample period as possible given liquidity and data availability, with the U.S. providing the longest sample period from January 3, 2000 to December 29, 2017. The dataset provides information on stock market indices based on the local currency, and consists of information on trading time, open price, high price, low price, and last price for every trading minute.

In order to process the high-frequency dataset, we broadly follow the data-cleaning steps outlined in Barndorff-Nielson et al. (2009) and Hollstein et al. (2020), with a few additions. First, we exclude Belgium, Denmark, Finland, Israel, and Italy since TRTH does not provide liquid data for these countries for a long enough period for our study. Second, we use only data with a time-stamp during the exchange trading hours for that market. For instance, we use data for the U.S. market between 9:30AM and 4:00PM Eastern Standard Time. For some countries, the records do not always correspond to the trading hours and exceed the market closing time with unchanged prices. To address this issue, we use the last actively changed price as the closing price. Third, we remove all non-trading days and recording errors. In particular, we filter out extreme prices that are higher (lower) than 1.2 (0.8) of the highest (lowest) daily price over the sample period, recorded on Thomson Reuters Datastream.

Finally, in order to study the cross-sectional and time series relation of market characteristics with ITSM returns, we take the perspective of the U.S. dollar investor, and hence we convert all local currency data into U.S. dollars. Specifically, we convert index prices based on the contemporaneous 1-minute exchange rate. While some scholars argue that using the U.S. dollar as the common numeraire might generate misleading conclusions on return predictability (Jordan et al., 2015), our approach is consistent with Lawrenz and Zorn (2017) and our results are robust to using local currencies, as shown in Tables C.1 and C.2 of the Internet Appendix. We exclude Hong Kong and Singapore from our sample due to the lack of 1-minute foreign exchange data. Of the 16 remaining MSCI developed countries, the sample period varies from country to country due to data availability. Full details of the data, sample periods and trading hours used in this paper are available in Table 1.

[Table 1 about here.]

[1] MSCI market classification guide: https://www.msci.com/market-cap-weighted-indexes.

2.2. Calculation of the first and last half-hour returns

Following Heston et al. (2010), Komarov (2017) and Gao et al. (2018) among others, we divide each trading day into 30-minute non-overlapping intervals. Gao et al. (2018) show that the length of the intervals does not significantly affect intraday time series momentum since most news and announcements are released overnight; hence, investors need a short time period to digest the information after (before) the markets open (close). In this study, we focus only on the first and the last half-hour returns due to the heterogeneity of the market setting across countries.[2] The first and last half-hour returns are defined as follows:

$$r_t^F = \frac{p_{first30,t}}{p_{close,t-1}} - 1, \qquad r_t^L = \frac{p_{close,t}}{p_{last30,t}} - 1, \tag{1}$$

where r_t^F denotes the first half-hour return on day t, $p_{first30,t}$ stands for the last price in the first 30 minutes after market open on day t, $p_{close,t-1}$ is the closing price on day $t-1$, r_t^L is the last half-hour return on day t, $p_{last30,t}$ is the first price in the last 30 minutes before market close on day t, and $p_{close,t}$ is the closing price on day t. Note that for the calculation of the first half-hour return, we also take the overnight information into account.

[Table 2 about here.]

Table 2 presents the summary statistics of the annualized first and last half-hour returns and reports the number of days, mean, standard deviation, skewness, and kurtosis. Excluding Spain and Sweden, the mean return for all markets in the first half hour is substantially higher and more volatile than in the last half hour. The high return during the first half hour may reflect the incorporation of overnight information in stock returns, while the high variability of the first half-hour returns may reflect the discrepancy in understanding this overnight information. The low variability in the last half-hour returns indicates less disagreement on the pricing of stocks. This is consistent with the hypothesis that traders who trade in the morning are more informed and have stronger information processing power while those who trade in the last half hour are followers who have less access to the information and are less

[2] For instance, the New York Stock Exchange operates continuously from 09:30 to 16:00, whereas the Tokyo Stock Exchange trades from 09:00 to 15:00 with an hour lunch break from 11:30 to 12:30.

informed as a result (Barclay and Hendershott, 2003; Gao et al., 2018). Most of the returns have a slightly negative skewness with a kurtosis around 3, indicating that these intraday returns are not as non-normal as found with daily returns.

3. Intraday return predictability around the world

3.1. Estimating the relation between first and last half-hour returns

We start our analysis by investigating the in-sample predictability of the first half hour on the last half-hour return in the 16 equity market indices respectively. To do so, we follow Gao et al. (2018) and run the following predictive regression for each market:

$$r_t^L = \alpha + \beta^F r_t^F + \epsilon_t, \quad t = 1, \cdots, T, \tag{2}$$

where r_t^L and r_t^F denote the last and the first half-hour returns at time t, respectively, and T is the total number of trading days in the sample.

Table 3 provides the in-sample estimation results of the predictive regression shown in equation (2) for each equity market, over the full sample period. The last row shows the results from a pooled regression where we run a panel model with country dummies, clustering the standard errors by country. This model allows for the observations of the same country at different time points to be correlated. To control for the heteroskedastisity and autocorrelation, we adjust the standard errors using the Newey and West (1987) correction modified for a panel framework. In Table C.1 of the Internet Appendix, we also report the results for the full sample based on local currency.

Over the full sample period, our results suggest that 12 out of 16 countries exhibit a statistically significant in-sample predictability of the first half hour on the last half-hour return. Among them, 10 markets have statistically significant positive slope coefficients at the 1% level. When all 16 markets are pooled, we find a positive and statistically significant relation between the first and the last half-hour returns. The coefficient of the first half-hour return is 2.68 and statistically significantly different from zero (t-statistic = 7.53).

While we observe a significant intraday time series momentum effect in most of the countries, the evidence in Austria, Canada, Ireland, and New Zealand is rather weak and deserves further investigation. First, we examine whether the periodic institutional trading behavior that is documented in Murphy and Thirumalai (2017) and Etula et al. (2019) can explain this evidence. Our evidence is mixed and support Gao et al. (2018), who find that, on the U.S. market, institutional trading is more strongly associated with the predictability of the second last half-hour return on the last half-hour return, compared to that of the first half-hour return. We provide a detailed discussion in Section A of the Internet Appendix.

Second, we investigate the possibility that the weak evidence in Austria, Canada, Ireland, and New Zealand is due to that these four markets are led by other larger international markets in close proximity to them. Our motivation stems from Rapach et al. (2013), who document the strong cross-country predictability of the U.S. market on other international markets in a monthly setting. While a comprehensive study of intraday cross-country predictability is beyond the scope of our paper, in Section B of the Internet Appendix we follow the approach of Rapach et al. (2013) and perform a pair-wise examination of the first-last half-hour relation. Our evidence does not suggest significant predictability of the U.S. market on the Canadian market, despite the fact that they are in the same timezone. Similarly, the first half-hour return of the U.K. does not appear to significantly predict the last half-hour return of Ireland. However, we find strong cross-market predictability of the U.S. market on the European markets, confirming the dominating role of the U.S. market (Rapach et al., 2013).

Collectively, we provide strong evidence that the first half-hour return positively forecasts the last half-hour return. This relationship is pervasive across countries and is consistent with the evidence found by Gao et al. (2018) for the U.S. stock market.

[Table 3 about here.]

3.2. Intraday time series momentum under various conditions

We now investigate the relation between the first and last half-hour returns under the following market conditions: the financial and non-financial crisis periods and the business cycle. We follow Gao et al. (2018) and set the financial crisis period from December 2, 2007 to June 30, 2009, while the OECD recession and expansion indicators are sourced from the St. Louis FRED website.[3] Panels A and B of Table 4 show that the predictability of the first half hour on the last half-hour return is economically stronger during the financial crisis compared to the non-crisis period; 12 out of 16 markets exhibit larger slope coefficients during financial crisis, while the magnitude of the adjusted R^2s is much larger compared to the one in the non-crisis period. Among the 16 markets, the predictive power of the first half hour is more pronounced in the U.S. stock market, which has a (scaled) coefficient of the first half hour equal to 18.28 during the financial crisis, four times larger than the corresponding one observed when we exclude the financial crisis period from our full sample period (the coefficient is equal to 4.24). In the pooled regression, we find a stronger positive relation between the first and the last half-hour returns during the financial crisis period relative to the non-crisis period; the coefficients of the first half-hour returns are 3.71 and 2.09, for the financial and non-financial crisis periods, respectively. Note that both coefficients are statistically distinguishable from zero. Similarly, the adjusted R^2 is equal to 1.18% during financial crisis; this is almost two times larger than the one observed in the non-crisis period (i.e., 0.63%). Panels C and D show that the predictive ability of the first half hour on the last half-hour return is stronger during recessions compared to expansions, with an average slope and adjusted R^2 equal to 4.04 (2.57) and 1.67% (0.65%) for the recession (expansion) periods.[4] The ITSM exhibits larger slope coefficients in 12 out of 16 markets during recession compared to expansion periods.

Collectively, Table 4 provides strong evidence that the positive relation between the first half hour and the last half-hour return is more pronounced during the financial crisis and recession periods. Our findings extend the evidence shown in Gao et al. (2018) for the U.S. stock market to a comprehensive set of countries around the world.

[Table 4 about here.]

[3]St. Louis FRED website: https://fred.stlouisfed.org/. Note that the methodology used by St. Louis FRED for computing OECD expansion/recession indicators is different from the methodology used by NBER from January 2009.

[4]Note that since the recession and expansion periods are country-specific, we restrict our analysis to individual predictive regressions and do not run a pooled regression.

3.3. Out-of-sample predictability

Up to this point, we have examined the in-sample predictability of the first half hour on the last half-hour return, which is based on the entire sample period. In this subsection, we formally examine the out-of-sample (OOS) predictive power of the first half-hour return on the last half-hour return for each individual stock market index. This enables us to assess the parameter instability over time in the predictive regressions (Ashley et al., 1980; Welch and Goyal, 2008).

Based on an expanding window approach, we use the first five years of our sample for each market as the initial estimation period and recursively regress equation (2) on each market by adding one day at a time. Then we evaluate the OOS performance of our predictive model by comparing it with that of a simple historical mean model via three statistics.

The first statistic is the Campbell and Thompson (2008) out-of-sample R^2 calculated as follows:

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T}(r_t^L - \hat{r}_t^L)^2}{\sum_{t=1}^{T}(r_t^L - \bar{r}_t^L)^2}, \tag{3}$$

where T is the number of observations in the out-of-sample period, r_t^L is the realized value of the last half-hour return at time t, $\bar{r}_t^L$ is the value estimated by using historical mean of the last half-hour return with data until time $t-1$, and $\hat{r}_t^L$ is the estimated value from the predictive regression using information available up to time $t-1$. This statistic compares the mean squared prediction error (MSPE) of our predictive model with that of the historical mean model; a positive value implies that the predictive model (2quation (2)) outperforms the historical mean model.

We then test the null hypothesis that the MSPE of the historical mean model is equal to or less than that of the predictive model (equivalent to H_0: $\mathrm{R}^2_{\mathrm{OOS}} \leq 0$ against H_1: $\mathrm{R}^2_{\mathrm{OOS}} > 0$). In order to do so, we use the Clark and West (2007) MSPE-adjusted. To calculate the statistic, we first compute a time series of $\hat{f}_t$ as follows:

$$\hat{f}_t = (r_t^L - \bar{r}_t^L)^2 - [(r_t^L - \hat{r}_t^L)^2 - (\bar{r}_t^L - \hat{r}_t^L)^2], \tag{4}$$

and then regress $\hat{f}_t$ against a constant. The Clark and West (2007) MSPE-adjusted is the one-sided (upper-tail) Student-t statistic of the constant term. We also apply the Newey and West (1987) corrections to this t-statistic.

Furthermore, we investigate whether the historical mean model forecasts encompass the predictive model forecasts. This gives us a sense of whether the latter provides useful predictive information relative to the former. To this end, we conduct a forecast encompassing test that is valid for nested models, using $\mathrm{ENC_{NEW}}$ proposed by Clark and McCracken (2001).[5] The null hypothesis is that the forecasts of the historical mean model encompass those of the predictive model; the one-sided (upper-tail) alternative hypothesis is that the forecasts of the historical mean model do not encompass those of the predictive model:

$$ENC_{NEW} = \frac{\sum_{t=1}^{T}[(r_t^L - \bar{r}_t^L)^2 - (r_t^L - \hat{r}_t^L)(r_t^L - \bar{r}_t^L)]}{T^{-1}\sum_{t=1}^{T}(r_t^L - \hat{r}_t^L)^2}. \tag{5}$$

Table 5 provides the three OOS statistics along with the average recursive regression coefficients for each country. As shown in the table, the average slope coefficient is positive for all countries and significant for 10 countries. Eleven out of 16 countries exhibit positive $\mathrm{R^2_{OOS}}$, while the Clark and West (2007) MSPE-adjusted rejects the null ($\mathrm{R^2_{OOS}} \leq 0$) in 12 markets. Interestingly, we observe a negative $\mathrm{R^2_{OOS}}$ in Germany, along with a MSPE-adjusted that is significant at the 1% level, which indicates that the MSPEs for the predictive model are significantly less than that of the historical mean model in this market.[6] The last column of Table 5 reports results of the forecast encompassing test. The null hypothesis (the historical mean forecasts encompass the predictive forecasts) is rejected for 12 out of 16 countries, implying that the first half-hour return provides additional predictive information relative to the simple historical mean of the last half-hour return in those markets. Overall, our OOS analysis provides strong evidence of OOS predictability in the first half-hour return on the last hour-hour return in most countries.

[Table 5 about here.]

[5] This statistic is also employed by Rapach and Wohar (2006); Barroso and Maio (2019) among others. Since its asymptotic distribution is nonstandard, we use the critical values given by Clark and McCracken (2001). That is, we use 1.280 and 2.085 for the 5% and 10% significance levels, respectively.

[6] In a study of technical indicator predictability, Neely et al. (2014) find similar results and argue, in Footnote 21, that this is plausible when comparing nested models. For further discussions, see Clark and West (2007); McCracken (2007).

3.4. The profitability of ITSM

The statistical performance demonstrated in the previous subsections does not necessarily translate into economic benefits from an investment perspective. Cenesizoglu and Timmermann (2012) compare the economic and statistical performance of 60 return prediction models and find weak evidence of a close relationship between economic and statistical performances. They argue that this is due to the fact that statistical measures generally focus on the accuracy of mean prediction, whereas the focal point of economic measures is whether the model can predict movements of the whole return distribution associated with the weights given by the utility function. Kandel and Stambaugh (1996) show that variables with relatively weak statistical predictive power can still produce significant economic benefits in a portfolio context. Therefore, we next examine the economic value of the ITSM in each of the 16 stock markets and compare the country ITSM with a passive benchmark strategy, namely the buy-and-hold strategy.

For the ITSM strategy, we consider the sign of the first half-hour return as the trading/timing signal: if the first half-hour yields a positive return, we take a long position in the last half-hour on the same day; if the first half-hour yields a negative return, we take a short position in the last half-hour on the same day. We close all the positions at the market close everyday. The market timing strategy can be summarized as follows:

$$r_{I,t} = \begin{cases} r_t^L, & \text{if } r_t^F > 0; \\ -r_t^L, & \text{if } r_t^F \leq 0, \end{cases} \tag{6}$$

where $r_{I,t}$ is the market timing return of ITSM on day t, and r_t^F and r_t^L are the first and last half-hour return at time t, respectively. On the other hand, the passive buy-and-hold benchmark strategy takes a long position of the equity index at the beginning of the sample period, and holds the index until the end of the period.

[Table 6 about here.]

Table 6 provides the mean, standard deviation (SD), skewness, kurtosis, and the Sharpe ratio of the ITSM strategy, and the buy-and-hold benchmark for each of the 16 equity markets. Over the full sample period, the ITSM strategy exhibits positive average annualized returns in all countries. Thirteen out of 16 countries show a statistically significant ITSM strategy return, of which 11 are significant at the 5% level following the Newey and West (1987) correction. We also observe a positive Sharpe ratio for the ITSM strategy in all countries, ranging from 0.02 for Canada to 1.24 for the U.K. The skewness of the ITSM return is positive in 9 out of 16 markets, suggesting a low crash risk. In contrast, 15 out of 16 countries exhibit a positive buy-and-hold strategy return, of which only two show statistical significance at the 5% level. In addition, the standard deviation of the benchmark strategy is significantly greater than that of the ITSM strategy (4 to 10 times higher) in all countries, resulting in a trivial Sharpe ratio compared to the ITSM. While the Sharpe ratio of the buy-and-hold strategy varies from -0.02 to 0.68, for example, it is smaller than its ITSM counterpart in 12 countries. We find that the results in Table C.2 of the Internet Appendix remain intact when the sample is based on local currencies.

4. Intraday time series momentum and market characteristics: Hypothesis development

The empirical implications shown in the previous section naturally raise the following questions: Why is the ITSM strategy return considerable and significant in some countries while less significant in others? Why is it more profitable when market conditions are worse? What are the sources of its profitability? In an attempt to answer these questions, we propose four hypotheses that link ITSM with market characteristics and test them in the next section of the paper.

4.1. Liquidity provision and market impact

Building on the slow moving capital model of Duffie (2010), Bogousslavsky (2016) develops a theoretical framework in which there are two types of traders that trade in the market: *frequent traders* who trade constantly and *infrequent traders* who need to be inactive for a period after each trade due to the costs of being always attentive. When liquidity trading is transient, Bogousslavsky (2016) shows formally in his model that return autocorrelations can switch sign from negative to positive, as a result of the presence of infrequent traders. Intuitively, this is because infrequent traders absorb a liquidity shock by taking a sub-optimal position at time t and then unload their excess position at time $t+k$, where k is the length of the inactive period, causing another liquidity shock in the same direction.

In the intraday context, the overnight information accumulation causes naturally transient liquidity shocks at the market open. Infrequent traders, who supply liquidity with a price concession at the open might have the intention to unload their sub-optimal positions at a later time. Given the well-known U-shape of the intraday trading volume and volatility (Jain and Joh, 1988), the optimal timing of this unloading may be the trading period immediately prior to the market close, during which the market is the deepest and most liquid (together with the market open).[7] This unloading is therefore in the same direction as the initial shock and causes the intraday momentum.

If this explanation holds, we argue that the level of liquidity plays a vital role. In particular, when the liquidity is low, there should be a relatively large market impact for both the initial liquidity shock and the infrequent rebalancing at the close, so a stronger intraday momentum would be expected. Conversely, when the liquidity is high, the market impact of both the initial liquidity shock and the infrequent rebalancing at the close is expected to be smaller, resulting in a weaker intraday momentum. Hence, Hypothesis 1 is as follows:

Hypothesis 1: Stronger ITSM should be observed when the liquidity provision is low.

4.2. Limited attention and inattentive "frogs"

Studies show that attention is a scarce cognitive resource of investors and the strategic allocation of it can affect asset prices (Peng and Xiong, 2006). While Hirshleifer et al. (2009) show investors have an upper attention threshold and can be overwhelmed by huge amounts of information, Da et al. (2014) propose the "frog-in-the-pan" (FIP) hypothesis in which there exits a lower attention threshold that is required for investors to respond to the news. Da et al. (2014) posit that investors are inclined to be inattentive and under-react to small amounts of information arriving continuously. This underreaction can be adjusted later in time causing momentum. They document that the cross-sectional momentum is stronger when the information in the formation period arrives continuously. Similarly, Lim et al.

[7]Another motivation of rebalancing at the close is to avoid overnight risk (Gao et al., 2018).

(2018) test this hypothesis on the time series momentum of Moskowitz et al. (2012) and find that the time series momentum performs better in the group of stocks in which the information arrives gently and continuously in the formation period.

Gao et al. (2018) conjecture that ITSM might be caused by that some traders are simply slower than others in processing and reacting to the overnight information. We argue that the traders who react slowly are likely inattentive, which is caused by information continuously arriving in small amounts. Therefore, in Hypothesis 2, we expect to observe stronger intraday momentum in markets where information arrives continuously.

Hypothesis 2: Stronger ITSM should be observed when the information arrives continuously.

4.3. Self-attribution bias

Equally important as to how the investor receives the information, is how the investor interprets it. Chan et al. (1996), Barberis et al. (1998), Daniel et al. (1998) and Daniel et al. (2001) document that investor overconfidence can help explain the observed momentum effect. For example, overconfident investors are believed to be ignorant towards the news that is against their priors (self-attribution bias), thus underreact to the news. Daniel and Titman (1999) and Zhang (2006) state that the overconfidence bias is likely to be more severe for companies with vague and subjective information. Whereas both Daniel and Titman (1999) and Zhang (2006) measure the information ambiguity on individual firm and long-term basis, we consider the ambiguity of high-frequency overnight information while the market as a whole is regarded as the receiver. Specifically, we argue that if the market as a whole is unclear about the implications of the overnight information at the market open, the return continuity should be amplified due to stronger behavioral biases of the traders. Thus, Hypothesis 3 is that stronger ITSM should be observed when the market is ambiguous about overnight information.

Hypothesis 3: Stronger ITSM should be observed when the information uncertainty is high.

4.4. Cultural differences

Investors' perception of information might also be affected by their cultural backgrounds. Specifically, psychologists differentiate cultures into two categories: individualistic cultures and collective cultures (Hofstede, 2001). People from individualistic cultures are believed to be more likely to suffer from the self-attribution bias and be ignorant to objective news, whereas people from collective cultures are believed to prioritize communal goals over individual goals. Examining the relationship between conventional cross-sectional momentum and cultural differences, Chui et al. (2010) claim that countries in highly individualistic cultures exhibit a stronger momentum effect. Therefore, in Hypothesis 4, we inspect the relationship between ITSM and culture differences. That is, we hypothesize that ITSM is stronger in countries with high individualism cultures. Consistent with Chui et al. (2010), we collect the data from the Hofstede (2001) Individualism Index that is constructed by conducting a cross-country psychological survey.[8]

Hypothesis 4: Stronger ITSM should be observed in countries with high individualism cultures.

5. Intraday time series momentum and market characteristics: Empirical tests

5.1. Estimating market characteristic variables

5.1.1. Intraday liquidity

Due to the lack of information on intraday quotes and volume in most countries, estimating the liquidity at the frequency of our data is rather challenging. The simplest measure that does not require information on trading volume is perhaps the one by Roll (1984): $2\sqrt{-cov(r_t, r_{t-1})}$. However the autocovariance of minutely returns are positive in nearly half of the days in our sample, making the adjustment for positive autocovariance costly. Consequently, we adopt the percent-cost *High-Low* liquidity measure by Corwin and Schultz (2012) that uses only the high and low prices of two consecutive time periods to estimate the percentage spread. The *High-Low* liquidity is computed as follows:

[8] Data are available at: https://www.hofstede-insights.com.

$$
\begin{aligned}
S &= \frac{2(e^{\alpha}-1)}{1+e^{\alpha}} \\
\alpha &= \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}} \\
\beta &= \sum_{j=0}^{1}\left[\ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2, \quad \gamma = \left[\ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2,
\end{aligned}
\tag{7}
$$

where S denotes the *High-Low* liquidity measure, H_t and L_t are the high price and low price at time t, and $H_{t,t+1}$ and $L_{t,t+1}$ are the high price and the low price over two consecutive time periods t and $t+1$.

For each country, we generally follow the procedure in Corwin and Schultz (2012) and estimate the spread in the first half hour by averaging the estimates across overlapping five-minute intervals.[9] Specifically, we calculate the *High-Low* liquidity measure over every two consecutive five-minute intervals and then take the average across the overlapping intervals within the first half hour.

5.1.2. Information discreteness

Following Da et al. (2014) and Lim et al. (2018) among others, we define information discreteness (ID) as follows:

$$ID_t = sign(r_t^F) \times (\%neg_t - \%pos_t), \tag{8}$$

where r_t^F is the first half-hour return on day t, and $\%neg_t$ and $\%pos_t$ are the percentage of minutes associated with a negative and positive return within the first 30 minutes, respectively, on day t.

To see how ID measures the information incorporation process, consider the first half-hour returns from two days on the same market, r_k^F and r_s^F, triggered by equally effective overnight information, ϕ_k^O and ϕ_s^O, which lead to an upward price movement.[10] Now suppose ϕ_k^O is smoothly incorporated into the price while ϕ_s^O is absorbed by a few sudden price

[9] A supplementary note to Corwin and Schultz (2012) detailing the use of the *High-Low* estimate in intraday setting is available at: `http://sites.nd.edu/scorwin/files/2019/11/Application_Intraday_Analysis.pdf`.

[10] In fact, so long as both ϕ_k^O and ϕ_s^O are positive, it is not necessary to assume equality. But we keep it for simplicity.

movements. This can be translated into that r_k^F has a higher proportion of positive minutely returns than does r_s^F. Collectively:

$$\begin{aligned} &\phi_k^O = \phi_s^O \\ &r_k^F = r_s^F > 0 \\ &0 \leq p_s < p_k \leq 1, \end{aligned} \tag{9}$$

where p_k and p_s are the proportion of positive minutely returns in r_k^F and r_s^F. Assuming there is no zero-return minutes, we have:[11]

$$1 - 2p_k = ID_k < ID_s = 1 - 2p_s. \tag{10}$$

Therefore, a small ID implies that the information is relatively more gently absorbed while a large ID is a sign of a high degree of information discreteness.

5.1.3. Information uncertainty and individualism

For estimating the information uncertainty, we follow Zhang (2006) and use stock return volatility as a proxy. Intuitively, the more ambiguous the market is about news, the larger the volatility of stock returns. In particular, we estimate stock return volatility by computing the standard deviation of minute returns in the first half hour for each country. While the volatility of returns contains the uncertainty of information, it accounts for the variation in the information itself. The high-frequency nature of our study effectively mitigates this problem, given that the intrinsic value of an asset is believed to change less in thirty minutes than in weeks or months.

For measuring cultural individualism, we follow Chui et al. (2010) and adopt the Hofstede (2001) Individualism Index as the proxy for cultural individualism. The index assigns each country a number denoting the strength of the ties that people have in their community. A high index number indicates a high degree of individualism and it does not change over time.

[11] $sign(r_k^F) = sign(r_s^F) = 1$, $\%neg_k - \%pos_k = (1-p_k) - p_k = 1-2p_k$, and $\%neg_s - \%pos_s = (1-p_s) - p_s = 1 - 2p_s$.

5.1.4. Descriptive statistics of characteristic variables

Table 7 reports the summary statistics of our estimates for liquidity, information discreteness, and volatility for each country. It also reports the Hofstede (2001) Individual Index numbers for each country. Due to the high frequency nature of our study and data quality, we observe extreme outliers in the estimates. To address this issue, we winsorize our estimates in the time series using the 5th and 95th percentiles, that is, we set any value below the 5th percentile to the 5th percentile and any value above 95th percentile to the 95th percentile.[12]

Table 8 presents the Pearson correlation coefficients among all characteristic variables but individualism, which is constant over time. Generally, we do not observe a strong correlation between characteristic variables. For example, the correlation between Spread and Volatility ranges from 0.16 in New Zealand to 0.52 in both Germany and U.S. In addition, the correlation between ID and the other two characteristic variables is virtually neglectable, ranging from -0.07 to 0.08.

[Table 7 about here.]

[Table 8 about here.]

5.2. Hypothesis testing in the cross-section

5.2.1. Fama-MacBeth regressions

Our hypothesis testing starts with a Fama and MacBeth (1973) regression analysis; we study the cross-sectional relationship between the ITSM profitability and the characteristic variables. In particular, we first perform the following univariate cross-sectional regressions at each day t:

$$r_{I,i,t} = \alpha_t + \beta_t^C Char_{i,t} + \epsilon_{i,t}, \tag{11}$$

where $r_{I,i,t}$ is the ITSM return for country i at time t, and $Char_{i,t}$ is the characteristic variable for country i at time t. We perform this analysis with each of our characteristic variables,

[12]Regarding the sorting analyses presented below, we report the results using pre-winsorized data in Tables C.3 and C.4 of the Internet Appendix. Our main conclusion remains largely unchanged.

namely, liquidity, ID, volatility, and individualism, which are standardized across markets at every time t. Next, we conduct the following multivariate cross-sectional regressions at each day t:

$$r_{I,i,t} = \alpha_t + \boldsymbol{\beta}_t^{C\prime} \boldsymbol{C}_{i,t} + \epsilon_{i,t}, \tag{12}$$

where $\boldsymbol{C}_{i,t}$ is a 4-dimensional vector of all characteristic variables for country i at t. Likewise, we standardized characteristic variables across markets at t.

Despite that the dependent and independent variables share the same time index, t, both regression analyses are ex ante. This is because all of our characteristic variables (except individualism) are computed based on information in the first half hour, whereas our ITSM return, $r_{I,i,t}$, is computed from the last half hour.

The time difference issue in our global sample is a major concern before we run the regressions. For example, the U.S. is lagged behind all other countries in the sample, thus opens the latest. However, the New Zealand Stock Exchange, which is located in Wellington, is 16 hours ahead of New York Stock Exchange, meaning that the local time at the New Zealand Stock Exchange is 02:00 am on the next calendar day ($t + 1$) when the New York Stock Exchange hits 10:00 am on day t. This fact makes it impossible to invest in New Zealand based on the first half-hour information from the U.S. on the same day. The same problem applies to Australia and Japan as well. Therefore, we exclude Australia, Japan, and New Zealand from our sample in the cross-market analysis. Note that at the beginning of our sample (January 2000), 11 country indices are available. The complete set of 13 country indices is available from October 2005 until the end of our sample (December 2017).

[Table 9 about here.]

Table 9 reports the average annualized coefficients of the Fama and MacBeth (1973) regressions, which correspond to the average profit of a long–short trading strategy over time; the corresponding t-statistics are estimated using Newey and West (1987) standard errors. Table 9 shows that liquidity, information discreteness, and individualism exhibit a significant cross-sectional relationship with ITSM return. For example, the annualized average ITSM return of a long-short strategy based on the Spread, ID, and individualism is equal to 1.19%, -1.92%, and 0.89%, associated with Newey and West (1987) t-statistics of

2.37, -3.01, and 2.24, respectively. The statistical significance of the Spread and ID remains intact, when we regress ITSM returns against all variables collectively, while individualism remains marginally significant at a 10% significance level. Our evidence suggests that the ITSM return is higher in markets with lower liquidity, smaller information discreteness, and higher individualism, endorsing Hypotheses 1, 2, and 4.

In contrast, although the sign of the coefficient of volatility is consistent with our Hypothesis 3 (i.e., the higher the volatility, the larger the ITSM return), it is not statistically significant in the univariate regressions or in the multivariate Fama-Macbeth regressions.

5.2.2. Cross-sectional sorting analysis

To further investigate our hypotheses in a more realistic setting, we perform a cross-market sorting analysis, that is, we sort the indices based on the characteristic variables estimated from the first half hour after the market opening and calculate the equally-weighted return of the bottom, medium, and top 30% group of country ITSM.

[Table 10 about here.]

The clear monotonic cross-group pattern in portfolio returns shown in Panels A and B of Table 10 largely confirm our Fama-MacBeth regression results and support Hypotheses 1 and 2. For example, when we sort the countries by the first half-hour High-Low spread, we observe a monotonic increase in the ITSM portfolio returns from 2.67% to 5.43% as liquidity shrinks (Panel A). The significance levels of the portfolio returns also increase from the 5% significance level in the small spread (liquid) group to the 1% significance level in the medium and large spread (illiquid) groups. A long-short portfolio that takes a long position in the large spread group and a short position in the small spread group enjoys an annualized average return of 2.76%, which is significant at the 5% level. This evidence is consistent with Hypothesis 1 that ITSM is stronger in markets with low liquidity.

Similarly in Panel B, the portfolio performance deteriorates from a return of 5.83% that is significant at the 1% significance level to an insignificant return of 1.27% as information discreteness enlarges. A long-short portfolio that buys the large ID group and sells the small ID group delivers an annualized average return of -4.6%, which is significant at the 1% level.

As shown in Panel C, we do not observe a monotonic pattern across groups when we sort the portfolios by volatility. While the portfolio return is 4.50% for the large volatility group, higher than 3.86% for the small volatility group, the medium volatility group exhibits an average return of 4.74% that is greater than both the small and large volatility groups. Moreover, a strategy that buys the large volatility group and sells the small volatility group delivers a trivial return of 0.64%, which is not statistically significant. This is again consistent with our Fama-MacBeth regression analysis, implying that volatility has a week effect on ITSM profitability in the cross-section.

Finally, Panel D provides the results when we sort ITSM country returns by individualism. The large individualism group exhibits a ITSM portfolio return of 5.04%, which is greater than that of both the small and medium individualism groups (3.82% and 3.78%, respectively), however this difference is not statistically significant. A long-short ITSM strategy yields a return of 1.22% with no statistical significance, in contrast to the Fama and MacBeth (1973) analysis, which suggests a significant relationship between ITSM and individualism. Note that the difference between the slope coefficients of the Fama and MacBeth (1973) regressions and the cross-sectional analysis is that the former represent portfolio returns with specific characteristics combined linearly, while the later represent portfolio returns based on a non-parametric ranking of the characteristic values (Back et al., 2013).

Overall, our cross-market analysis provides evidence in strong support of Hypotheses 1 and 2. The findings imply that intraday liquidity and information discreteness might contribute to the profitability of ITSM, leaving the contribution of volatility and individualism unclear.

5.3. Time series sorting analysis

As shown in the previous subsection, a cross-market analysis reveals a strong relationship between the profitability of ITSM and market characteristics, such as intraday liquidity provision and information discreteness. However, all characteristics but the Hofstede (2001) Individualism Index are intraday and thus can vary across days, making it interesting to examine the relationship asserted by our cross-market analysis in the time series dimension. Therefore, we turn now to the time series sorting analysis that is based on the characteristics considered in the previous subsection except for the individualism index because it is constant over time.

For each market, we sort all trading days by the characteristic variables and split them into three groups similar to the cross-market sorting. In each group, we first perform the predictive regression and then form the equally-weighted ITSM portfolio as in the cross-market sorting analysis. We report the slope coefficients and portfolio returns, in Panels A and B of Table 11, respectively.

[Table 11 about here.]

As shown in Panel A of Table 11, the estimated slope coefficients exhibit a clear cross-group pattern in both magnitude and significance for liquidity and ID, echoing our cross-market findings shown in the previous section. For example, 10 out of 16 countries show a positive and significant slope coefficient in the large Spread (illiquid) group, in contrast to 7 and 9 in the small (liquid) and medium Spread groups. Moreover, in 10 countries, the large Spread group exhibits the largest slope coefficient across groups. In addition, when we sort the days by ID, we observe 11 countries with a positive and significant slope coefficient in the small group, 7 of which are significant at the 1% level. In contrast, two countries in the large ID group have a slope coefficient that is significant at the 1% level. Panel B of Table 11 provides portfolio returns for each group. In 11 out of 16 countries, the most illiquid group enjoys the largest ITSM portfolio return across groups. Similarly, 12 out 16 countries show the strongest portfolio performance in the small ID group compared to that of the medium and large ID groups.

While the effect of volatility on ITSM is not clear-cut in the cross-section, it is distinctive in the time series. In particular, 12 countries exhibit positive and strongly significant slope coefficients on the large volatility days, whereas only 3 and 7 countries show significance (mostly at the 10% or 5% significance level) in the small and medium volatility days, respectively. With respect to the magnitude of the estimates, the large volatility group exhibits the largest slope estimate in 12 out of 16 countries. Economically, 12 out of 16 markets deliver the largest portfolio return, of which 10 are statistically significant. We also notice that the difference between the returns of the large volatility portfolios and the small or medium volatility portfolios is remarkable. Eight of 16 large volatility portfolios yield returns that are greater than 10% per year, whereas the largest return of the small and medium portfolios combined is 5.46% per year in Ireland. The time series evidence presented here supports our Hypothesis 3 and echoes with our previous findings that ITSM is stronger in tough market conditions. It is also consistent with Gao et al. (2018), who argue that ITSM seems to to be highly correlated with volatility.

Overall, our time series sorting analysis results confirm the cross-market sorting analysis results of the effect of liquidity and ID on ITSM and, in addition, strongly support Hypothesis 3, which states that ITSM is stronger when the market is volatile.

6. Conclusion

With the rise of high-frequency trading, a growing number of academic studies are documenting intraday anomalies in asset prices. The recent paper by Gao et al. (2018) introduces intraday time series momentum (ITSM) in which the first half-hour return significantly predicts the final half-hour return in U.S. ETFs. We examine ITSM in a broader space of 16 international stock markets, with particular attention to the link of ITSM with market characteristics.

Specifically, we first show that the phenomenon is both statistically and economically pervasive around the world. Twelve out of 16 developed markets in our sample exhibit statistical evidence of intraday time series momentum. The widely observed in-sample evidence of the intraday return predictability is also confirmed in a thorough out-of-sample analysis in the majority of the developed countries. Specifically, 11 out of 16 markets show positive out-of-sample R^2, while according to the Clark and West (2007) test, in 12 out of 16 countries, the forecasts based on the first half hour returns provide statistically significant reductions in mean squared predictive error (MSPE) relative to the historical mean forecast. Overall, our international evidence is largely consistent with the evidence in Gao et al. (2018) in the U.S. market, indicating that ITSM is not a U.S.-only effect.

Having confirmed ITSM globally, we then study the relationship between market characteristics and ITSM. We start by proposing four hypotheses that are based on market microstructure and behavioral finance theories. In particular, we consider the intraday effect from the perspective of market liquidity provision, intraday volatility, information discreteness, and cultural differences (individualism). Relating ITSM with previous theoretical literature, we hypothesize that the intraday phenomenon is stronger in the market where liquidity is low, volatility is high, and information arrives discretely. We also hypothesize that cultural differences, such as individualism, explain ITSM. Finally, we test our hypotheses both in the cross-section and time series, and find that in both cases that empirical evidence supports the claim that the ITSM is driven by both market microstructure and behavioral factors.

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Table 1: Indices

	Sample Period	Index	RIC	Trading Hours (local time)
Australia	2000/04/04 - 2017/12/29	S&P ASX 200	.AXJO	10:00 - 16:00
Austria	2000/01/04 - 2017/12/29	Austrian Traded Index	.ATX	09:00 - 17:30
Canada	2002/05/02 - 2017/12/29	S&P/TSX Composite Index	.GSPTSE	09:30 - 16:00
France	2000/01/04 - 2017/12/29	CAC 40 Stock Market Index	.FCHI	09:00 - 17:30
Germany	2000/01/04 - 2017/12/29	DAX PERFORMANCE-INDEX	.GDAXI	09:00 - 17:30
Ireland	2000/01/05 - 2017/12/29	ISEQ Overall Index	.ISEQ	08:00 - 16:30
Japan	2000/01/05 - 2017/12/29	Nikkei Stock Average 225	.N225	09:00 - 15:00
Netherlands	2000/01/04 - 2017/12/29	AEX Amsterdam Index	.AEX	09:00 - 17:30
New Zealand	2001/02/06 - 2017/12/29	NZX 50 Index Gross	.NZ50	10:00 - 18:00
Norway	2003/03/04 - 2017/12/29	Oslo Exchange All-share Index	.OSEAX	09:00 - 16:30
Portugal	2000/01/04 - 2017/12/29	PSI 20 INDEX	.PSI20	08:00 - 16:30
Spain	2000/01/04 - 2017/12/29	Ibex 35 Index	.IBEX	09:00 - 17:30
Sweden	2005/10/04 - 2017/12/29	OMX Stockholm All-share Index	.OMXSPI	09:00 - 17:30
Switzerland	2000/01/05 - 2017/12/29	SMI Index	.SSMI	09:00 - 17:30
United Kingdom (U.K.)	2000/01/05 - 2017/12/29	FTSE 100	.FTSE	08:00 - 16:30
United States (U.S.)	2000/01/03 - 2017/12/29	S&P500	.SPX	09:30 - 16:00

This table presents the 16 developed markets based on the MSCI classification list along with their corresponding stock market indices. RIC stands for the Reuters Instrument Code.

Table 2: Summary statistics of the first and last half-hour returns

		No. Days	Mean (%)	SD (%)	Skewness	Kurtosis
Australia	First	4410	6.46	20.15	-0.01	3.02
	Last	4410	5.08***	5.42	-0.04	3.06
Austria	First	4373	19.71***	17.03	0.01	3.07
	Last	4373	16.22***	6.14	0.10	3.08
Canada	First	3899	10.53***	11.17	0.02	3.05
	Last	3899	2.81**	4.37	0.00	3.12
France	First	4530	12.28***	16.11	-0.02	3.04
	Last	4530	3.79***	5.91	-0.01	3.01
Germany	First	4522	11.93***	15.86	-0.03	3.02
	Last	4522	8.02***	7.37	0.08	3.07
Ireland	First	4476	16.81***	15.98	0.11	3.26
	Last	4476	6.60**	12.61	-2.07	9.02
Japan	First	4373	15.59***	23.50	-0.01	3.01
	Last	4373	1.42	6.20	0.02	3.07
Netherlands	First	4520	13.11***	15.52	-0.02	3.03
	Last	4520	5.17***	5.59	-0.02	3.01
New Zealand	First	3564	4.89	16.07	-0.01	3.03
	Last	3564	1.73***	1.60	0.02	3.02
Norway	First	4182	18.94***	13.42	-0.02	3.01
	Last	4182	5.72***	6.96	-0.01	3.04
Portugal	First	4500	17.73***	14.45	-0.03	3.05
	Last	4500	9.24***	5.09	-0.02	3.01
Spain	First	4512	9.15***	16.47	-0.02	3.05
	Last	4512	9.84***	5.63	-0.01	3.00
Sweden	First	3011	0.21	12.02	-0.01	3.01
	Last	3011	7.76***	4.39	-0.02	3.01
Switzerland	First	4475	9.34***	13.53	0.01	3.02
	Last	4475	-0.18	5.69	-0.01	3.01
U.K.	First	4477	8.25***	13.91	-0.06	3.07
	Last	4477	3.66***	5.28	0.00	3.01
U.S.	First	4214	1.10	11.12	-0.02	3.01
	Last	4214	1.05	5.55	-0.01	3.07

This table reports the summary statistics for the first and last half-hour returns of the 16 developed equity market indices. The first and last half-hour returns are defined in equation (1). The table reports the number of days (i.e., No. Days), mean, standard deviation (i.e., SD), skewness, and kurtosis for each equity market index. The sample periods for each market are reported in Table 1. For each market, we exclude a day if the first or the last half-hour return is not available. The mean, standard deviation, skewness and kurtosis are annualized. We also compute one sample t-statistic for the returns and account for autocorrelation and heteroskedasticity by Newey and West (1987) correction. *, **, and *** denote the 10%, 5%, and 1% significant levels, respectively.

Table 3: In-sample evidence of intraday time series momentum

	Intercept	β^F	Adj.R^2 (%)
Australia	4.85***	3.65***	1.82
	(4.21)	(4.22)	
Austria	16.04***	0.93	0.04
	(9.19)	(0.78)	
Canada	2.85**	-0.43	-0.01
	(2.37)	(-0.34)	
France	3.09**	5.63***	2.34
	(2.10)	(6.73)	
Germany	7.52***	4.19***	0.79
	(4.06)	(4.52)	
Ireland	6.44**	0.94	-0.01
	(2.15)	(0.93)	
Japan	0.90	3.38***	1.62
	(0.68)	(3.75)	
Netherlands	4.43***	5.67***	2.45
	(3.28)	(6.00)	
New Zealand	1.72***	0.17	0.00
	(3.95)	(0.55)	
Norway	5.02***	3.74***	0.50
	(3.00)	(3.20)	
Portugal	8.95***	1.64**	0.19
	(6.79)	(2.13)	
Spain	9.45***	4.16***	1.46
	(6.41)	(5.03)	
Sweden	7.75***	2.89**	0.59
	(5.29)	(2.46)	
Switzerland	-0.56	4.03***	0.90
	(-0.36)	(3.77)	
U.K.	3.23**	5.19***	1.84
	(2.47)	(5.11)	
U.S.	0.96	7.97***	2.53
	(0.76)	(3.82)	
Pooled	3.97**	2.68***	0.78
	(2.19)	(7.53)	

This table presents the in-sample regression results over the full sample period. In the individual country-based regressions, we regress the last half-hour return against the first half-hour return: $r_t^L = \alpha + \beta^F r_t^F + \epsilon_t$. In the pooled panel regressions, we regress the last half-hour return against the first half-hour return and country dummy variables: $r_{i,t}^L = \alpha + \beta^F r_{i,t}^F + \sum_{j=2}^{16} \beta_j D_{j,t} + \epsilon_{i,t}$. Note that the first half-hour return includes the overnight return in order to take into account the impact of information released overnight. The Newey and West (1987) t-statistics are reported in parentheses. In the pooled regression, we also cluster the standard errors by country. The slope coefficients are scaled by 100. The sample periods for each market are shown in Table 1. In the pooled regression we use only days on which all the markets have available data. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Table 4: Intraday time series momentum in different market conditions

	Intercept	β^F	Adj.R^2 (%)	Intercept	β^F	Adj.R^2 (%)	Intercept	β^F	Adj.R^2 (%)	Intercept	β^F	Adj.R^2 (%)
	Panel A: Financial Crisis			**Panel B: Excluding Financial Crisis**			**Panel C: Recession**			**Panel D: Expansion**		
Australia	13.33*	4.76**	3.01	4.11***	2.97***	1.16	5.77***	3.20***	1.40	3.68**	4.48***	2.65
	(1.91)	(2.26)		(3.81)	(4.14)		(3.47)	(2.63)		(2.28)	(3.93)	
Austria	34.77***	0.36	-0.25	14.16***	1.25*	0.10	21.24***	0.88	0.00	12.45***	1.07	0.06
	(3.09)	(0.13)		(9.67)	(1.93)		(6.70)	(0.40)		(6.77)	(1.38)	
Canada	14.64*	2.62	0.06	1.71*	-1.93**	0.29	6.68***	0.41	-0.05	0.16	-1.68*	0.17
	(1.83)	(0.87)		(1.81)	(-2.35)		(2.98)	(0.23)		(0.13)	(-1.65)	
France	10.51	7.81***	5.91	2.54*	4.77***	1.50	6.69**	6.53***	3.45	0.78	3.98***	0.95
	(1.32)	(3.96)		(1.80)	(5.62)		(2.50)	(5.63)		(0.49)	(3.75)	
Germany	-0.56	5.14**	2.41	8.36***	3.78***	0.52	13.72***	5.02***	0.93	2.38	3.16***	0.62
	(-0.07)	(2.44)		(4.42)	(3.45)		(4.24)	(3.43)		(1.26)	(3.29)	
Ireland	-3.12	-0.25	-0.25	7.19**	1.99	0.01	2.73	-0.31	-0.04	10.38***	5.30***	0.93
	(-0.34)	(-0.18)		(2.25)	(1.37)		(0.55)	(-0.27)		(4.19)	(3.86)	
Japan	7.22	7.40***	8.88	0.65	1.75***	0.39	0.14	5.45***	4.33	1.77	1.22*	0.17
	(1.05)	(3.71)		(0.49)	(2.60)		(0.07)	(3.88)		(1.01)	(1.93)	
Netherlands	4.90	7.97***	5.71	4.56***	4.68***	1.54	10.45***	7.81***	4.65	1.03	2.37**	0.40
	(0.65)	(4.16)		(3.58)	(4.58)		(4.16)	(5.97)		(0.72)	(2.48)	
New Zealand	-0.24	-0.28	-0.14	1.93***	0.43*	0.12	1.64***	0.05	-0.05	1.79***	0.38	0.05
	(-0.12)	(-0.43)		(4.62)	(1.88)		(2.62)	(0.12)		(3.08)	(1.12)	
Norway	-2.81	8.09*	0.94	5.90***	2.57***	0.31	6.38**	5.03**	0.66	3.94**	2.33**	0.27
	(-0.23)	(1.95)		(4.13)	(2.90)		(2.12)	(2.51)		(2.12)	(2.26)	
Portugal	10.59	3.78**	1.28	8.94***	0.85	0.03	12.21***	1.77	0.18	7.22***	1.59	0.18
	(1.56)	(2.31)		(6.82)	(1.02)		(5.01)	(1.40)		(4.66)	(1.62)	
Spain	16.70**	6.87***	4.67	8.90***	3.26***	0.83	14.88***	5.11***	2.18	5.16***	2.88**	0.68
	(2.24)	(3.29)		(6.27)	(3.87)		(6.34)	(4.19)		(2.96)	(2.53)	
Sweden	12.24*	-0.11	-0.26	6.97***	4.47***	1.52	10.27***	1.99	0.20	5.62***	4.24***	1.41
	(1.94)	(-0.04)		(5.31)	(4.29)		(4.04)	(1.15)		(3.58)	(3.08)	
Switzerland	-3.99	6.12**	2.13	-0.20	3.36***	0.59	1.87	5.40***	1.84	-1.90	1.33	0.04
	(-0.53)	(2.17)		(-0.13)	(3.35)		(0.68)	(3.74)		(-1.16)	(1.21)	
U.K.	11.04	6.88***	4.05	2.59**	4.35***	1.14	6.20**	6.25***	3.41	2.13	3.95***	0.82
	(1.36)	(3.29)		(2.18)	(4.42)		(2.08)	(4.21)		(1.57)	(3.16)	
U.S.	4.80	18.28***	7.53	1.00	4.24***	0.95	2.26	10.11***	3.62	0.32	4.54**	0.98
	(0.53)	(3.14)		(0.90)	(3.36)		(1.03)	(3.43)		(0.23)	(2.29)	
Pooled	5.83	3.71***	1.18	3.84**	2.09***	0.63	–	–	–	–	–	–
	(0.61)	(4.60)		(2.41)	(7.28)		–	–	–	–	–	–

This table presents the in-sample regression results under various market conditions, namely financial crisis (Panel A), non-crisis period (Panel B), recession (Panel C), and expansion (Panel D). In the individual country-based regressions, we regress the last half-hour return against the first half-hour return: $r_t^L = \alpha + \beta^F r_t^F + \epsilon_t$. In the pooled panel regressions, we regress the last half-hour return against the first half-hour return and country dummy variables: $r_{i,t}^L = \alpha + \beta^F r_{i,t}^F + \sum_{j=2}^{16} \beta_j D_{j,t} + \epsilon_{i,t}$. Note that the first half-hour return includes the overnight return in order to take into account the impact of information released overnight. The financial crisis period spans form 2 December 2007 to 30 June 2009 (Gao et al., 2018). Recession indicators are sourced from St. Louis FRED website. The returns are annualized and in percentages. The Newey and West (1987) t-statistics are reported in parentheses. In the pooled regression, we also cluster the standard errors by country. The slope coefficients are scaled by 100. The sample periods for each market are shown in Table 1. In the pooled regression we use only days on which all the markets have available data. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Table 5: Out-of-sample analysis

	Ave. Intercept	Ave. β^F	R^2_{OOS}	MSPE-adj.	ENC_{NEW}
Australia	4.95***	3.70***	1.82	3.03***	73.09***
Austria	17.30***	0.46	-0.24	-0.64	-2.01
Canada	2.63*	0.19	-0.19	-1.31	-2.11
France	3.52*	7.09***	1.48	3.60***	100.64**
Germany	11.27***	5.74***	-0.10	2.74***	50.63***
Ireland	6.90	0.64	-0.10	-0.69	-0.89
Japan	2.02	2.92***	2.20	3.37***	66.41***
Netherlands	6.30***	7.74***	0.32	3.03***	103.49**
New Zealand	1.81***	0.25	-0.43	-0.47	-2.60
Norway	5.21**	2.98**	0.48	3.23***	10.06**
Portugal	9.02***	1.34	0.09	1.31*	6.95***
Spain	8.93***	5.35***	1.01	2.96***	69.48***
Sweden	9.56***	2.26	1.36	3.48***	16.81**
Switzerland	0.59	4.49***	0.46	1.99**	26.05***
U.K.	4.97***	7.15***	0.69	2.63***	94.62***
U.S.	1.79	8.03***	2.86	2.91***	95.56***

This table reports the individual out-of-sample analysis results. For each market, we use the first five years as the initial estimation period and recursively perform the predictive regression by adding one day at a time. The intercept and slope coefficients are averaged from individual regressions. The stars next to them are assigned based on average Newey and West (1987) t-statistics (unreported). For each country, we also report Campbell and Thompson (2008) R^2_{OOS}, Clark and West (2007) MSPE-adjusted, and Clark and McCracken (2001) ENC_{NEW} respectively. We apply Newey and West (1987) corrections in computing the Clark and West (2007) MSPE-adjusted, which is an one-tailed (upper-tail) t-statistic. For ENC_{NEW}, we use critical values of 1.280 and 2.085 for the 5% and 10% significance levels, given by Clark and McCracken (2001). The slope coefficients are scaled by 100. The sample periods are reported in Table 1. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Table 6: Profitability of individual intraday time series momentum

	Strategy	Mean (%)	SD (%)	Skewness	Kurtosis	SR
Australia	ITSM	4.91***	5.42	0.06	3.07	0.91
	BH	6.86	24.15	-0.02	3.03	0.28
Austria	ITSM	2.47*	6.22	-0.08	3.09	0.40
	BH	10.58*	26.43	0.00	3.03	0.40
Canada	ITSM	0.07	4.38	-0.07	3.13	0.02
	BH	4.56	15.63	0.00	3.03	0.29
France	ITSM	7.18***	5.90	0.02	3.02	1.22
	BH	4.95	25.63	0.01	3.03	0.19
Germany	ITSM	6.33***	7.38	0.06	3.08	0.86
	BH	8.23	25.99	0.00	3.02	0.32
Ireland	ITSM	2.41	12.61	-1.37	9.01	0.19
	BH	5.30	24.28	-0.04	3.03	0.22
Japan	ITSM	4.63***	6.20	0.01	3.08	0.75
	BH	5.92	29.90	-0.01	3.02	0.20
Netherlands	ITSM	5.87***	5.59	0.02	3.02	1.05
	BH	4.89	24.80	0.01	3.03	0.2
New Zealand	ITSM	0.68	1.60	0.00	3.03	0.42
	BH	12.75***	18.69	-0.02	3.02	0.68
Norway	ITSM	5.92***	6.96	0.02	3.05	0.85
	BH	10.58**	21.91	-0.02	3.01	0.48
Portugal	ITSM	2.66**	5.12	0.00	3.02	0.52
	BH	-0.51	22.38	-0.01	3.03	-0.02
Spain	ITSM	4.61***	5.65	0.01	3.02	0.81
	BH	3.39	26.72	0.01	3.03	0.13
Sweden	ITSM	3.03**	4.41	-0.01	3.02	0.69
	BH	6.98	20.25	0.00	3.01	0.34
Switzerland	ITSM	2.21*	5.69	0.00	3.03	0.39
	BH	2.50	23.89	-0.02	3.06	0.10
U.K.	ITSM	6.51***	5.27	0.04	3.03	1.24
	BH	1.95	22.02	0.00	3.04	0.09
U.S.	ITSM	6.19***	5.54	0.07	3.08	1.12
	BH	5.57	19.40	0.00	3.04	0.29

This table presents the performance of intraday time series momentum (i.e. ITSM) and the buy-and-hold benchmark for each of the 16 equity markets. The ITSM strategy opens a long (short) position at the beginning of the last half hour if the return during the first half hour on the same trading day is positive (negative), and closes the positions at the market close. The buy-and-hold benchmark strategy opens a long position at the beginning of our sample and hold it throughout the sample period. We report the mean, standard deviation (SD), skewness, kurtosis, and the Sharpe ratio (SR) of the two strategies for each market. *, **, and *** denote 10%, 5%, and 1% significance levels after Newey and West (1987) correction, respectively. The sample periods are reported in Table 1.

Table 7: Characteristic variable estimates

	Spread (%)					ID					Volatility					Individualism
	No.Obs	Mean	SD	Skew	Kurt	No.Obs	Mean	SD	Skew	Kurt	No.Obs	Mean	SD	Skew	Kurt	
Australia	4450	0.00013	0.00011	0.90836	2.93762	4479	-0.02005	0.05249	0.01610	2.21160	4454	0.00059	0.00028	1.17525	3.67324	90
Austria	4422	0.00030	0.00021	0.69747	2.65570	4448	-0.03242	0.04141	-0.21515	2.24867	4423	0.00081	0.00041	1.34740	4.09586	55
Canada	3924	0.00024	0.00017	0.91186	3.07701	3928	-0.02914	0.04229	-0.05344	2.18832	3924	0.00052	0.00019	1.01428	3.32125	80
France	4566	0.00025	0.00018	0.82760	2.85001	4593	-0.01895	0.03232	-0.02104	2.17949	4567	0.00063	0.00026	0.86725	2.90216	71
Germany	4553	0.00035	0.00023	0.91671	3.04740	4565	-0.01599	0.03115	0.02419	2.10991	4555	0.00071	0.00036	1.11991	3.49978	67
Ireland	4519	0.00015	0.00013	0.99918	3.12727	4537	-0.02246	0.03348	-0.10498	2.26682	4523	0.00098	0.00055	1.06948	3.27487	70
Japan	4385	0.00021	0.00017	0.78830	2.81525	4405	-0.02418	0.06379	0.01276	2.31548	4389	0.00076	0.00035	1.06908	3.42655	46
Netherlands	4557	0.00026	0.00019	0.92685	3.07890	4594	-0.02141	0.03184	-0.05918	2.17733	4557	0.00061	0.00027	1.00094	3.15502	80
Norway	4213	0.00028	0.00019	0.72905	2.74269	4229	-0.02940	0.03808	-0.14261	2.21304	4215	0.00071	0.00032	1.09386	3.39975	69
NZ	3705	0.00004	0.00005	1.21258	3.47739	3729	-0.05320	0.06324	-0.30972	2.43510	3700	0.00041	0.00024	1.45029	4.49473	79
Portugal	4529	0.00026	0.00019	0.79072	2.84631	4573	-0.02446	0.03470	-0.12497	2.21760	4530	0.00061	0.00021	0.79613	2.92273	27
Spain	4540	0.00039	0.00025	0.79929	2.84906	4559	-0.01921	0.03267	-0.00949	2.18470	4542	0.00072	0.00028	0.62982	2.59394	51
Sweden	3068	0.00012	0.00010	0.92365	3.03195	3077	-0.02521	0.03531	-0.08294	2.23727	3068	0.00060	0.00028	1.20201	3.66091	71
Switzerland	4502	0.00035	0.00020	0.76322	2.88181	4516	-0.02241	0.03222	-0.12696	2.19979	4502	0.00056	0.00020	1.01048	3.27391	68
UK	4528	0.00022	0.00015	0.78595	2.83536	4538	-0.02240	0.03321	-0.02880	2.15460	4529	0.00051	0.00022	1.01770	3.26123	89
US	4502	0.00023	0.00017	1.04490	3.35760	4519	-0.02652	0.04716	0.02224	2.14999	4502	0.00051	0.00026	1.06021	3.33801	91

For each country, we report the number of observations (No.Obs), standard deviation (SD), skewness (Skew), and kurtosis (Kurt) of the estimated characteristic variables with missing values excluded. Spread is the first half-hour liquidity estimated from Equation (7); ID is the first-half hour information discreteness estimated from Equation (8); Volatility is the standard deviation of minutely return in the first half hour. Individualism is the Hofstede (2001) individualism index and is constant over time. To address the issue of outliers, Spread, ID, and Volatility are winsorized in the time series using the 5th and 95th percentiles. The sample periods are reported in Table 1.

Table 8: Correlation of characteristic variables

	Spread	ID	Volatility	Spread	ID	Volatility	Spread	ID	Volatility	Spread	ID	Volatility
	Australia			Austria			Canada			France		
Spread	1	0.02	0.26	1	0.03	0.33	1	-0.01	0.46	1	0.00	0.47
ID		1	0.08		1	-0.01		1	-0.03		1	-0.02
Volatility			1			1			1			1
	Germany			Ireland			Japan			Netherlands		
Spread	1	-0.01	0.52	1	-0.01	0.25	1	-0.02	0.22	1	-0.03	0.50
ID		1	-0.03		1	-0.04		1	0.03		1	-0.05
Volatility			1			1			1			1
	Norway			NZ			Portugal			Spain		
Spread	1	0.01	0.20	1	0.05	0.16	1	0.00	0.42	1	-0.01	0.43
ID		1	-0.02		1	-0.04		1	-0.07		1	-0.03
Volatility			1			1			1			1
	Sweden			Switzerland			UK			US		
Spread	1	0.01	0.29	1	-0.02	0.46	1	0.02	0.40	1	-0.07	0.52
ID		1	0.02		1	-0.04		1	-0.01		1	-0.06
Volatility			1			1			1			1

This table reports pair-wise Pearson correlation coefficients of Spread, ID, and Volatility for each country. Spread is the first half-hour liquidity estimated from equation (7); ID is the first-half hour information discreteness estimated from equation (8); Volatility is the standard deviation of minutely return in the first half hour. To address the issue of outliers, Spread, ID, and Volatility are winsorized in the time series using the 5th and 95th percentiles. The sample periods are reported in Table 1.

Table 9: Fama-MacBeth regression analysis

	(1)	(2)	(3)	(4)	(5)
Spread	1.19**				1.15**
	(2.37)				(1.96)
ID		-1.92***			-2.33***
		(-3.01)			(-2.60)
Volatility			0.49		0.56
			(0.99)		(0.76)
Individualism				0.89**	1.05*
				(2.24)	(1.93)

This table reports the average slope coefficients and the corresponding t-statistics (computed through Newey and West (1987) standard errors) from the Fama and MacBeth (1973) regressions. The first four columns report the results where we regress the ITSM returns against Spread, ID, Volatility, and Individualism in the cross section, respectively. In the last column we perform cross-sectional regressions where the ITSM returns is regressed against all variables collectively. The characteristic variables are standardized in the cross-section before entering the regression model. The coefficients are annualized and in percentage. *, **, *** denote 10%, 5%, 1% significance levels. The sample period spans from January 4, 2000 to December 29, 2017.

Table 10: Intraday time series momentum and market characteristics: Cross-market sorting

	Small	Medium	Large	L - S	Small	Medium	Large	L - S
	Panel A: Spread				Panel B: ID			
AVE(%)	2.67**	4.97***	5.43***	2.76**	5.83***	5.24***	1.27	-4.56***
	(2.30)	(5.73)	(5.67)	(2.19)	(6.44)	(5.52)	(0.90)	(-3.00)
SD	4.96	3.46	4.03	5.55	3.77	3.85	5.86	6.23
Sharpe Ratio	0.54	1.44	1.35	0.50	1.54	1.36	0.22	-0.73
Skewness	-0.77	0.05	0.02	0.58	0.02	0.21	-2.07	-1.76
Kurtosis	5.98	3.04	3.04	5.02	3.04	3.29	9.93	8.59
	Panel C: Volatility				Panel D: Individualism			
AVE(%)	3.86***	4.74***	4.50***	0.64	3.82***	3.78***	5.04***	1.22
	(4.59)	(4.55)	(4.39)	(0.60)	(4.12)	(2.75)	(5.68)	(1.26)
SD	3.66	4.18	4.29	4.68	4.16	5.94	3.30	3.88
Sharpe Ratio	1.05	1.13	1.05	0.14	0.92	0.64	1.53	0.32
Skewness	0.54	-0.68	-0.02	-0.27	0.01	-1.87	0.06	0.00
Kurtosis	4.15	4.67	3.03	3.44	3.03	9.70	3.04	3.04

This table presents the results for the cross-market sorting analysis that tests the hypotheses introduced in Section 4. At 10:00 am New York time each day, we sort in ascending order the markets based on the characteristic variables computed from the first half hour of the same calendar day. The markets are then split into three groups. Within each group, we form an equally weighted portfolio of ITSM and report the average return, standard deviation, Sharpe ratio, Skewness, and Kurtosis of the portfolio. All numbers are annualized. We also present results for a strategy that takes a long position in the large group and a short position in the small group (L - S). In parentheses, we report the t-statistics for the portfolio returns that are corrected for autocorrelation and heteroskedasticity through Newey and West (1987) correction. *, **, *** denote 10%, 5%, 1% significance levels. The sample period spans from 04 January 2000 to 29 December 2017.

Table 11: Intraday time series momentum and market characteristics: time series sorting

	Spread			ID			Volatility		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
	Panel A: Slope Coefficient								
Australia	3.41***	2.05	4.85**	2.56	4.80***	3.72**	0.29	-0.08	4.56***
Austria	1.95	1.52	0.06	2.26	2.54	-1.40	1.56	-0.33	1.09
Canada	-0.79	-0.38	0.47	3.42*	-3.33*	-3.66**	-1.26	0.23	-0.13
France	3.68**	6.04***	6.12***	6.22***	6.05***	4.47***	1.92	2.30**	7.15***
Germany	1.08	2.82*	5.77***	6.37***	2.55*	3.48	-0.05	2.05*	5.63***
Ireland	-0.95	4.92*	0.61	3.16	0.89	-1.12	1.01	4.25**	0.45
Japan	3.68**	2.99***	3.27***	2.78**	3.58***	3.69**	1.83**	0.96	4.30***
Netherlands	3.73**	3.33**	7.15***	6.52***	7.87***	2.32*	-0.63	2.64**	7.38***
Norway	2.97*	4.63***	3.65	2.46	4.23**	4.80	2.52*	1.27	4.73***
NZ	0.04	-0.26	0.59	0.06	0.27	0.18	0.25	0.14	0.17
Portugal	-0.38	2.75*	1.85	4.85***	0.23	-1.77	1.16	-0.26	2.20**
Spain	0.84	5.72***	4.97***	3.90**	3.78***	4.77***	1.11	2.26*	5.30***
Sweden	2.48	2.55	3.36*	3.64*	3.49*	1.37	2.03	1.14	3.65**
Switzerland	2.01	1.90	5.81***	6.83***	2.11	2.04	0.88	0.26	5.43***
UK	5.44***	0.93	7.33***	7.74***	4.94***	3.03*	1.35	2.41*	6.43***
US	6.33***	3.73**	11.10***	12.65***	9.00***	-0.88	2.47*	4.88***	9.43***
	Panel B: Portfolio Return (%)								
Australia	5.46***	1.61	7.46**	4.82*	6.09***	3.83	0.04	0.19	14.38***
Austria	1.75	3.90	1.75	6.30**	4.74**	-3.63	4.63***	1.58	1.21
Canada	0.96	-1.35	0.61	2.58	-0.64	-1.73	-1.58	1.97	-0.18
France	5.55***	4.72**	11.26***	7.37***	7.38***	6.77***	3.69**	3.19	14.67***
Germany	1.69	5.13*	12.08***	8.27***	3.48	7.23**	1.18	2.69	15.05***
Ireland	-3.08	6.88	3.44	5.65*	2.56	-0.96	-2.15	5.46**	3.91
Japan	4.57*	4.66**	4.81	3.17	5.44**	5.29*	1.17	1.44	11.35***
Netherlands	3.74*	1.16	12.78***	7.20***	6.57***	3.84*	1.26	3.96**	12.45***
Norway	3.92	6.92***	6.91**	6.38**	5.94**	5.44*	2.23	2.25	13.28***
NZ	0.99	0.30	0.75	1.00	0.86	0.17	0.65	0.83	0.54
Portugal	-0.65	4.27**	4.15*	6.44***	3.51*	-1.97	2.25	1.84	3.74
Spain	1.40	6.10***	6.20**	2.38	5.77***	5.67**	1.04	3.38	9.36***
Sweden	1.00	3.09*	5.02*	8.96***	0.73	-0.59	2.39	2.39	4.42
Switzerland	0.17	-0.71	7.18***	6.65**	-1.15	1.12	0.59	-0.63	6.67**
UK	6.44***	2.29	10.81***	12.38***	4.74**	2.42	2.41**	3.97**	13.16***
US	4.94***	2.20	11.36***	10.75***	8.31***	-0.60	0.12	3.77**	14.60***

This table presents the time series sorting analysis results. For each market, we sort all trading days by the characteristic variables and split into three groups using a similar approach as in the cross-market sorting. Within each group, we first perform the predictive regression and report the slope coefficient estimates in Panel A. Then we form an equally weighted portfolio within each group and report the portfolio returns in Panel B. *, **, *** denote 10%, 5%, 1% significance levels after the Newey and West (1987) correction. The slope coefficients are scaled by 100. Returns are annualized and in percentage. The sample periods are reported in Table 1.

Internet Appendix for "Intraday Time Series Momentum: Global Evidence and Links to Market Characteristics"

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This Internet Appendix comprises three sections. In Sections A and B we explore potential explanations of the weak evidence of intraday time series momentum (ITSM) observed in the 4 out of the 16 countries (i.e. Austria, Canada, Ireland, and New Zealand) shown in the main analysis of the study. In particular, we examine whether this weak evidence can be explained by institutional trading behavior or that these markets are led by other larger international markets in close proximity to them, such as Canada being led by the U.S. and Ireland being led by the U.K. Finally, Section C presents additional tables to those in the main study.

A. The effect of institutional trading

Periodic trading of institutional investors has been well studied in the literature. For example, Bertsimas and Lo (1998) derive a dynamic trading strategy for institutional traders where the minimal execution cost is achieved by splitting large parent orders into small child orders that are traded over equal time intervals. Murphy and Thirumalai (2017) show that the intraday return pattern documented by Heston et al. (2010) is related to the repetitive activity of institutional traders. Etula et al. (2019) document a monthly pattern of institutional trading due to month-end cash demand. In this section, we provide an examination of the effect of institutional trading on ITSM.

Due to the lack of institutional ownership and trading data, we follow Gao et al. (2018) and split each month into month-end days and non-month-end days to study the effect of institutional trading on ITSM. Specifically, for each market we split our data into two subsamples: (1) days from $T - n$ to $T + 3$ and (2) rest of the days, where T is the last trading day of each month and n is the number of days needed for settlement. The rationale is, due to the month-end cash demand and settlement rules, institutions tend to trade more intensively before day $T - n$ and less so over the month-end days, $T - n$ to $T + 3$ (Gao et al., 2018; Etula et al., 2019). Note that the number of settlement days (n) varies across markets and sometimes within the same market due to change of regulations. We use the information of settlement rules from Etula et al. (2019) and present it in Panel A of Table A.1.

[Table A.1 about here.]

For each market, we first run the predictive regression of equation 2 in the main analysis over the month-end and non-month-end days respectively. Panel B of Table A.1 reports the results. While the magnitude of the slope coefficient β^F is slightly larger in the month-end days, we do not observe substantial differences in the significance of the slope for most countries. However, this is not the case for Austria, Norway, and Sweden in which the ITSM is stronger in the non-month-end days, and for Japan and Portugal in which it is the opposite. Therefore our initial findings are quite mixed and inconclusive.

In order to further test the significance of the difference observed over the month-end days and non-month-end days, we introduce a dummy variable, D, that takes the value of 1 on month-end days and 0 on rest of the days and perform the following regression:

$$r_t^L = \alpha + \beta^F r_t^F + \beta_D D_t + \beta_{prod} D_t \cdot r_t^F + \epsilon_t, \tag{A.1}$$

where $D_t \cdot r_t^F$ is the product of the dummy variable and the first half-hour return at time t. When $D_t = 0$, Equation (A.1) reduces to the predictive regression in the main text, whereas when $D_t = 1$, it can be re-written as $r_t^L = (\alpha + \beta_D) + (\beta^F + \beta_{prod}) r_t^F + \epsilon_t$. Therefore, a significance β_{prod} implies significant difference of the ITSM effect between the two sub-samples.

As shown in Panel C of Table A.1, the difference in ITSM between the two sub-samples is statistically insignificant in most countries; only in Austria, Norway, and New Zealand we document a significant β_{prod} at 5% level and in Japan at 1%. Moreover, in three out of these four countries we find positive increase in the slope coefficient, β^F, over the month-end days while in the remaining one (New Zealand) we document a decrease.

Gao et al. (2018) by employing SPY ETF data state that the ITSM effect is present on both types of days but is weaker near month-end days. With more detailed information on institutional ownership and order imbalance, they further show that, on the U.S. market, institutional trading is associated with the predictability of the second last half-hour return on the last half-hour return, but the evidence is less clear for the predictability of the first half-hour return. Supported by this finding of Gao et al. (2018), our overall evidence on the relation between institutional trading and ITSM is not clear cut. However, it is worth noting that our approach is constrained by institutional data availability and a more in-depth investigation is left for future research.

B. Intraday cross-country predictability

We now turn our attention to studying the first-last half hour return relationship in a cross-country setting. It is known that international stock markets correlate with each other and there exists cross-market predictability. For example, at monthly frequency, Campbell and Hamao (1992) present evidence that the U.S. macroeconomic variables such as the dividend-price ratio and the short interest rate can help predict Japanese stock returns. Rapach et al. (2013) show that the U.S. stock returns Granger cause stock returns in 11 international markets even after controlling for interest rate and dividend yield. At a higher frequency, Becker et al. (1990) state the daily open-to-close U.S. stock return can predict that of Japanese stock market on the next day. It is therefore natural to investigate such cross-country predictability in our intraday setting.

To this end, we follow Rapach et al. (2013) and perform a pair-wise examination. More specifically, for each country i, we regress its last half-hour return r_i^L on the first half-hour return of country j, r_j^F, for all $i \neq j$. Note that the Asia-Pacific markets in our sample close before the open of their European and American counterparts, making it impossible to invest in these markets based on signals from the European or American markets on the same calendar day. To address this issue, we regress the last half-hour return of country i on the lagged first half-hour return of country j, if i is an Asia-Pacific country and j is not. In doing so, we ensure that the return r_j^F included in the regression is always the immediately available first half-hour return from country j before r_i^L. We also control for the local intraday time series momentum (ITSM) effect of county i by including the local first half-hour return r_i^F in the regression. That is, we fit the following predictive model:

$$r_{i,t}^L = \begin{cases} \alpha + \beta_{i,j} r_{j,t-1}^F + \beta_i r_{i,t}^F + \epsilon_t, & \text{if } i \text{ is an Asia-Pacific country and } j \text{ is not;} \\ \alpha + \beta_{i,j} r_{j,t}^F + \beta_i r_{i,t}^F + \epsilon_t, & \text{otherwise,} \end{cases} \tag{B.1}$$

where $i \neq j$. We are mainly interested in the significance of $\beta_{i,j}$. Note that even though our model contains $r_{j,t}^F$ and $r_{i,t}^F$, it is ex ante.

Given the cross-country nature of the analysis, we use only the data from the common sample period, namely, from 4th October 2005 to 29th December 2017 (Sweden has the shortest sample period starting from 4th October 2005). Before the examination of cross-country predictability, we first repeat our main predictive regression of local ITSM using this shortened sample period. The results are shown in the first two columns of Table B.1 and confirm the evidence presented in the main analysis of the study; the ITSM effect is again observed in the same 12 countries, leaving Austria, Canada, Ireland, and New Zealand being the only four countries in which we do not observe significant ITSM.

[Table B.1 about here.]

The last 16 columns of Table B.1 report our estimates of the $\beta_{i,j}$s. We do not observe significant predictability of the U.S. market on the Canadian market, despite they are in the same timezone. Similarly, the first half-hour return of U.K. does not appear to significantly predict the last half-hour return of Ireland.

However, we find strong cross-market predictability of the U.S. market on the European markets, confirming the dominating role of the U.S. market (Rapach et al., 2013). For example, in 8 out of the 11 European markets in our sample, the U.S. first half-hour return exhibits positive and significant predictability. In contrast, none of the Asia-Pacific countries can be predicted by either American countries or European countries. One possible explanation is that the first half-hour returns of American and European countries realize during the overnight period of the Asia-Pacific countries, thus their cross-country predictability might be undermined by the overnight information newly arrived on the Asia-Pacific markets. Furthermore, while Rapach et al. (2013) find strong predictability of the Swedish and Swiss markets over other international markets at monthly level and attribute this to their small market capitalization and high institutional holdings, we do not observe significant cross-country predictability for markets with such characteristics at intraday level, implying a different channel of the effect of institutional trading on cross-market return predictability at higher frequency.

In addition to the slope coefficient $\beta_{i,j}$, we also pay our attention to the adjusted R^2 of Equation (B.1). Particularly, we compute the difference between the adjusted R^2 of Equation (B.1) and that of the ITSM predictive regression in the main text:

$$\Delta Adj.R_i^2 = Adj.R_{i,c}^2 - Adj.R_{i,l}^2, \tag{B.2}$$

where $Adj.R_{i,c}^2$ is the adjusted R^2s of Equation (B.1) and $Adj.R_{i,l}^2$ is the adjusted R^2s of local ITSM regressions using common sample period (reported in the second column of Table B.1). Table B.2 reports the $\Delta Adj.R^2$s. Consistent with the evidence shown in Table B.1, adding the U.S. first half-hour return into the model yields an increase in the adjusted R^2 for all but one international countries, implying its explanatory power on the variance of the last half-hour return of international markets.

[Table B.2 about here.]

Due to the contemporaneous correlation between international stock markets, one may argue that, in the case that r_j^F realizes after r_i^F but before r_i^L, the shown predictability of r_j^F might be simply due to the fact that it is closer to r_i^L and it is the contemporaneous half-hour return of country i that truly possesses the predictability. To address this concern, we conduct an additional analysis where the contemporaneous half-hour return of country i is also included in the regression, if r_j^F realizes after r_i^F but before r_i^L:

$$r_{i,t}^L = \alpha + \beta_{i,j} r_{j,t}^F + \beta_i r_{i,t}^F + \beta_c r_{i,t}^C + \epsilon_t, \tag{B.3}$$

where $r_{i,t}^C$ is the contemporaneous half-hour return of country i. This model is applicable only to certain combinations of i and j, in which r_j^F realizes after r_i^F but before r_i^L, Table B.3 provides detailed information. The regression results are presented in Table B.4. Again, we are mainly interested in the slope coefficient of the first half-hour return from country j, $\beta_{i,j}$. As shown in the table, the cross-market predictability of the U.S. first half-hour return remains significant in most of the countries even after controlling for local contemporaneous half-hour return, suggesting that the in-sample evidence of the U.S. dominance is robust at intraday level.

[Table B.3 about here.]

[Table B.4 about here.]

C. Additional tables with local currency data & pre-winsorized data

In this section, we repeat several analyses in the main text with data based on local currency or pre-winsorized data. Specifically, in Table C.1 and Table C.2 we re-examine the statistical and economic significance of ITSM on each market using data based on local currency, whereas in Table C.3 and Table C.4 we repeat the cross-sectional and time series sorting analysis using pre-winsorized data.

[Table C.1 about here.]

[Table C.2 about here.]

[Table C.3 about here.]

[Table C.4 about here.]

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Table A.1: Institutional trading & ITSM

	Panel A: Settlement period (days)		Pabel B: Month-end vs non-month-end				Panel C: Regression with dummy			
	Prior to 06 Oct 2014	06 Oct 2014 onward	Month-end β^F	Month-end $Adj.R^2$	Non-month-end β^F	Non-month-end $Adj.R^2$	β^F	β_D	β_{prod}	$Adj.R^2$
Australia	3	3	4.57***	2.65	3.26***	1.47	3.26***	-0.01	1.32	1.84
Austria	3	2	2.95*	0.41	0.10	-0.03	0.10	0.02	2.86**	0.19
Canada	3	3	1.23	0.02	-1.17	0.05	-1.17	0.01	2.40*	0.07
France	3	2	7.03***	2.94	5.07***	2.06	5.07***	0.01	1.96*	2.38
Germany	2	2	5.76***	1.34	3.63***	0.60	3.63***	0.01	2.13	0.81
Ireland	3	2	1.55	0.05	0.72	-0.03	0.72	0.02	0.83	-0.04
Japan	3	3	5.04**	2.68	2.66***	1.15	2.66***	0.03**	2.37***	1.88
Netherlands	3	2	5.79***	2.19	5.62***	2.55	5.62***	0.02	0.18	2.46
Norway	3	2	6.74***	1.32	2.49*	0.21	2.49***	0.04**	4.25**	0.77
NZ	3	3	-0.33	0.04	0.42	0.13	0.42**	0.00	-0.76**	0.10
Portugal	3	2	1.98	0.20	1.50*	0.16	1.50**	0.01	0.49	0.19
Spain	3	3	4.65***	1.52	3.96***	1.41	3.96***	0.01	0.69	1.43
Sweden	3	2	3.78**	0.91	2.54*	0.45	2.54***	0.01	1.24	0.61
Switzerland	3	2	3.43**	0.59	4.31***	1.03	4.31***	0.02	-0.88	0.91
UK	3	2	6.10***	2.14	4.78***	1.67	4.78***	0.02**	1.32	1.94
US	3	3	8.68***	2.93	7.66***	2.33	7.66***	-0.02*	1.02	2.57

Panel A presents the settlement days of each market. We obtain this information from Etula et al. (2019). For some European countries, there was a regulation change on 06 October 2014. Panel B reports the predictive regression results from two sub-samples. The first sub-sample consists of only the month-end days, $T-n$ to $T+3$, where T is the last trading day of a month and n is the number of settlement days. The second sub-sample consists of the rest trading days, i.e., non-month-end days. In Panel C, we introduce a dummy variable that takes the value of 1 on month-end days and 0 on other days. Then we include this dummy variable along with its product with the first half-hour return into the main predictive regression. Sample periods are reported in Table 1 in the main text. *, **, and *** represent the significance levels of 10%, 5%, and 1% after Newey and West (1987) correction, respectively.

Table B.1: Cross-country predictability

	Local ITSM		Cross-country predictability of r_j^F on r_i^L: $\beta_{i,j}$															
	β^F	$Adj.R^2$	Australia	Austria	Canada	France	Germany	Ireland	Japan	Netherlands	Norway	NZ	Portugal	Spain	Sweden	Switzerland	UK	US
Australia	3.98***	2.31		-0.62	0.74	-1.41	-1.38	-0.35	1.02*	-0.44	-0.20	-4.43*	-1.29	-0.91	-0.95	-1.77	-1.75	-2.48
	(4.05)			(-0.64)	(0.58)	(-0.98)	(-1.05)	(-0.31)	(1.79)	(-0.35)	(-0.14)	(-1.83)	(-0.82)	(-0.75)	(-0.69)	(-0.99)	(-1.02)	(-1.46)
Austria	1.13	0.07	0.25		1.16	-1.03	0.03	0.92	-0.62	-1.46	-2.19	0.54	-0.31	0.93	-1.35	0.34	-1.82	4.70**
	(0.84)		(0.16)		(0.86)	(-0.38)	(0.01)	(0.44)	(-0.62)	(-0.56)	(-1.41)	(0.33)	(-0.17)	(0.42)	(-0.84)	(0.27)	(-0.71)	(2.38)
Canada	-0.71	0.00	-0.23	-1.35		-1.63	-1.41	-0.84	-0.68	-2.98***	-0.30	-1.24	-0.93	-1.31	-0.42	0.14	-1.17	-0.63
	(-0.46)		(-0.20)	(-1.10)		(-1.17)	(-0.93)	(-0.79)	(-0.76)	(-2.88)	(-0.21)	(-1.03)	(-0.64)	(-1.06)	(-0.29)	(0.07)	(-0.62)	(-0.45)
France	4.83***	1.94	-0.48	4.32*	1.50		0.64	3.23***	-0.49	0.52	1.37	-1.04	1.61	4.02*	0.96	1.29	1.37	4.64***
	(4.87)		(-0.56)	(1.85)	(1.11)		(0.28)	(2.85)	(-0.81)	(0.17)	(1.21)	(-1.15)	(0.87)	(1.68)	(0.71)	(0.98)	(0.57)	(3.09)
Germany	2.97***	0.78	-1.21	0.43	1.47	-3.85		1.63	-0.63	-5.07	0.63	-2.80*	-0.01	0.35	0.62	0.10	-1.30	2.99**
	(3.25)		(-1.40)	(0.25)	(1.03)	(-0.60)		(1.39)	(-1.02)	(-0.82)	(0.57)	(-1.83)	(0.00)	(0.10)	(0.52)	(0.08)	(-0.36)	(2.05)
Ireland	1.18	0.07	-0.13	2.65**	1.09	1.24	1.98		0.28	0.82	-0.30	-1.36	0.86	2.58*	-0.31	-0.45	2.12	6.77***
	(1.28)		(-0.14)	(2.30)	(0.83)	(0.85)	(1.57)		(0.39)	(0.50)	(-0.24)	(-1.26)	(0.51)	(1.86)	(-0.23)	(-0.34)	(1.21)	(4.48)
Japan	4.14***	2.97	2.44**	-0.96	1.77	-0.18	0.75	-0.45		0.21	1.57	1.39	0.02	-0.26	0.72	-0.54	0.38	0.71
	(4.07)		(2.28)	(-0.52)	(0.91)	(-0.12)	(0.63)	(-0.46)		(0.13)	(1.28)	(0.86)	(0.01)	(-0.19)	(0.54)	(-0.31)	(0.23)	(0.37)
Netherlands	4.04***	1.42	-0.35	4.66**	1.05	0.64	-1.47	4.19***	-0.24		1.75	-0.47	0.96	2.73	0.99	1.66	0.60	3.84**
	(3.77)		(-0.42)	(2.14)	(0.82)	(0.23)	(-0.84)	(2.92)	(-0.40)		(1.46)	(-0.55)	(0.57)	(1.60)	(0.68)	(1.26)	(0.27)	(2.43)
Norway	5.44***	0.83	1.84	3.64**	3.49	4.48***	4.21***	3.08**	-0.25	5.22***		0.97	3.90**	3.79***	1.06	4.92*	4.98***	13.58***
	(3.40)		(1.21)	(2.26)	(1.52)	(2.82)	(2.66)	(1.96)	(-0.27)	(2.75)		(0.57)	(2.42)	(3.01)	(0.49)	(1.74)	(2.98)	(6.36)
NZ	0.08	-0.03	0.36	-0.31	0.10	-0.18	-0.12	-0.01	0.01	-0.19	0.12		-0.19	-0.16	0.04	-0.01	-0.20	-0.35
	(0.25)		(1.35)	(-1.12)	(0.32)	(-0.60)	(-0.43)	(-0.04)	(0.03)	(-0.62)	(0.40)		(-0.62)	(-0.56)	(0.12)	(-0.03)	(-0.55)	(-0.79)
Portugal	2.21**	0.42	0.00	2.73	0.55	-0.19	-1.61	0.89	0.17	0.32	1.54	-0.03		1.58	1.79*	1.22	-0.79	0.95
	(2.48)		(0.00)	(1.59)	(0.44)	(-0.14)	(-1.09)	(0.58)	(0.31)	(0.19)	(1.41)	(-0.03)		(1.33)	(1.67)	(1.44)	(-0.58)	(0.77)
Spain	3.71***	1.31	-0.06	3.12*	0.65	1.61	-1.70	3.38***	-0.30	0.39	1.80	-0.56	1.46		1.38	1.91	1.40	2.36
	(3.73)		(-0.07)	(1.95)	(0.51)	(0.72)	(-0.71)	(3.31)	(-0.48)	(0.19)	(1.56)	(-0.55)	(0.96)		(1.03)	(1.43)	(0.67)	(1.60)
Sweden	2.89**	0.59	1.54**	2.59***	-0.25	3.55***	3.84***	2.06**	-0.09	3.36***	1.91	0.88	3.30***	3.40***		3.09**	3.85***	4.51***
	(2.46)		(2.22)	(3.55)	(-0.19)	(4.42)	(4.94)	(2.14)	(-0.18)	(3.88)	(1.41)	(0.96)	(3.89)	(4.53)		(2.33)	(4.07)	(4.52)
Switzerland	3.40**	0.65	1.14	0.83	0.15	-0.28	-0.04	0.65	-0.11	-0.44	-0.21	1.76**	-0.34	-0.45	-0.52		0.21	1.49
	(2.39)		(1.53)	(0.95)	(0.13)	(-0.29)	(-0.04)	(0.76)	(-0.21)	(-0.44)	(-0.17)	(2.02)	(-0.36)	(-0.54)	(-0.34)		(0.18)	(1.08)
UK	4.18***	1.44	0.45	3.84*	1.03	0.71	-1.08	4.00***	0.11	0.65	1.03	0.15	1.11	0.25	1.48	2.73**		2.58**
	(3.61)		(0.47)	(1.90)	(0.90)	(0.41)	(-0.69)	(3.65)	(0.19)	(0.32)	(0.94)	(0.15)	(0.86)	(0.20)	(1.22)	(2.17)		(2.17)
US	9.57***	3.41	-2.15	-1.93	-1.17	-4.05***	-2.55	-2.82**	-2.10**	-4.29***	-1.09	-4.21*	-3.22**	-3.28***	-0.02	0.19	-4.77***	
	(3.45)		(-1.30)	(-1.17)	(-0.48)	(-3.04)	(-1.40)	(-2.26)	(-2.18)	(-3.01)	(-0.72)	(-1.66)	(-2.43)	(-2.77)	(-0.01)	(0.11)	(-3.05)	

This table reports the results of the ITSM predictive regression using the common sample period from 04 October 2005 to 29 December 2017, and the point estimate of $\beta_{i,j}$ in Equation (B.1), through which we study the predictability of the first half-hour return of the column country (country j) on the last half-hour return of the row country (country i). We control for the local ITSM effect by including the first half-hour return of the row country into the regression. When the row country is an Asia-Pacific country and the column country is not, we use the first half-hour return of the column country that is immediately available before the last half-hour return of the row country. The Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The sample period spans from 04 October 2005 to 29 December 2017.

Table B.2: Cross-country predictability – $\Delta Adj.R^2(\%)$

	Australia	Austria	Canada	France	Germany	Ireland	Japan	Netherlands	Norway	NZ	Portugal	Spain	Sweden	Switzerland	UK	US
Australia		-0.41	-0.16	0.25	0.18	0.13	-0.32	-0.37	-0.02	0.38	0.20	0.12	0.13	0.15	0.28	0.07
Austria	-0.03		-0.03	-0.01	-0.03	-0.02	-0.05	0.00	0.11	0.03	-0.03	-0.02	-0.01	-0.03	0.03	0.54
Canada	-0.03	0.25		0.30	0.20	0.08	0.11	1.00	-0.03	0.21	0.06	0.20	-0.03	-0.03	0.11	0.02
France	0.06	0.51	-0.36		-0.02	0.46	-0.44	-0.18	0.12	0.10	0.03	0.15	-0.20	0.02	0.05	0.65
Germany	0.18	0.00	-0.10	0.13		0.12	-0.14	0.09	0.01	1.14	-0.01	-0.04	-0.17	-0.05	-0.01	0.17
Ireland	-0.02	0.19	-0.02	0.01	0.07		-0.05	-0.05	-0.02	0.10	-0.01	0.18	-0.01	-0.04	0.07	1.25
Japan	0.27	-0.03	0.08	-0.06	-0.04	0.00		-0.05	0.02	0.20	-0.07	-0.09	-0.05	-0.15	-0.08	0.12
Netherlands	0.01	0.97	-0.25	-0.03	-0.01	0.77	-0.34		0.18	0.01	-0.01	0.09	-0.07	0.08	-0.01	0.48
Norway	0.35	0.61	0.05	0.85	0.70	0.35	-0.10	1.03		0.03	0.59	0.67	-0.01	0.35	0.77	3.85
NZ	0.08	0.13	-0.03	0.01	-0.01	-0.02	-0.04	0.01	-0.02		0.01	0.00	-0.03	-0.02	0.01	0.01
Portugal	-0.05	0.55	-0.19	-0.03	0.05	0.04	-0.11	0.06	0.09	-0.06		0.04	0.20	0.02	-0.01	-0.04
Spain	0.08	0.27	-0.29	0.03	0.02	0.63	-0.29	-0.25	0.14	0.02	0.05		-0.22	0.10	0.06	0.18
Sweden	0.54	0.94	-0.02	1.53	1.72	0.60	-0.08	1.07	0.11	-0.05	1.19	1.57		0.40	1.33	1.29
Switzerland	0.20	-0.23	-0.16	-0.01	-0.03	-0.02	-0.22	-0.26	0.00	0.22	0.00	-0.01	-0.04		0.00	0.06
UK	0.02	0.66	-0.26	0.00	0.00	0.79	-0.36	-0.24	0.08	0.15	0.04	-0.03	-0.11	0.31		0.34
US	0.75	0.49	-0.54	1.11	0.42	0.82	0.23	1.04	0.07	1.53	0.62	0.84	0.08	0.10	1.21	

This table reports the increase in the adjusted R^2 of Equation (B.1), compared to that of the local ITSM predictive regression. The row names denote local countries (country i) and the column names denote foreign countries (country j).

Table B.3: Cross-country predictability – r^C

	Country j	Time interval (local)	Mean (%)	SD (%)	Skewness	Kurtosis
Austria	Canada/US	15:30 - 16:00	-0.33	4.64	-0.01	3.03
France	Canada/US	15:30 - 16:00	-1.53	6.01	0.02	3.04
Germany	Canada/US	15:30 - 16:00	-2.10	6.51	0.00	3.04
Ireland	Canada/US	14:30 - 15:00	-1.86	10.09	1.95	8.21
Netherlands	Canada/US	15:30 - 16:00	-1.76	5.81	0.02	3.04
Norway	Canada/US	15:30 - 16:00	0.71	4.83	-0.01	3.02
NZ	Australia/Japan	13:00 - 13:30	0.18	2.62	-0.03	3.02
Portugal	Canada/US	14:30 - 15:00	-2.59	4.30	0.00	3.02
Spain	Canada/US	15:30 - 16:00	-0.92	5.96	0.02	3.04
Sweden	Canada/US	15:30 - 16:00	-0.33	4.53	-0.01	3.02
Switzerland	Canada/US	15:30 - 16:00	-4.79	5.22	-0.01	3.04
UK	Canada/US	14:30 - 15:00	-1.99	5.15	0.02	3.07

This table provides detailed information of the local contemporaneous half-hour return included in Equation (B.3). The first column indicates adding which country (country j) into the model might result in the necessity of controlling for local contemporaneous half-hour return. Note that while there is one hour time difference between Canberra (Australia) and Tokyo (Japan), their stock markets open at the same time due to different arrangement on trading hours. The second column specifies the local contemporaneous half-hour interval, it is the same time period as the first half hour of country-j's trading hours. The rest four columns report annualized summary statistics. The sample period spans from 04 October 2005 to 29 December 2017.

Table B.4: Cross-country predictability – $\beta_{i,j}$ (r^C included)

	Canada	US	Australia	Japan
Austria	0.60	3.57	-	-
	(0.44)	(1.42)	-	-
France	1.33	4.27***	-	-
	(0.96)	(2.63)	-	-
Germany	1.45	3.09**	-	-
	(1.04)	(2.13)	-	-
Ireland	0.50	5.36***	-	-
	(0.40)	(3.77)	-	-
Netherlands	0.85	3.37**	-	-
	(0.66)	(2.02)	-	-
Norway	1.14	11.49***	-	-
	(0.54)	(5.73)	-	-
Portugal	0.57	0.68	-	-
	(0.45)	(0.52)	-	-
Spain	0.58	2.18	-	-
	(0.45)	(1.33)	-	-
Sweden	-0.41	4.55***	-	-
	(-0.32)	(4.32)	-	-
Switzerland	0.17	1.68	-	-
	(0.15)	(1.02)	-	-
UK	0.80	2.14	-	-
	(0.69)	(1.56)	-	-
NZ	-	-	0.31	0.00
	-	-	(1.06)	(-0.01)

This table reports our estimate of $\beta_{i,j}$ in Equation (B.3). In addition to controlling for the local ITSM effect, we also control for the contemporaneous half-hour return of the local market. The row names denote the local market (country i) and the column names denote the foreign market (country j). The Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The sample period spans from 04 October 2005 to 29 December 2017.

Table C.1: Individual ITSM in local currency

	Intercept	β^F	$Adj.R^2$ (%)
Australia	3.00***	4.15***	2.83
	(3.97)	(5.35)	
Austria	15.19***	0.40	-0.01
	(9.04)	(0.28)	
Canada	3.24***	2.24	0.30
	(2.78)	(1.31)	
France	1.79	6.64***	3.01
	(1.30)	(6.88)	
Germany	5.63***	4.84***	0.85
	(3.13)	(4.19)	
Ireland	3.95	1.58	0.01
	(1.34)	(1.56)	
Japan	1.22	4.16***	1.64
	(1.00)	(3.66)	
Netherlands	3.18**	7.14***	3.60
	(2.53)	(6.08)	
Norway	3.66**	5.64***	1.21
	(2.02)	(3.97)	
NZ	0.08	0.01	-0.03
	(0.62)	(0.15)	
Portugal	7.08***	2.27***	0.38
	(6.16)	(2.99)	
Spain	8.99***	5.08***	1.87
	(6.64)	(5.18)	
Sweden	7.62***	5.46***	3.20
	(5.75)	(6.58)	
Switzerland	2.65**	5.91***	2.51
	(2.28)	(5.24)	
UK	5.64***	4.83***	0.85
	(3.14)	(4.18)	
US	0.96	7.97***	2.53
	(0.76)	(3.82)	

In this table, we replicate the in-sample statistical analysis conducted in the main text but with data in local currency. Returns are annualized and in percentage. The Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Table C.2: Profitability of ITSM in local currency

	Strategy	Mean (%)	SD (%)	Skewness	Kurtosis	SR
Australia	ITSM	4.27***	3.12	0.03	3.03	1.37
	BH	4.57	15.74	-0.02	3.02	0.29
Austria	ITSM	2.62*	5.81	-0.09	3.12	0.45
	BH	8.03	22.70	-0.01	3.03	0.35
Canada	ITSM	1.41	4.40	0.05	3.13	0.32
	BH	6.13	16.84	-0.03	3.04	0.36
France	ITSM	6.34***	5.32	0.02	3.03	1.19
	BH	3.43	23.24	0.01	3.02	0.15
Germany	ITSM	4.56***	7.14	0.05	3.09	0.64
	BH	6.89	23.90	0.01	3.02	0.29
Ireland	ITSM	1.07	12.18	-1.55	9.94	0.09
	BH	4.30	21.90	-0.03	3.03	0.20
Japan	ITSM	5.26***	5.69	0.03	3.06	0.93
	BH	3.32	24.02	-0.01	3.02	0.14
Netherlands	ITSM	5.46***	5.07	0.04	3.03	1.08
	BH	3.80	22.70	0.01	3.03	0.17
Norway	ITSM	7.67***	6.89	0.02	3.07	1.11
	BH	11.29**	22.13	-0.03	3.02	0.51
NZ	ITSM	0.06	0.51	0.26	3.72	0.12
	BH	11.21***	10.51	-0.02	3.02	1.07
Portugal	ITSM	1.87*	4.35	0.00	3.02	0.43
	BH	-2.08	19.12	-0.01	3.02	-0.11
Spain	ITSM	5.09***	5.22	0.01	3.02	0.98
	BH	1.69	23.89	0.01	3.02	0.07
Sweden	ITSM	7.89***	3.83	0.01	3.02	2.06
	BH	7.90	21.26	0.00	3.02	0.37
Switzerland	ITSM	4.43***	4.20	0.04	3.03	1.05
	BH	3.74	18.88	0.00	3.03	0.2
UK	ITSM	4.49***	7.19	0.05	3.09	0.63
	BH	2.66	19.07	0.00	3.03	0.14
US	ITSM	6.19***	5.54	0.07	3.08	1.12
	BH	5.57	19.40	0.00	3.04	0.29

This table presents the performance of intraday time series momentum (i.e. ITSM) and the buy-and-hold benchmark for each of the 16 equity markets based on local currencies. The ITSM strategy opens a long (short) position at the beginning of the last half hour if the return during the first half hour on the same trading day is positive (negative), and closes the positions at the market close. The buy-and-hold benchmark strategy opens a long position at the beginning of our sample and hold it throughout the sample period. We report the mean, standard deviation (SD), skewness, kurtosis and the Sharpe ratio (SR) of the two strategies for each market. *, **, and *** denote significance at 10%, 5%, and 1% significance levels after Newey and West (1987) correction, respectively.

Table C.3: Cross-market sorting using pre-winsorized estimates

	Small	Medium	Large	L - S	Small	Medium	Large	L - S
	Panel A: Spread				Panel B: ID			
AVE(%)	2.70**	4.89***	5.48***	2.78**	5.75***	5.32***	1.33	-4.42***
	(2.30)	(5.86)	(5.75)	(2.20)	(6.35)	(5.61)	(0.95)	(-2.91)
SD	4.97	3.45	4.06	5.58	3.79	3.81	5.86	6.22
Sharpe Ratio	0.54	1.42	1.35	0.50	1.52	1.39	0.23	-0.71
Skewness	-0.76	0.05	0.02	0.57	0.01	0.23	-2.07	-1.77
Kurtosis	5.93	3.04	3.04	4.98	3.04	3.30	9.93	8.63
	Panel C: Volatility				Panel D: Individualism			
AVE(%)	3.97***	4.35***	4.84***	0.86	3.82***	3.78***	5.04***	1.22
	(4.75)	(4.27)	(4.66)	(0.78)	(4.12)	(2.75)	(5.68)	(1.26)
SD	3.67	4.23	4.27	4.75	4.16	5.94	3.30	3.88
Sharpe Ratio	1.08	1.03	1.13	0.18	0.92	0.64	1.53	0.32
Skewness	0.54	-0.67	0.00	-0.26	0.01	-1.87	0.06	0.00
Kurtosis	4.13	4.60	3.03	3.42	3.03	9.70	3.04	3.04

This table presents the results for the cross-market sorting analysis using pre-winsorized estimates. At 10:00 am New York time each day, we sort in ascending order the markets based on the characteristic variables computed from the first half hour of the same calendar day. The markets are then split into three groups. Within each group, we form an equally weighted portfolio of ITSM and report the average return, standard deviation, Sharpe ratio, Skewness, and Kurtosis of the portfolio. All numbers are annualized. We also present results for a strategy that takes a long position in the large group and a short position in the small group (L - S). In parentheses, we report one sample t-statistic for the portfolio returns that are corrected for autocorrelation and heteroskedasticity through Newey and West (1987) correction. *, **, *** denote 10%, 5%, 1% significant levels. The sample period spans from 04 January 2000 to 29 December 2017.

Table C.4: Time series sorting using pre-winsorized estimates

	Spread			ID			Volatility		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
	Panel A: Slope Coefficient								
Australia	3.41***	2.05*	4.85***	2.56	4.80***	3.72*	0.29	-0.08	4.56***
Austria	1.95	1.52	0.06	2.26	2.54*	-1.40	1.56	-0.33	1.09
Canada	-0.79	-0.38	0.47	3.42	-3.33*	-3.66*	-1.26	0.23	-0.13
France	3.68**	6.04***	6.12***	6.22***	6.05***	4.47***	1.92	2.30**	7.15***
Germany	1.08	2.82**	5.77***	6.37***	2.55	3.48	-0.05	2.05*	5.63***
Ireland	-0.95	4.92**	0.61	3.16*	0.89	-1.12	1.01	4.25*	0.45
Japan	3.68**	2.99***	3.27**	2.78**	3.58**	3.69**	1.83**	0.96	4.30***
Netherlands	3.73*	3.33**	7.15***	6.52***	7.87***	2.32*	-0.63	2.64**	7.38***
Norway	2.97*	4.63**	3.65	2.46	4.23*	4.80**	2.52	1.27	4.73***
NZ	0.04	-0.26	0.59	0.06	0.27	0.18	0.25	0.14	0.17
Portugal	-0.38	2.75*	1.85*	4.85***	0.23	-1.77	1.16	-0.26	2.20**
Spain	0.84	5.72***	4.97***	3.90***	3.78***	4.77***	1.11	2.26*	5.30***
Sweden	2.48	2.55	3.36	3.64*	3.49	1.37	2.03	1.14	3.65**
Switzerland	2.01	1.90	5.81***	6.83***	2.11	2.04	0.88	0.26	5.43***
UK	5.44***	0.93	7.33***	7.74***	4.94**	3.03**	1.35	2.41*	6.43***
US	6.33***	3.73**	11.10***	12.65***	9.00***	-0.88	2.47*	4.88***	9.43***
	Panel B: Portfolio Return (%)								
Australia	5.46***	1.61	7.46***	4.82*	6.09***	3.83	0.04	0.19	14.38***
Austria	1.75	3.90*	1.75	6.30**	4.74**	-3.63	4.63***	1.58	1.21
Canada	0.96	-1.35	0.61	2.58	-0.64	-1.73	-1.58	1.97	-0.18
France	5.55***	4.72*	11.26***	7.37***	7.38***	6.77***	3.69**	3.19	14.67***
Germany	1.69	5.13**	12.08***	8.27***	3.48	7.23**	1.18	2.69	15.05***
Ireland	-3.08	6.88	3.44	5.65*	2.56	-0.96	-2.15	5.46**	3.91
Japan	4.57*	4.66**	4.81	3.17	5.44*	5.29*	1.17	1.44	11.35***
Netherlands	3.74*	1.16	12.78***	7.20***	6.57**	3.84*	1.26	3.96**	12.45***
Norway	3.92	6.92**	6.91*	6.38*	5.94*	5.44**	2.23	2.25	13.28***
NZ	0.99	0.30	0.75	1.00	0.86	0.17	0.65	0.83	0.54
Portugal	-0.65	4.27**	4.15*	6.44***	3.51*	-1.97	2.25	1.84	3.74
Spain	1.40	6.10***	6.20**	2.38	5.77***	5.67**	1.04	3.38	9.36***
Sweden	1.00	3.09	5.02*	8.96***	0.73	-0.59	2.39*	2.39	4.42
Switzerland	0.17	-0.71	7.18***	6.65***	-1.15	1.12	0.59	-0.63	6.67**
UK	6.44***	2.29	10.81***	12.38***	4.74*	2.42	2.41*	3.97**	13.16***
US	4.94***	2.20	11.36**	10.75***	8.31**	-0.60	0.12	3.77***	14.60***

This table presents the time series sorting analysis results using pre-winsorized estimates, of which the results are largely consistent with our main analysis. For each market, we sort all trading days by the characteristic variables and split into three groups using a similar approach as in the cross-market sorting. Within each group, we first perform the predictive regression and report the slop coefficient estimates in Panel A. Then we form an equal-weighted portfolio within each group and report the portfolio returns in Panel B. *, **, *** denote 10%, 5%, 1% significant levels after the Newey and West (1987) correction. The slope coefficients are scaled by 100. Returns are annualized and in percentage.