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Intraday Time Series Momentum: International Evidence

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Abstract

This paper provides the first study of intraday time-series momentum (ITSM) in a global setting. By studying 16 developed markets, we show that ITSM is both economically and statistically significant around the world. Although global commonality across individual markets is limited, stronger regional commonality is observed. We also find that the US first half-hour return exhibits cross-country intraday predictability which is economically exploitable. A global equally-weighted ITSM portfolio generates significant alphas against global equity factors and a time-varying factor manifests as a major contributor. Finally, market micro-characteristics like liquidity provision and information continuity are shown to be associated with ITSM.

Keywords: High frequency trading, Intraday, International markets, Momentum

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 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 US stock returns both empirically and theoretically, while Griffin et al. (2003), Liu et al. (2011), Menkhoff et al. (2012), Fama and French (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, that has also been extensively studied in a variety of asset classes and factors both in- and outside of the US (Georgopoulou and Wang (2016), Goyal and Wahal (2015), Gupta and Kelly (2019), Ham et al. (2019), He and Li (2015), Huang et al. (2019), Hurst et al. (2017), Kim et al. (2016), Lim et al. (2018), and Moskowitz et al. (2012)).

While most forms of momentum are studied at monthly, weakly, or daily frequency settings, 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 academic studies to start examining the trading behavior of financial markets at a much higher frequency (Brogaard et al. (2014), Chaboud et al. (2014), and Hendershott and Riordan (2013)).

In this paper, we provide the first cross-country study on intraday momentum based on the work of Gao et al. (2018). Gao et al. (2018), analyzing US ETFs, provide strong evidence of intraday time-series momentum (ITSM) that the first half-hour return of the trading day significantly predicts the last half-hour return. We show that this ITSM is economically and statistically significant in the international stock markets. However, we find that the pervasiveness of the effect does not necessarily translate into a strong global common risk factor, leaving space for constructing global intraday time-series momentum (GITSM) portfolios that provide economic gains on top of individual country ITSM portfolios. Moreover, we find that the US first half-hour return possesses strong predictability on the last half-hour returns of international markets and that this cross-country predictability is economically exploitable. In addition, we identify a time varying component that largely explains the profitability of the GITSM. We also find that ITSM is strongly associated with certain market micro-characteristics such as liquidity provision and information absorption.

Our research contributes to the existing literature in five ways. Firstly, we confirm both the economic and statistical significance of the intraday momentum effect across 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. Our results reveal significant predictability of the first half-hour return to the last half-hour return in 12 out of 16 markets. This intraday predictability is also confirmed in various market conditions. We also perform a thorough out-of-sample (OOS) evaluation, of which the results imply significant OOS forecasting power (of the first half-hour return on the last half-hour return) in most countries.

To further assess the economic significance of the strong predictability shown in the statistical analysis, we follow Gao et al. (2018) and compare the performance of a simple market timing ITSM strategy with that of two passive investment strategies: *always-long* that repeatedly takes long position in the last half-hour everyday and *buy-and-hold* that holds a long position throughout the whole sample period. Individual country ITSM strategies generate significant alphas ranging between 2.66% and 7.45% (2.60% and 7.28%) per year when regressed against the *always-long* (*buy-and-hold*) strategies. Collectively, our evidence confirms the effect of intraday time-series momentum in the international setting and is consistent with the US evidence found in Gao et al. (2018).

Secondly, we document a modest comovement of ITSM across equity markets that is slightly stronger among countries that are geographically clustered. Following the methodology from the liquidity commonality literature (Brockman et al. (2009) and Chordia et al.

(2000)) along with a principal component analysis, we find a modest comovement of ITSM across equity markets suggesting the existence of a common global factor that can only explain a small proportion of the variation in global ITSM. On the other hand, repeating the principal component analysis with geographically grouped data implies relatively stronger regional commonality.

Thirdly, we show that the US first half-hour return exhibits cross-country intraday predictability. Rapach et al. (2013) document the leading predictive role of the US market on its international counterparts at monthly frequency. It is then natural to examine whether this cross-country predictability of the US market holds at intraday level. We tackle this issue by regressing the last half-hour return of the international markets against the US first half-hour return. With the local first half-hour return included as a control variable, the US first half-hour return manifests statistically strong predictability in more than half of the markets; and the predictive R^2 (adjusted) increases in all but one of the countries after the inclusion of the US returns. Our analysis therefore implies that the cross-country predictability of the US market in Rapach et al. (2013) exists even at intraday level.

Fourthly, we find that investing in ITSM globally produces significant economic gains than investing individually. We propose three types of GITSM portfolios that are based on individual ITSM, regional equally-weighted ITSM, and the US first half-hour return signal. For each type of GITSM, we adopt six portfolio weighting schemes: equally-weighted, value-weighted, inverse variance (Kirby and Ostdiek (2012)), maximum-diversification (Choueifaty and Coignard (2008)), mean-variance, and minimum-variance, resulting in total 18 global portfolios. Eleven out of the 18 portfolios yield a Sharpe ratio that is greater than one, ranging from 1.01 to 1.77. Most strategies yield remarkable positive spanning alphas when regressed against individual ITSM strategies, implying that the global intraday momentum strategies subsume the country individual ones and provide considerable economic gains. In contrast, when we regress individual ITSM against the global portfolios, only Norway persistently exhibits positive and significant alphas. It is worth noting that among the three types of GITSM proposed, the one based on the US intraday first half hour return signal is the strongest.

We further find that the global ITSM portfolio returns cannot be explained by global equity factors, generating significant alphas of nearly 3%. But where do these alphas come from? Goyal and Jegadeesh (2018) show that the time-series momentum of Moskowitz et al. (2012) incorporates a time-varying market factor that is responsible for the out-performance of the former with respect to the cross-sectional momentum of Jegadeesh and Titman (1993). Consistent with Goyal and Jegadeesh (2018), we identify a time-varying global investment factor which constitutes a significant source of the strategy profitability. We show that this time-varying factor explains around 73% of the variation of the global portfolio return and emanates from market timing rather than stock index picking ability, attributed to the positive autocorrelation between the first and the last hour returns in the global market.

Finally, we show that ITSM is closely related to certain market micro-characteristics such as liquidity provision and information digestion process. Gao et al. (2018) assert that the ITSM effect is originated 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 in the literature (Bogousslavsky (2016), Duffie (2010), Heston et al. (2010), and Rakowski and Wang (2009)). The model by Bogousslavsky (2016) suggests that the infrequent traders who absorb a liquidity shock by taking 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 has association 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 market impact causing stronger (weaker) price movements in the same direction. We test this hypothesis by grouping individual ITSM based on the Corwin and Schultz (2012) liquidity measure computed from the first half hour, and evaluate equally-weighted ITSM across groups. 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 suggested justification to the 'frog-in-the-pan' hypothesis of Da et al. (2014), wherein investor under-react to the information that is slowly incorporated into the price and over-react to the information that comes as a surprise. Therefore, our second hypothesis is that ITSM is stronger when the overnight information is digested smoothly and weaker when the market reacts swiftly with strong emotion. Similar to testing the first hypothesis, we group individual ITSM by 'information discreteness' (ID) that is introduced by Da et al. (2014), and evaluate the equally-weighted portfolios across groups. Our empirical analysis supports both hypotheses.

Our paper is also related to recent academic studies addressing intraday return predictability and financial market microstructure from a cross-sectional perspective. 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. While these studies mainly focus on the cross-sectional predictability of US stocks or commodity future market returns, 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. Section 2 describes the data. Section 3 examines the pervasiveness of intraday time-series momentum around the world both statistically and economically. Section 4 investigates the commonality among individual ITSM portfolios and explores the cross-country predictability of the US market. Section 5 evaluates the economic meaningfulness of investing ITSM globally. Section **??** proposes two hypotheses and studies ITSM with two market micro-characteristics. Section 7 concludes.

2. Data and Intraday Returns

2.1. Data

We collect 1-minutely quote data from the Thomson Reuters Tick History (TRTH) database of stock market indices[1] and restrict our analysis to developed markets classified by the MSCI.[2,3] We restrict our analysis to developed markets since intraday data are very illiquid in emerging and frontier markets. The dataset provides information on stock market indices based on the local currency, and consists of information on trading time, open price,

[1]Country-specific ETFs are available; however they lack liquidity and a long enough history to provide a robust study.

[2]For a detailed description of this database please refer to Fong et al. (2017).

[3]We classify the developed countries following the MSCI market classification guide `https://www.msci.com/market-cap-weighted-indexes.`

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. (2019), 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.[4] Second, we use only data with a time-stamp during the exchange trading hours for that market. For instance, we use data for the US market between 9:30AM and 4:00PM Eastern Standard Time and in Table 1 we report all market trading hours for each market studied.[5] Third, we remove all non-trading days and recording errors. To be more specific, 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 economic significance of ITSM in a portfolio setting, we take the perspective of US dollar investor, and hence we convert all local currency data into US dollars.[6] Specifically, we convert index prices based on the contemporaneous 1-minute exchange rate. We exclude Hong Kong and Singapore from our sample due to the lack of 1-minutely foreign exchange data. Of the 16 remaining MSCI developed countries, data from Sweden starts 4th October 2005 and therefore we take that as our start date for all countries and the end date is 29th December 2017, thereby capturing over 12 years' worth of data. Table 1 tabulates the list of the 16 developed stock market indices employed in this study along with their RICs and trading hours.

[Table 1 about here.]

[4]For these countries, there are many missing values throughout the sample and even aggregating to the 30-minute frequency still leaves many missing values.

[5]For some countries, the trading records do not correspond to the trading hours, and exceed market closing time with observations that remain unchanged. This is mostly pronounced over the early period of our sample. To address this issue we use the timestamp of the first observation on a day as opening time and the timestamp of the last actively changed observation as closing time.

[6]Though some scholars argue that using US 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 the evidence reported in Table B.1 and B.2 of Appendix B shows stronger intraday time-series momentum effect when using local currency.

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.[7] 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 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 informative 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

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

less informative as a result (Barclay and Hendershott (2003) and 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 individual 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 stand for 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 tabulates the in–sample estimation results of the predictive regression shown in Equation (2) for each equity market, over the full sample period (Panel A) and over a set of different periods such as the financial crisis (Panel B), non-crisis period (Panel C), recession (Panel D), and expansion (Panel E).[8] The last row in Panels A, B and C of Table 3 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 same country at different time points to be correlated, and to control for the heteroskedastisity and autocorrelation We also adjust the standard errors using the Newey and West (1987) correction modified for a panel framework.

Over the 2005–2017 period (Panel A) our empirical evidence suggests that 12 out of 16 countries exhibit a statistically significant in–sample predictability of the first half hour on the

[8]We follow Gao et al. (2018) and set the financial crisis period from 2^{nd} Dec 2007 to 30^{th} June 2009 while the OECD recession and expansion indicators are sourced from FRED St. Louis: `https://fred.stlouisfed.org/`. Note that the methodology for computing OECD expansion/recession indicators differentiates from the methodology by NBER effective from January 2009. Full-sample analysis results based on local currency are reported in Table B.1 of Appendix B.

last half-hour return.[9] Among them, nine 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 2.86 and statistically significantly different from zero (t-statistic 7.53).

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 it is consistent with the evidence found in the US stock market (Gao et al. (2018)).

[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 various market conditions, i.e. during the financial and non-financial crisis periods and the business cycle. Panels B and C of Table 3 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 adjusted R^2s is much larger compared to the one in the non-crisis period. Amongst the 16 markets, the predictive power of the first half hour is more pronounced in the US 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 4.28). 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

[9] Gao et al. (2018) document an R^2 equal to 1.6% and argue that the level is considered impressive and relatively large compared to other predictors, especially at this data frequency. In our empirical analysis, 4 out 12 equity markets exhibit an adjusted R^2 above 1.6%. The large proportion of the markets showing strong positive significance is rather striking and may imply intraday time-series momentum exists not only on the US market but across the world.

times larger than the one observed in the non-crisis period (i.e. 0.63%). Panels D and E 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 4.05 (2.52) and 1.72% (0.81%) for the recession (expansion) periods.[10] The ITSM exhibits larger slope coefficients in 12 out of 16 markets during recession compared to expansion periods.

Collectively, Table 3 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 US stock market to a comprehensive set of countries around the world.

3.3. Out–of–sample predictability

Up to this point, we have examined the in-sample predictability of the first on the last half-hour return, which was based on the entire sample period. In this section, 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) and Welch and Goyal (2008)).

Based on an expanding window approach, we use the first five years (2005-2010) of our sample 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 four statistics.[11]

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

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

[11]Goyal and Welch (2003) and Welch and Goyal (2008) show it is difficult for a predictive model to outperform the historical mean model in an out-of-sample setting.

follows:[12]

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

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 $t-1$. A positive value of the R^2_{OOS} implies that the predictive model (equation 2) outperforms the historical mean model.[13]

While the R^2_{OOS} is commonly used in the literature (Ferreira and Santa-Clara (2011), Gao et al. (2018), Neely et al. (2014), and Rapach et al. (2010)), Campbell and Thompson (2008) argue that perverse estimates in the recursive regressions can be easily generated due to short estimation period and thus add no value in practice. In our case, a negative slope estimation would not help someone make an out-of-sample investment decision if they believe that the theoretical relation between the first and the last half-hour returns is positive. In addition, one would not follow the trading signal generated by the predictive regression if the forecast return in the last half hour next day is negative. To examine the OOS predictability in a more realistic setting, we follow Campbell and Thompson (2008) and compute the constrained R^2 as our second statistic, denoted as $Rst.R^2_{OOS}$. The $Rst.R^2_{OOS}$ imposes two restrictions on the R^2_{OOS}. In particular, we first set the slope coefficient to zero whenever its estimated value is negative, then set $\hat{r}_t^L$ to zero if it is negative. Similar to its unconstrained counterpart, a positive value of $Rst.R^2_{OOS}$ indicates superior OOS performance of the predictive model over

[12] This statistic essentially compares the Mean Squared Prediction Error (MSPE) of our predictive model with that of the historical mean model. Welch and Goyal (2008) employ a similar statistic with adjustment for degree-of-freedom. Since we have only one predictor and a relatively large sample size with high data frequency, the effect of degree-of-freedom adjustment would be trivial.

[13] In a finite sample and under the null that the predictor does not help prediction, Clark and West (2006) state that the predictive model should have larger MSPE due to the noise caused by estimating extra parameters, resulting in a negative R^2_{OOS}. In contrast, a positive R^2_{OOS} implies smaller MSPE of the predictive model compared to that of the historical mean model, thus indicating out-of-sample predictability of the predictor.

that of the historical mean model.

We then test the null hypothesis that the MSPE of the historical mean model is equal or less than that of the predictive model (equivalent to H_0: $R^2_{OOS} \leq 0$ against H_1: $R^2_{OOS} > 0$). In order to do so, we use the Clark and West (2007) $MSPE - adjusted$.[14] To calculate the statistic, we first compute a time series of $\hat{f}_t$ as follows:

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

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 information in prediction relative to the former.[15] To this end, we conduct an forecast encompassing test that is valid for nested models, using ENC_{NEW} proposed by Clark and McCracken (2001).[16] 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:

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

Table 4 tabulates the four OOS statistics along with the average recursive regression coefficients for each country. As shown in the table, the average slope coefficient is positive

[14]The $MSPE - adjusted$ is an adjusted version of the Diebold and Mariano (2002) and West (1996) statistic that is used to test the MSPE hypothesis in a non-nested setting. Clark and McCracken (2001) and McCracken (2007) point out that the Diebold and Mariano (2002) and West (1996) statistic has a nonstandard distribution when used for nested models, like in our case. Clark and West (2007) show the $MSPE - adjusted$ has an approximately standard normal asymptotic distribution when used for comparing nested models, leading to valid inferences.

[15]For a textbook discussion of forecast encompassing, see Clements and Hendry (1998).

[16]This statistic is also employed by Barroso and Maio (2019) and Rapach and Wohar (2006) 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 5% and 10% confidence levels, respectively.

for all countries. Five out of 16 countries exhibit positive R^2_{OOS}, while 10 show positive $Rst.R^2_{OOS}$.[17] Although only five markets give positive R^2_{OOS}, the Clark and West (2007) $MSPE-adjusted$ rejects the null ($R^2_{OOS} \leq 0$) in 10 markets. This interesting result suggests that a negative R^2_{OOS} (or/and $Rst.R^2_{OOS}$) does not necessarily imply complete denial of the OOS predictability of the first half-hour return. If we take the example of the Japanese market, both R^2_{OOS} and $Rst.R^2_{OOS}$ are shown negative, yet this gives a significant $MSPE-adjusted$ at the 1% confidence level, indicating that the MSPEs for the predictive model are significantly less than that of the historical mean model in this market.[18] The last column of Table 4 reports results of the forecast encompassing test. The null (the historical mean forecasts encompass the predictive forecasts) is rejected in 14 out of 16 countries, implying that the first half-hour return does provide additional predictive information relative to a simple historical mean of the last half-hour return in thoes markets. Overall, our OOS analysis furnishes strong evidence of OOS predictability of the first half-hour return on the last hour-hour return in most countries.

[Table 4 about here.]

3.4. Economic significance

The statistical performance demonstrated in the previous subsection does not necessarily translate into economic benefits from an investment perspective.[19] Kandel and Stambaugh (1996) show that variables with relatively weak statistical predictive power can still produce

[17] Most estimated slope coefficients steadily remained positive in the recursive regressions, making the effect of the sign restriction trivial. It is the forecast restriction that contributes most to the improvement in the $Rst.R^2_{OOS}$ performance.

[18] 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) and McCracken (2007).

[19] 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.

significant economic benefits in a portfolio context. We now examine the economic value of the ITSM in each of the 16 stock markets and compare the profitability of the country ITSM strategy with two passive country strategies – namely the *Always-long* and *Buy-and-hold* – as in Gao et al. (2018).

For the ITSM strategy we consider the sign of the first half-hour return as the trading/timing signal – i.e. 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.

The *Always-long* strategy takes an always-long position at the beginning of the last half-hour and a closing position at the market close. The *Buy-and-hold* strategy is a passive strategy which 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 5 about here.]

Table 5 tabulates the mean, standard deviation (SD), skewness, kurtosis and the Sharpe ratio of the intraday time-series momentum (i.e. ITSM) and the two benchmark strategies, *Always-long* and *Buy-and-hold*, for each of the 16 equity markets as well as the correlation (ρ) between the ITSM and the benchmark strategies returns.[20] The alpha (α) and Appraisal Ratio (ARatio) are based on the following regression:

$$r_{I,t} = \alpha + \beta r_{benchmark,t} + \epsilon_t, \tag{7}$$

[20]We conduct the same analysis using data based on local currencies and report the results in Table B.2 of Appendix B.

where $r_{I,t}$ and $r_{benchmark,t}$ stand for the returns from ITSM and benchmark strategies, respectively. The appraisal ratio is calculated as α/σ_ϵ where σ_ϵ is the standard error of the regression. Standard errors are adjusted using the Newey and West (1987) correction. We test the hypothesis that the Sharpe ratios of the ITSM and the *Always-long* or *Buy-and-hold* strategies are equal following the HAC inference method proposed by Ledoit and Wolf (2008).[21]

Table 5 shows that ITSM exhibits positive return over the 2005-2017 period across markets. The volatility of the ITSM strategy is lower compared to the *Always-long* and *Buy-and-hold* strategies in seven and 16 out of 16 markets, respectively. ITSM has a positive skewness in 10 out of 16 markets suggesting low crash risk while the ITSM and the passive strategies appear to be unrelated (i.e. the correlation between ITSM and the benchmark strategy returns is close to 0). Finally, the ITSM strategy possesses higher Sharpe ratios compared to *Always-long* and *Buy-and-hold* strategies in eight and 14 out of 16 markets, respectively, albeit not statistically significant in all cases. ITSM has positive statistically significant (at the 1% level in most cases) alphas in 10 out of 16 countries, ranging between 2.66% (for the UK) and 7.45% (for Norway) per annum when regressed against the *Always-long* strategy, and between 2.60% (for the UK) and 7.28% (for Norway) per annum when regressed against *Buy-and-hold* strategy. Similarly, among countries giving significant alphas, the annualized appraisal ratios range between 0.52 (for UK) and 0.99 (for Norway) when regressed against the *Always-long* strategy and between 0.51 (for the UK) and 0.97 (for Norway) when regressed against the *Buy-and-hold* strategy.

4. Cross-country Relationship of Intraday Time-series Momentum

4.1. Global and regional commonality

Given the pervasiveness of ITSM portfolio profitability shown in the previous sections, the question that arises is whether these portfolios are global, regional, or country-specific. If these portfolios are mainly driven by common global factors, there would not be any differ-

[21]The R code used in this study is available on Wolf's website: `\https://www.econ.uzh.ch/en/people/faculty/wolf/publications.html#9`.

ence for a US investor to invest in the US ITSM strategy or in a global strategy that combines the country ITSM portfolios. Accordingly, a global ITSM momentum diversification strategy should also perform similarly to a local ITSM strategy, which involves an investment in the individual country ITSM strategies. In contrast, if the local ITSM portfolios contain sizable country-specific or regional components, these country ITSM strategies would allow the investor to expand their investment opportunity set significantly beyond what can be achieved by the country ITSM portfolios alone. Using the methodology in Brockman et al. (2009) and the principal component analysis (PCA), we address this question both globally and regionally.

We compute the correlation coefficients between country momentum portfolios. Table 6 shows that the correlation coefficients between most countries are close to zero. However, we observe larger correlations between countries that are geographically closer, compared to the coefficients between countries across regions. For example, the coefficients between the UK and most European countries are significantly larger than those between the UK and other countries. We discuss in more detail this regional relationship in ITSM later in this subsection.

[Table 6 about here.]

To investigate the commonality in ITSM, we first test for potential common variation across the country individual ITSM portfolios. We follow the methodology adopted by Chordia et al. (2000) and Brockman et al. (2009) in their studies on commonality in market liquidity, and run the following time series regression:

$$r_{I,i,t} = \alpha_i + \beta_t r_{I,g,t} + \beta_{t+1} r_{I,g,t+1} + \beta_{t-1} r_{I,g,t-1} + \epsilon_{i,t}, \tag{8}$$

where $r_{I,i,t}$ is the ITSM return in country i at time t, $r_{I,g,t}$ is the contemporaneous equally-weighted ITSM return based on the country ITSMs excluding country i, $r_{I,g,t+1}$ is the equally-weighted ITSM return based on the country ITSMs excluding country i at $t+1$, and $r_{I,g,t-1}$ is the equally-weighted ITSM return based on the country ITSMs excluding country i at $t-1$.[22] The inclusion of the control variables $r_{I,g,t+1}$ and $r_{I,g,t-1}$ eliminates the lag effect induced

[22]Both studies of Chordia et al. (2000) and Brockman et al. (2009) employ the percentage change of the

by the time difference issue. A positive and significant contemporaneous slope coefficient β_t indicates influence of the globe-level ITSM returns on $r_{I,i,t}$, while the magnitude of the adjusted R^2 of Equation (8) measures the strength of such influence.

Panel A of Table 7 shows that the country ITSMs are influenced by the globe-level ITSM. The β_ts are statistically significant in 12 out of 16 markets and the average coefficient has a magnitude of 73.79 (scaled by 100) (see the last row of Table 7). However, the adjusted R^2s show the strength of such influence varies from country to country. Apart from Switzerland, the adjusted R^2s for most European countries are relatively large ranging from 12.39% (Austria) to 52% (France), whereas that of the rest countries are fairly low ranging from 0.43% (US market) to 2.62% (Austria). The significant contemporaneous slope coefficients together with the disagreement in the adjusted R^2s imply that only part of the expected return in each country intraday momentum is captured by a common global component and stronger regional commonality may exist, consistent with the previous correlation analysis.

[Table 7 about here.]

Asness et al. (2013) employ the principal component analysis (PCA) to the returns of value and momentum portfolios across asset classes and find a global commonality in value and momentum strategies. We carry out a PCA in the individual ITSM market timing return series, which are normalized and standardized to eliminate the effect of idiosyncratic characteristics in each market. Panel A of Figure 1 depicts the variance explained by each component. The first principal component (PC1) accounts only for 27.7% of the covariance matrix of the ITSM returns.[23] Panels B to D in Figure 1 plot the front view, top view, and

liquidity measures to study the co-movement of liquidity and to avoid econometric issues, e.g., nonstationarity. In our case, we are interested more in commonality in the ITSM across countries than the co-movement of the returns. In addition, as we are analyzing strategy returns, it is less likely to encounter the potential econometric issues faced in their studies.

[23]One concern with our approach is the 16 markets are non-synchronized, i.e. they have different operating periods, leading to possible underestimation of commonality. In order to account for this issue, we repeat our principal component analysis with monthly aggregated ITSM returns and the conclusion remains largely unchanged. Results can be found in Appendix C. In the following regional commonality analysis, we also group countries based on the geographical location, further alleviate the non-synchronized issue.

end view of the rotated data plotted in a 3-D space of which the axes are the first, second, and third principal components (PC1, PC2, and PC3), respectively. These plots visualize the relation between the variance of returns of ITSM in each market and the first three PCs. Specifically, we plot the rotated data using the scores on PC1, PC2, and PC3. Then we use arrows to indicate the relationship between the variance of ITSM returns in each market and the PCs. The arrows are obtained by projecting the return data into the principal component space.[24] The length and angle of the arrows show how heavily and speedily the ITSM returns in each market respond each of the first three principal components. The ITSM returns are concentrated in mainly three directions that are roughly orthogonal. Firstly, all European markets, apart from Switzerland, point to the same direction as does the PC1. Secondly, Switzerland, the two Scandinavian countries, and all Pacific countries in the sample point roughly to the same direction that is perpendicular to the PC1. Finally, the two North American countries point to a direction that is roughly perpendicular to the first two PCs. Again, consistent with both the correlation analysis and the commonality regressions shown above, we find weak evidence of global commonality but seemingly strong evidence of regional commonality.

[Figure 1 about here.]

We further confirm regional commonality in ITSM by applying PCA analysis to three geographical sub-samples, namely, American countries, Asia-Pacific countries, and European countries. Figure 2 plots the first principal components obtained from each group. Splitting the sample geographically leads to PC1s that explain a relatively large proportion of variance in each region. The first principal component from the American countries explains 63.1% of the ITSM return variance while that from the Asia-Pacific and European countries explains 41.5% and 40.3% respectively.

[Figure 2 about here.]

[24]The rotated data are obtain by multiplying return data matrix and the component loading matrix (rotation matrix).

Our empirical evidence suggests that the country ITSM strategies share a universal risk factor. However, this factor explains only part of their variation whereas countries geographically close exhibit stronger regional risk factors, suggesting potential diversification benefits from investing in a combined portfolio of country ITSM strategies globally.

4.2. What is the role of US?

It is known that US market may possess cross-market predictability on returns of international markets. At monthly frequency, Campbell and Hamao (1992) present evidence that the US 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 US stock returns Granger cause stock returns in 11 international markets. At a higher frequency, Becker et al. (1990) state the daily open-to-close US stock return can predict that of the Japanese stock market on the next day.

It is therefore natural to investigate the predictive role of US first half-hour returns in a cross-market setting. In particular, we regress the local last half-hour return of a country (apart from US) against the immediately previous US first half-hour return available and the local first half-hour return as a control variable of local ITSM. That is, for non-Asia-Pacific countries, we fit the following model:

$$r^L_{local,t} = \alpha + \beta_{US} r^F_{US,t} + \beta_{local} r^F_{local,t} + \epsilon_t \tag{9}$$

Where $r^F_{local,t}$ is the first half-hour return of the local country on day t, $r^F_{US,t}$ is the first half-hour return from the US market on day t, and $r^L_{local,t}$ is the last half-hour return of the local country on day t. For Australia, Japan, and New Zealand, whose markets close before the US market open on the same calendar day, we use the US first half-hour return from the previous day:

$$r^L_{local,t} = \alpha + \beta_{US} r^F_{US,t-1} + \beta_{local} r^F_{local,t} + \epsilon_t \tag{10}$$

Significant β_{US} of Equation (9) and Equation (10) imply predictability of the US first half-hour return on the local last half-hour return.

Panel B of Table 7 reports the results. The US first half-hour return is found to be associated with a positive slope coefficient in 12 out of 15 international countries, while 8 of the coefficients are significant. In the last column, we report the increase in the adjusted R^2 by including the US first half-hour return as an additional predictive variable, which is the difference between the adjusted R^2 of Model (9) or (10) and that of Model (2):

$$\Delta_{Adj.R^2} = Adj.R^2_{cross} - Adj.R^2_{local} \tag{11}$$

Where $Adj.R^2_{local}$ is the adjusted R^2 of Model (2), and $Adj.R^2_{cross}$ is the adjusted R^2 of Model (9) or (10), depending on the local country.

Using wild bootstrapped data, we also test the null hypothesis of no US first half-hour return predictability ($H_0 : \beta_{US} = 0$ vs $H_1 : \beta_{US} > 0$ or $\beta_{US} < 0$). In particular, we take Equation (9) and Equation (10) as benchmark predictive regressions and, given the research on intraday return persistence (Heston et al. (2010) and Lou et al. (2019)), we assume that the US first half-hour return follows a first order autoregressive process:

$$r^F_{US,t} = \delta + \theta r^F_{US,t-1} + v_t \tag{12}$$

where v_t is a white noise. We therefore simulate alternative data under the null hypothesis:

$$^*r^L_{local,t} = \hat{\alpha} + \hat{\beta}_{local} r^F_{local,t} + \hat{\epsilon}_t w_t \tag{13}$$

$$^*r^F_{US,t} = \hat{\delta} + \hat{\theta}^* r^F_{US,t-1} + \hat{v}_t w_t \tag{14}$$

where $\hat{\alpha}$, $\hat{\beta}_{local}$, and $\hat{\epsilon}_t$ are estimated from the benchmark equations; $\hat{\delta}$, $\hat{\theta}$, and $\hat{v}_t$ are estimated from Equation (12); w_t is randomly generated from the standard normal distribution; $^*r^F_{US,0}$ is set to be equal to $r^F_{US,0}$. We multiply both residual terms with the same random scalar to preserve the contemporaneous correlation between the local first half-hour return and the US first-half hour return and to maintain the conditional heteroskedastisity structure in the error terms (Rapach et al. (2013)).

We then collect the Newey and West (1987) t-statistic of β_{US} from the benchmark equations (either one of them depending on the local country) with the bootstrapped data:

$$^*r^L_{local,t} = \alpha + \beta_{US} {}^*r^F_{US,t} + \beta_{local} r^F_{local,t} + \epsilon_t \tag{15}$$

$$^*r^L_{local,t} = \alpha + \beta_{US} {}^*r^F_{US,t-1} + \beta_{local} r^F_{local,t} + \epsilon_t \tag{16}$$

Repeating the above process 2000 times leads to 2000 t-statistics, from which the p-value is computed as the proportion of the bootstrapped t-statistics that have a larger absolute value than the t-statistic obtained from the benchmark equations.

As shown in Panel B of Table 7, we reject the null of no US cross-market predictability at 10% level in 10 out of 16 markets, implying a strong leading role of the US market at intraday frequency.

5. Investing In Intraday Time-series Momentum Globally

5.1. Benefits from diversification

To exploit the potential diversification benefits in ITSM discussed in the previous subsection, we study three types of global intraday time-series momentum strategies (GITSM). We consider a (1) GITSM based on individual ITSM, (2) GITSM based on regional ITSM, (3) GITSM using the signal from US first half hour return. For each type of GITSM, we employ six portfolio construction techniques using equal, value, inverse-variance (Kirby and Ostdiek (2012)), maximum-diversification (Choueifaty and Coignard (2008)), mean-variance and minimum-variance weights.

For Type (1) GITSM, we first obtain individual ITSM return series by simply go long in the last half hour of a country equity index if the first half-hour return on that index is positive and go short if negative. Then, we calculate the realized GITSM returns based on the above mentioned techniques.[25]

[25] Although our sample consists of major stock indices across the globe and each stock market opens at different time, we do not suffer from the time difference issue when constructing the global portfolios. Geographically, the market that opens the earliest in our sample is the New Zealand market (GMT+12) while the US market is the latest (GMT-4). The time difference between Wellington and New York is 16 hours; that is, when the US market closes at New York time 4pm, the local time for the New Zealand market is 8am next day, which is two hours prior to the New Zealand market open. In practice, at the US market close on day t, a fund manager will have the last half-hour return for all the countries in sample on day t and be able to make decisions on the weights for day $t+1$. At this time, the local time for the earliest-opened market, New Zealand market, is 8am on day $t+1$, which is several hours prior to its last half hour on day $t+1$. Therefore, a daily global portfolio is realistic in practice without suffering from time difference issues.

For Type (2) GITSM, the base assets are regional ITSM instead of individual ITSM. That is, we average ITSM returns across American countries, Asia-Pacific countries, and Europe countries to get three regional ITSM return series before we construct GITSM portfolios accordingly.

For Type (3) GITSM, the base return series are generated by trading in the last half hour of each market guided by the signal from the US first-half return. If the US first-hour return is positive ($r_{US}^{F} > 0$) on day t, we go long in the last half hour on each market and vice versa if $r_{US}^{F} < 0$.

We use the first five years in the sample as the initial estimation period for the construction of the inverse-variance, maximum-diversification, mean-variance and minimum-variance portfolios. More specifically, we compute the weights based on information from the period 4th October 2005 to 1st October 2010, and invest from 4th October 2010 until the end of the sample period.[26] We compute the weights recursively by adding one day a time in the light of estimation stability of such expanding window approach.[27] Finally, we impose the constraints that assure the sum of weights is equally to one and short sales are not allowed.

Table 8 evaluates the three types of GITSM. Panel A reports the mean, standard deviation (SD), skewness, kurtosis, and Sharpe ratio of the global intraday time-series momentum under the different weighting schemes for each type. Panel B tabulates the alphas from the spanning regressions of global intraday momentum on country (individual) intraday momentum, while Panel C presents the alphas from the spanning regressions of country (individual) intraday momentum portfolios on global intraday momentum; Newey and West (1987) t-statistics are shown in parenthesis.

Over the 2005-2017 period, the annualized returns of the value-weighted GITSM (VW-GITSM) are generally higher than that of the equally-weighted GITSM (EW-GITSM) (4.75% vs 3.06%, 2.71% vs 2.78%, and 5.71% vs 5.17%). However, the VW-GITSM also has a higher volatility (3.22%, 2.41%, and 3.51%) for all types of GITSM compared to the volatility of the EW-GITSM (2.43%, 2.01% and 2.93%). The Sharpe ratio of the EW-GITSM is lower

[26] 1st October 2010 is a Friday and 4th October is the following Monday.

[27] Indeed, we also present results based on a rolling window approach in Table B.3 of Appendix B, the results do not change radically.

than that of the VW-GITSM for Type (1) GTISM while higher for both Type (2) and (3).

The spanning alphas of the EW- and VW-GITSM on the country individual ITSM are considerably large and positive and are statistically significant at 1% level in all cases but for Type (2) VW-GITSM against US-ITSM. The significant alphas range from 1.40% to 4.76% and 1.58% to 5.58% per annum for the EW- and VW-GITSM, respectively (Panel B). In the reverse regression on the country ITSM portfolios on the global EW and VW intraday momentum, we document no statistically significant alphas or even negative and statistically significant alphas for most countries with Norway being the only country that consistently gives positive and significant alphas. Our evidence suggests that the global portfolios subsume the individual country ITSM portfolios.

The remaining GITSM portfolios perform inconsistently across the three types of GITSM. The inverse-variance GITSM (IV-GITSM) yeilds lower average returns than the EW-GITSM and VW-GITSM do, yet gives positive and significant spanning alphas when against all individual ITSM for Type (2) and most of ITSM for Type (3). The maximum-diversification GITSM (MD-GITSM) gives larger returns than does the IV-GITSM in Type (1) and (3) GITSM, and exhibits positive and significant spanning alphas in when against most individual ITSM. Despite of the relatively weak economic significance of mean-variance GITSM (MV-GITSM) in Type (1) and (2) GITSM, the MV-GITSM of Type (3) GITSM manifests itself as the strongest strategy in our evaluation, with an annualized return of 6.75% and remarkable spanning alphas ranging from 5.63% to 7.19%.

Finally, the minimum-variance GITSM (MinV-GITSM) exhibits significant spanning alphas in only Type (2) GITSM. We also document that the GITSM portfolios exhibit higher Sharpe Ratios compared to country individual ones. Over the 2005-2017 period the annualized Sharpe ratios of the EW-GITSM are 1.26, 1.38, and 1.77 for all types and that of the VW-GITSM are 1.48, 1.12 and 1.63. In contrast, the Sharpe ratios of the country ITSM range between -0.40 and 1.12 over the same period.

Overall, our analysis shows investing ITSM globally produces significant economic gain and the global intraday momentum subsumes the country intraday momentum, but not the opposite.

[Table 8 about here.]

5.2. Factor exposure of GITSM and the source of its profitability

Taking the equally-weighted GITSM of Type (1) as an example, we further study the factor exposure of GITSM.[28] In particular, we define the global intraday momentum return as the equally-weighted 16 country ITSM portfolio return in excess of the 1-month T-bill rate, and regress it against the global market factor (CAPM), global Fama-French 3-factor model (FF3), global Fama-French 3-factor model plus the (cross-sectional) momentum factor (FF3+MOM), global Fama-French 5-factor model (FF5), and global Fama-French 5-factor model plus the momentum factor (FF5+MOM).[29]

Panel A of Table 9 tabulates the results from these regressions. The results show that the loadings of the GITSM on the global equity factors are insignificant, while we document statistically significant and positive alphas varying between 2.90% (FF3) and 2.97% (FF5) across the models, highlighting that the profitability of the global intraday time-series momentum strategy is not captured by global equity factors.

[Table 9 about here.]

So where does the profitability of GTISM come from? Goyal and Jegadeesh (2018) compare the performance of time-series momentum (Moskowitz et al. (2012)) and cross-sectional momentum (Jegadeesh and Titman (1993)), and conclude that the out-performance of the time-series momentum is largely due to a time-varying factor that is implicitly incorporated into the strategy. More specifically, they claim that the dollar value invested in the long leg and the short leg in the time-series momentum is not identical and varies over time, while cross-sectional momentum is a purely zero-cost strategy. This emanates from the fact that the time-series momentum holds long position in assets with buy signal and short position in assets with sell signal, while the number of assets with buy and sell signals varies over time.

[28] From now, we use words 'Type (1) EW-GITSM' and 'GITSM' interchangeably.

[29] The global factors are sourced from French Library, i.e. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The global factors are constructed from developed markets and represent the global stock market.

While our GITSM based on the intraday time-series momentum introduced by Gao et al. (2018) differs from the time-series momentum by Moskowitz et al. (2012), it does possess similar construction features. For instance, suppose on a given day t that 10 of the 16 country equity indices in our sample generate positive trading signals and the remaining six generate negative trading signals. In this case, the wealth we invest on day t in the long leg is by construction higher than that in the short leg. The reason is we are equally weighting all the 16 indices across the long and short legs rather than weighting within the long and short portfolios separately. As a result, our global intraday time-series momentum incorporates a time-varying net position, which is the difference in the wealth invested in each leg.[30]

Therefore, we examine the contribution of this time-varying factor to the profitability of GITSM. To do so we first compute this factor following the approach in Goyal and Jegadeesh (2018). To be specific, we invest, in total, two dollar value into the GITSM and invest the net position into the global market. Considering the previous example where we had 10 indices exhibiting positive signal and six indices exhibiting negative signal, the dollar value we invest in the long leg in this case is $\frac{10}{16} \times \$2 = \$1.25$, and the dollar value we invest in the short leg is $\frac{6}{16} \times \$2 = \$0.75$, hence we end up with a net long position of $\$1.25 - \$0.75 = \$0.5$ in the countries that possess positive trading signals. Because the unconditional probability of an asset return being positive/negative is 0.5, the net position between the long and short legs on average invests on the whole market, which is the equally-weighted ITSM across the 16 indices employed in our study. Therefore, the time-varying global factor is defined as follows:

$$TVC_t = EWM_t \times NPM_t, \tag{17}$$

where EWM_t is the equally-weighted last half-hour return across the 16 country indices – i.e. $EWM_t = \frac{1}{16} \times \sum_{i=1}^{16} r_{i,t}^L$, where $r_{i,t}^L$ stands for the last half hour of country i at time t, and NPM_t denotes the net position in the global market at time t – i.e. $NPM_t = (N_t^{long} - N_t^{short}) \times 2$. N_t^{long} (N_t^{short}) is the number of indices in the long (short) leg. It is worth noting that while EWM_t and NPM_t are on the same day, our construction of TVC_t

[30] Technically, this time-varying net position can be either net long or net short depending on the number of stock indices in the long and short legs.

is ex-ante. This is because NPM_t is computed from the first half hour of day t whereas EWM_t is the equally-weighted global market in the last half hour of day t.

Next, we regress $GITSM \times 2$ against Fama-French factors with TVC included on the right hand side as follows:

$$GITSM_t \times 2 = \alpha + \boldsymbol{\beta}'\mathbf{F_t} + TVC_t + \epsilon_t, \tag{18}$$

where $\boldsymbol{\beta}$ is a vector of slope coefficients and $\mathbf{F_t}$ is a vector of Fama-French pricing factors at time t. Multiplying GITSM by two ensures that the total value invested in the strategy is \$2 and will not affect the significance of coefficients. Panel B in Table 9 reports the regression results. Consistent with Panel A, GITSM does not show significant exposures to the Fama-French factors. However, the inclusion of the time-varying factor eliminates the significant and positive alpha as shown in Panel A and the slope coefficients of TVC are significant at the 1% confidence level in all cases. Moreover, the adjusted R^2s increase from 0.4% to around 73%. Our results suggest that the time-varying factor is a significant source of the GITSM profitability and can explain around 73% of the variation of the global time-series momentum.

To further understand the sources of TVC returns, we follow Goyal and Jegadeesh (2018) and decompose the time-varying factor into two terms as follows:

$$\overline{TVC_t} = \overline{NPM_t} \times \overline{EWM_t} + cov(NPM_t, EWM_t) \tag{19}$$

where the first term $\overline{NPM_t} \times \overline{EWM_t}$ is the expected return of the average net position, and is referred to as the risk premium factor in Goyal and Jegadeesh (2018); and the second term is the covariance between the net position in market determined by the information from the first half hour and the equally-weighted global market in the last half hour, and is referred to as the market timing component. Since NPM_t tend to be positive (negative) when more markets perform strongly (poorly) in the first half hour (e.g., an unexpected good news of global economy might result in an uplift in many markets during the first half hour), the second term will add to the strategy performance when there is a positive autocorrelation between the first and the last half-hour return in the global market.

Over our sample period, the average net position ($\overline{NPM_t}$) is 14.05% and the average TVC ($\overline{TVC_t}$) is 5.40% per annum. The decomposition of TVC reveals that the return from the risk premium term is 0.53% while that of the market timing component is 4.88%. The market timing component accounts for 90.37% of the return on TVC, highlighting that the profitability of the time-varying factor is largely due to the market timing and not asset picking ability.

6. What Drives Intraday Time-series Momentum?

6.1. 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 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 due to that the infrequent traders absorb a liquidity shock by taking sub-optimal position at time t and then unload the excess position at time $t+k$, causing another liquidity shock at the same direction.[31]

In the intraday context, the overnight information accumulation causes naturally transient liquidity shocks at 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).[32] This unloading is therefore in the same direction as the initial shock and causes the intraday momentum. Gao et al. (2018) conjecture this process as a possible explanation for the ITSM.

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

[31] k is the length of inactive period.

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

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, we hypothesize that the more illiquid the market is, the stronger return seasonality should be observed. To test this, we sort at the end of the first half hour of each day the 16 indices based on their estimated liquidity and then calculate the equally-weighted ITSM return of the top, medium, and bottom 30 percents of the indices.

Due to the lack of information on intraday quotes and volume in most countries, appropriately estimating the liquidity at the frequency of our data is rather challenging. The simplest-to-compute option that does not require information on trading volume is perhaps the measure by Roll (1984): $2\sqrt{-cov(r_t, r_{t-1})}$. However, maybe due to that the informational efficient market assuption is hardly hold at intraday level, the autocovariance of minutely returns are positive in nearly half of the days in our sample, making the adjustment for positive autocovariance informatioanlly costly. Therefore, 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 spread. The *High-Low* liquidity is computed as follows:

$$
\begin{aligned}
S &= \frac{2(e^{\alpha}-1)}{1+e^{\alpha}} \\
\alpha &= \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}} \\
\beta &= \sum_{j=0}^{1}\left[\ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2, \quad \gamma = \left[\ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2,
\end{aligned}
\tag{20}
$$

where S stands for the *High-Low* liquidity measure, H_t and L_t are the high price and low price at time t, $H_{t,t+1}$ 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 a note by Corwin and estimate the spread in the first half hour by averaging the estimates across overlapping five-minute intervals.[33] Specifically, we calculate the *High-Low* liquidity measure over every two consec-

[33] The note is given by one of the authors of Corwin and Schultz (2012), illustrating the use of the

utive five-minute intervals and then take the average across the overlapping intervals within the first half hour.[34]

The first three columns of Table 10 report the results. Panel A tabulates the equally-weighted ITSM strategy returns (multiplied by 2) and Sharpe ratio in the low, medium and high liquidity groups.[35] As shown in the table, we document a monotonic increase in the EW-ITSM portfolio returns from high to low liquidity groups. Specifically, the strategy yields almost doubled raw returns in the low liquidity group compared to the high liquidity group. A similar pattern can also be observed in the Sharpe ratios. This is consistent with our hypothesis discussed above.

Since we argue in the previous section that the time-varying component might be a major contributor of the equally-weighted ITSM strategy return, we next investigate the behavior of the time-varying component across the groups. The first three columns of Panel B of Table 10 tabulates the time-varying factor (TVC) within each group as well as its components, i.e. the risk premium and market timing. We do not observe a clear trend in the TVC return across liquidity groups, leading us to investigate the factor exposure for each group. Panel C of Table 10 tabulates the results from the regression of EW-ITSM on the Fama-French factors within each group. For simplicity, we report only the alphas and the slope coefficients of TVC with respect to five Fama-French factors and the cross-sectional momentum factor.[36] As in the previous analysis, we compare the alphas before and after the inclusion of TVC. The significant alphas in the regression that do not include TVC suggest the EW-ITSM

High-Low estimate in the intraday setting (http://sites.nd.edu/scorwin/files/2019/11/Application_Intraday_Analysis.pdf).

[34]While we have the high and low prices for most markets at minutely level, we do not have this information for some countries in certain periods, e.g., Ireland data gives exactly the same number for high, low, and last prices for each minute in the early phase of our sample period. By aggregating the data up to five-minute intervals, we mitigate this problem. Straightforwardly, we pick up the highest and the lowest price from the high, low, and last prices collectively in a five-minute interval, regardless if we have adequate high/low price information.

[35]Due to the inclusion of TVC in the Fama-French regressions later, we multiply the EW-ITSM excess return by 2. To get the actual excess return, one just needs to divide the figures in Table 10 by 2.

[36]For more detailed results, including the analysis with respect to other regression models, see Table B.4 and B.5 in Appendix B.

return in each group cannot be fully explained by Fama-French factors. However, a rather striking result shown in the table is that the alpha in the low liquidity group survives even with the inclusion of TVC. This infers that the EW-ITSM portfolio return in the bottom illiquid group is not fully captured by the time-varying factor.

[Table 10 about here.]

6.2. Information discreteness and inattentive 'frogs'

A second explanation for the intraday time-series momentum proposed by Gao et al. (2018) is that some traders are simply slower than others causing under-reaction to the overnight information. Da et al. (2014) propose the 'frog-in-the-pan' (FIP) hypothesis in which investors are inclined to be inattentive and under-react to gently arrived information. This under-reaction can be adjusted later in time causing momentum. In their paper, they document that the cross-sectional momentum is stronger when the information in the formation period is continuously arrived. A recent study by Lim et al. (2018) tests this hypothesis on the time-series momentum of Moskowitz et al. (2012) by grouping individual US stocks based on the information discreteness (ID), which is the measure of information arrival process proposed by Da et al. (2014). The authors 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.

Therefore, in our second hypothesis we expect to observe stronger intraday momentum in markets where information arrives continuously. Following Da et al. (2014) and Lim et al. (2018) among others we define information discreteness (ID) as follows:

$$ID_t = sign(r_t^F) \times (\%neg_t - \%pos_t), \tag{21}$$

where r_t^F is the first half-hour return on day t, $\%neg_t$ 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 information incorporation process, consider the first half-hour returns from two days on 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.[37] Now suppose ϕ_k^O is smoothly incorporated into the price while ϕ_s^O is absorbed by a few sudden price movements. This can be translated into that r_k^F has a higher proportion of positive minutely returns than does r_s^F. Collectively:

$$\begin{aligned} &\phi_k^O = \phi_s^O \\ &r_k^F = r_s^F > 0 \\ &0 \leq p_s < p_k \leq 1, \end{aligned} \tag{22}$$

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:[38]

$$1 - 2p_k = ID_k < ID_s = 1 - 2p_s, \tag{23}$$

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

Similar to the previous subsection, we divide the 16 indices into three groups, at the end of the first half hour of each day, based on the information discreteness, and then calculate the equally-weighted last half hour ITSM returns within each group.

The last three columns of Table 10 report the results. As in the liquidity groups, we observe a monotonic increase in the EW-ITSM portfolio returns from large to small ID groups. The results imply that the hypothesis of Da et al. (2014) is empirically related to our intraday time-series momentum. Panel B of Table 10 shows an increasing pattern in the TVC that is consistent with that of the EW-ITSM across ID groups. The market timing component takes advantage of the intraday autocorrelation between the first and the last half-hour returns. Thus, its increase might imply that markets in which the information arrives continuously tend to have stronger autocorrelation between the first and last half-hour returns which is consistent with the FIP hypothesis by Da et al. (2014) as well as other

[37] 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.

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

studies on the relation between investor attention and information arrival process in which investors tend to underreact when information arrives gently (Byun et al. (2016) and Hou et al. (2009)). Finally, Panel C of Table 10 shows that the significant alphas in the regression that do not include TVC become insignificant once the TVC is included.

7. 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 US ETFs. The current paper studies ITSM in a broader space of 16 international stock markets, with particular attention to their cross-country relationship, investing potential, and the association 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 countries. We examine a simple market timing strategy based on ITSM and we document significant economic benefits of country ITSM with respect to passive strategies where er find significant and positive alphas in most countries in the spanning regressions of the ITSM against passive strategies. Overall, our international evidence is largely consistent with that of Gao et al. (2018) in the US market indicating that ITSM is not a US-only effect.

Having confirmed ITSM globally, we then study the cross-country relationship of the effect. Particularly, we examine the existence and extent of the global and regional commonality across individual ITSM. Our evidence indicates that the ITSM strategy share some commonality across countries, but the explanatory power of the global factor is weak while relatively stronger regional factors are observed. We further investigate the leading predictive role of the US first half-hour return and find significant evidence in 9 out of 16 markets. Naturally, this leads to the possibility of constructing global portfolios.

By applying six commonly used portfolio construction techniques on three types of global intraday time-series momentum (GITSM), we document remarkable economic gains of investing ITSM globally than individually. We show that the profitability of an equally-weighted GITSM portfolio cannot be explained by global equity factors and further decomposition shows that a time varying factor is largely responsible for its profitability.

Finally, we explore the association of ITSM with two market characteristics, liquidity provision and information discreteness, that are closely related to the possible explanations of the phenomenon as proposed in Gao et al. (2018). The evidence implies that the effect of ITSM tends to be stronger when the liquidity provision is limited and when there is information continuity, which is consistent with our expectations based on the infrequent rebalancing model of Bogousslavsky (2016) and the 'frog-in-the-pan' model of Da et al. (2014).

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Appendix A. Annualizing Moments

We use the rescaling technique similar to Appendix B in Cumming et al. (2014) to annualize daily mean, standard deviation, skewness and kurtosis. Suppose r_i is the daily return on day i and R is the annual return. Under the assumption that there are 252 trading days in a year and the r_is are independently and identically distributed (i.i.d.), it is clear that the annualized mean $\bar{R} = \bar{r} \cdot 252$ and the annualized standard deviation $\sigma_R = \sigma_r \cdot \sqrt{252}$. Therefore, the annualized Skewness $Skew(R)$ is:

$$\begin{aligned}
Skew(R) &= \frac{E(R-\bar{R})^3}{\sigma_R^3} \\
&= \frac{E(\sum_{i=1}^{252} r_i - 252\bar{r})^3}{252\sqrt{252}\sigma_r^3} \\
&= \frac{E[\sum_{i=1}^{252}(r_i - \bar{r})]^3}{252\sqrt{252}\sigma_r^3} \\
&= \frac{\sum_{i=1}^{252}\sum_{j=1}^{252}\sum_{k=1}^{252} E[(r_i-\bar{r})(r_j-\bar{r})(r_k-\bar{r})]}{252\sqrt{252}\sigma_r^3} \\
&= \frac{\sum_{i=1}^{252} Skew(r_i)\sigma_r^3}{252\sqrt{252}\sigma_r^3} \\
&= \frac{Skew(r_i)}{\sqrt{252}},
\end{aligned}$$

where

$$\begin{aligned}
&E[(r_i-\bar{r})(r_j-\bar{r})(r_k-\bar{r})] \\
= &\begin{cases} E[(r_i-\bar{r})^3] = Skew(r_i)\sigma_r^3, & \text{if } i=j=k; \\ 0 & \text{otherwise.} \end{cases}
\end{aligned}$$

and the annualized Kurtosis $Kurt(R)$ is:

$$
\begin{aligned}
Kurt(R) &= \frac{E(R-\bar{R})^4}{\sigma_R^4} \\
&= \frac{E(\sum_{i=1}^{252} r_i - 252\bar{r})^4}{252^2\sigma_r^4} \\
&= \frac{E[\sum_{i=1}^{252}(r_i - \bar{r})]^4}{252^2\sigma_r^4} \\
&= \frac{\sum_{i=1}^{252}\sum_{j=1}^{252}\sum_{k=1}^{252}\sum_{l=1}^{252} E[(r_i-\bar{r})(r_j-\bar{r})(r_k-\bar{r})(r_l-\bar{r})]}{252^2\sigma_r^4} \\
&= \frac{\sum_{i=1}^{252} Kurt(r_i)\sigma_r^4 + \frac{252\cdot 251}{2}\cdot\frac{4\cdot 3}{2}\sigma_r^4}{252^2\sigma_r^4} \\
&= \frac{Kurt(r_i)}{252} + \frac{251}{84},
\end{aligned}
$$

where

$$
\begin{aligned}
& E[(r_i-\bar{r})(r_j-\bar{r})(r_k-\bar{r})(r_l-\bar{r})] \\
&= \begin{cases}
E[(r_i-\bar{r})^4] = Kurt(r_i)\sigma_r^4, & \text{if } i=j=k=l; \\
E[(r_i-\bar{r})^2(r_j-\bar{r})^2] = \sigma_r^4, & \text{if respective two of } i,j,k,l \text{ are equal;} \\
0 & \text{otherwise.}
\end{cases}
\end{aligned}
$$

Appendix B. Additional Tables

[Table B.1 about here.]

[Table B.2 about here.]

[Table B.3 about here.]

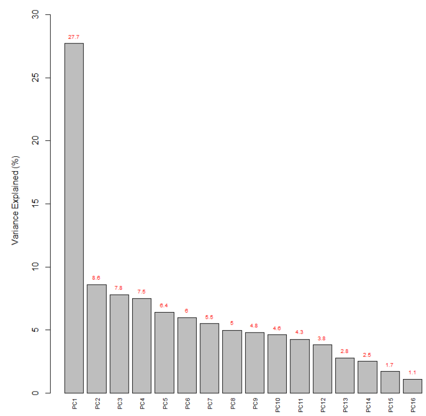
[Table B.4 about here.]

[Table B.5 about here.]

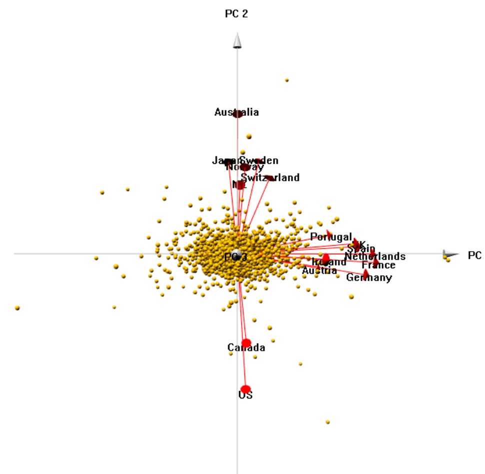
Appendix C. Principal Component Analysis With Monthly Aggregated ITSM Returns

[Figure C.1 about here.]

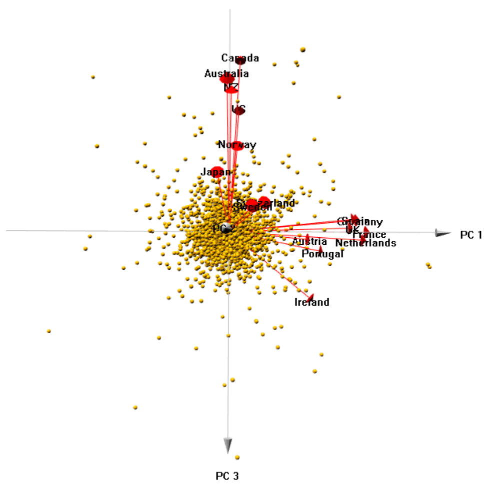
Figures



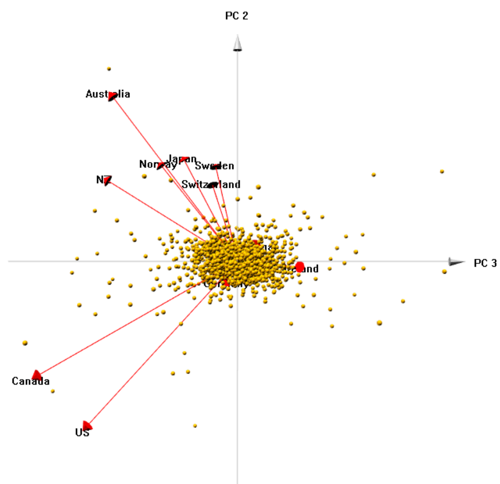
Panel A: Variance Explained



Panel B: Front View



Panel C: Top View



Panel D: End View

Figure 1: **Global Principal Component Analysis**

Plotted are the results of global principal component analysis. Panel A depicts the proportional eigenvalues associated with each eigenvector. It shows how much variance is explained by each principal component. The proportional values (in percentage) are stated above the bars. Panel B to D are the front view, top view, and end view of the rotated data plotted in a 3-D space of which the axes are the PC1, PC2, and PC3 respectively. Each point represents a rotated observation whereas the arrows are the projection of original return series onto the new principal component space, implying the relation of the series and the PCs. Data are normalized and standardized and the sample period spans from 04 October 2005 to 29 December 2017.

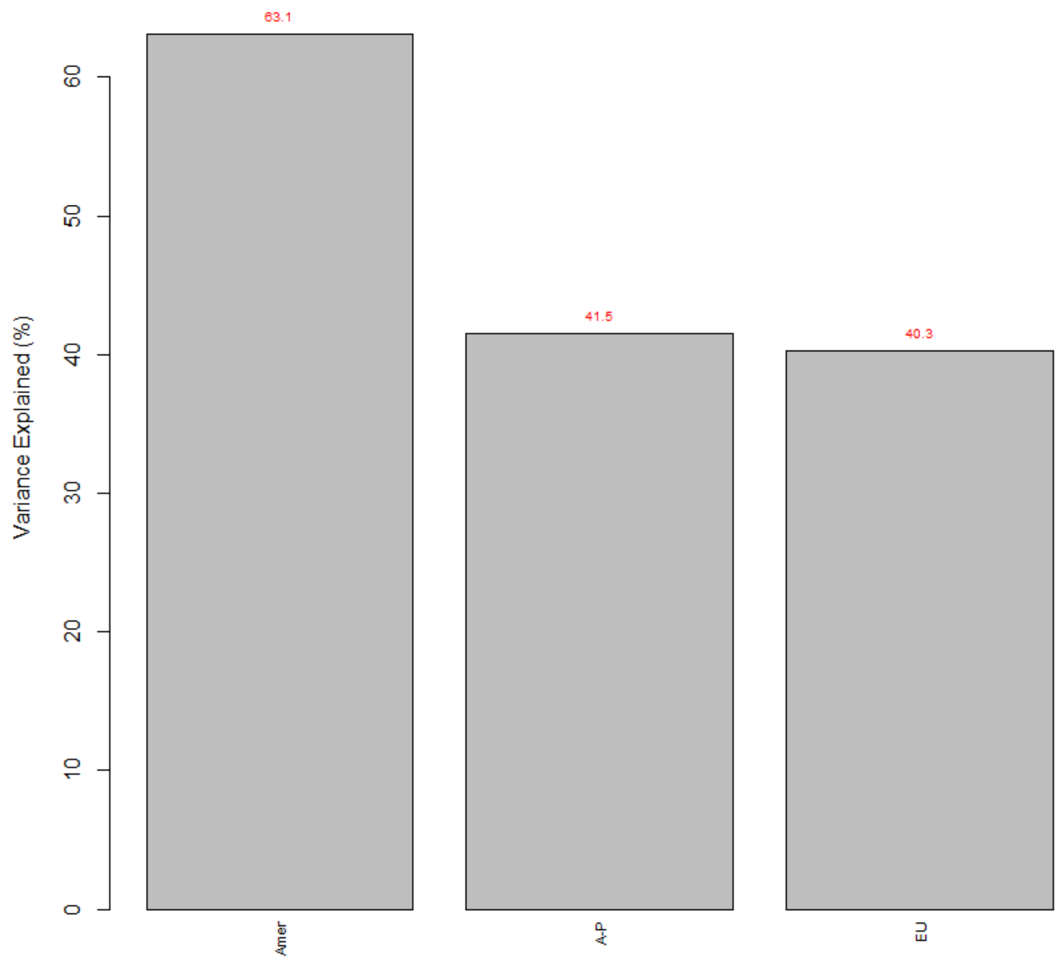


Figure 2: **Regional First Principal Components**

Plotted are the first principal components obtained from the regional principal component analysis which is applied to three geographical sub-samples, namely, American countries (Amer), Asia-Pacific countries (A-P), and European countries (EU). Data are normalized and standardized and the sample period spans from 04 October 2005 to 29 December 2017.

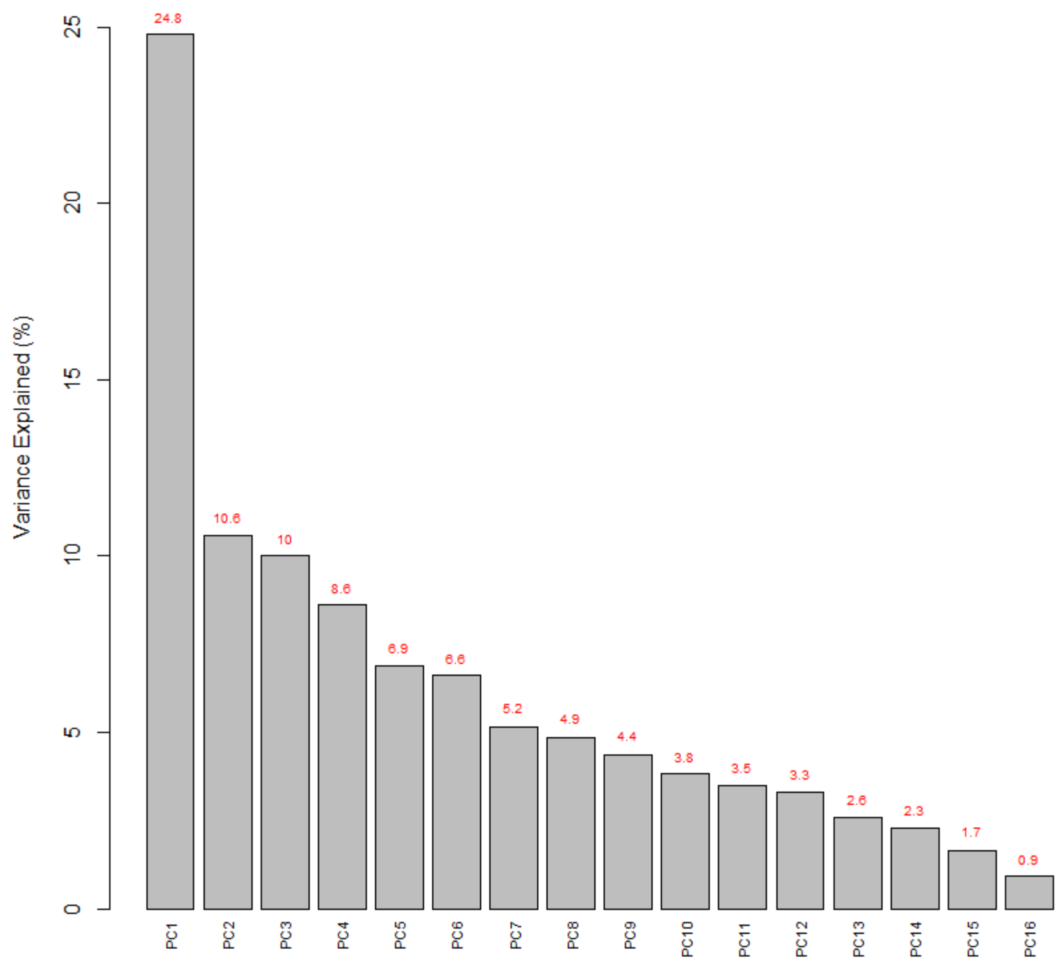


Figure C.1: **Principal Component Analysis With Monthly Aggregated ITSM Returns**

Plotted are the proportional eigenvalues associated with each eigenvector obtained from the principal component analysis on monthly aggregated ITSM returns. It shows how much variance is explained by each principal component. The proportional values (in percentage) are stated above the bars. Data are normalized and standardized and the sample period spans from 04 October 2005 to 29 December 2017.

Tables

Table 1: Indices

	Index	**RIC**	**Trading Hours (local time)**
Australia	S&P ASX 200	.AXJO	10:00 - 16:00
Austria	Austrian Traded Index	.ATX	09:00 - 17:30
Canada	S&P/TSX Composite Index	.GSPTSE	09:30 - 16:00
France	CAC 40 Stock Market Index	.FCHI	09:00 - 17:30
Germany	DAX PERFORMANCE-INDEX	.GDAXI	09:00 - 17:30
Ireland	ISEQ Overall Index	.ISEQ	08:00 - 16:30
Japan	Nikkei Stock Average 225	.N225	09:00 - 15:00
Netherlands	AEX Amsterdam Index	.AEX	09:00 - 17:30
New Zealand	NZX 50 Index Gross	.NZ50	10:00 - 18:00
Norway	Oslo Exchange All-share Index	.OSEAX	09:00 - 16:30
Portugal	PSI 20 INDEX	.PSI20	08:00 - 16:30
Spain	Ibex 35 Index	.IBEX	09:00 - 17:30
Sweden	OMX Stockholm All-share Index	.OMXSPI	09:00 - 17:30
Switzerland	SMI Index	.SSMI	09:00 - 17:30
United Kingdom	FTSE 100	.FTSE	08:00 - 16:30
United States	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	3104	7.826	22.508	-0.009	3.028
	Last	3104	5.105	5.866	-0.042	3.068
Austria	First	3050	22.191	19.346	0.007	3.067
	Last	3050	15.379	6.714	0.108	3.093
Canada	First	3073	8.538	11.345	0.029	3.067
	Last	3073	4.185	4.586	-0.007	3.135
France	First	3136	8.995	16.940	-0.023	3.053
	Last	3136	3.363	5.821	-0.006	3.023
Germany	First	3110	12.817	16.504	-0.036	3.042
	Last	3110	3.357	5.457	0.016	3.047
Ireland	First	3102	21.124	18.074	0.113	3.236
	Last	3102	6.557	6.646	0.027	3.070
Japan	First	3003	18.465	25.601	-0.011	3.021
	Last	3003	1.838	6.093	0.041	3.120
Netherlands	First	3134	12.490	15.879	-0.020	3.048
	Last	3134	2.459	5.363	-0.023	3.028
Norway	First	3075	20.800	12.765	-0.023	3.025
	Last	3075	4.453	7.491	-0.013	3.046
NZ	First	3078	3.153	16.875	-0.005	3.045
	Last	3078	1.289	1.549	0.038	3.034
Portugal	First	3134	16.246	15.676	-0.029	3.060
	Last	3134	8.974	5.177	-0.026	3.019
Spain	First	3124	5.731	17.656	-0.023	3.067
	Last	3124	11.022	5.651	-0.011	3.019
Sweden	First	3076	0.342	11.977	-0.014	3.020
	Last	3076	7.634	4.391	-0.016	3.021
Switzerland	First	3079	11.001	12.806	0.020	3.045
	Last	3079	-2.272	5.276	-0.019	3.035
UK	First	3102	9.201	15.108	-0.061	3.087
	Last	3102	1.733	5.211	0.020	3.024
US	First	3082	2.867	11.343	-0.022	3.023
	Last	3082	0.697	5.850	-0.013	3.094

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 period spans from 04 October 2005 to 29 December 2017. Note that the number of available trading days varies from country to country due to different holiday systems and data availability limitations. The mean, standard deviation, skewness and kurtosis are annualized. For the calculation of the annualized third and fourth moments see Appendix A.

Table 3: Predictability and Market Conditions

	Intercept	β^F	$Adj.R^2$ (%)	*Intercept*	β^F	$Adj.R^2$ (%)	*Intercept*	β^F	$Adj.R^2$ (%)	*Intercept*	β^F	$Adj.R^2$ (%)	*Intercept*	β^F	$Adj.R^2$ (%)
	Panel A: Full Sample			**Panel B: Financial Crisis**			**Panel C: Excluding Financial Crisis**			**Panel D: Recession**			**Panel E: Expansion**		
Australia	4.69***	3.98***	2.31	13.33*	4.76**	3.01	3.54***	3.37***	1.69	5.97***	3.48***	1.70	2.50	5.06***	3.88
	(3.22)	(4.05)		(1.91)	(2.26)		(2.65)	(3.94)		(3.08)	(2.62)		(1.12)	(3.63)	
Austria	15.22***	1.13	0.07	34.77***	0.36	-0.25	12.25***	1.69**	0.22	21.15***	1.21	0.02	11.80***	1.09	0.06
	(6.68)	(0.84)		(3.09)	(0.13)		(6.59)	(2.39)		(4.62)	(0.49)		(5.19)	(1.30)	
Canada	4.28***	-0.71	0.00	14.64*	2.62	0.06	2.99***	-3.03***	0.73	8.38***	0.52	-0.06	1.36	-3.08**	0.62
	(3.00)	(-0.46)		(1.83)	(0.87)		(2.73)	(-3.05)		(3.15)	(0.25)		(0.97)	(-2.40)	
France	2.96	4.83***	1.94	10.51	7.81***	5.91	2.13	3.03***	0.67	6.57**	5.15***	2.53	0.50	4.29***	1.17
	(1.63)	(4.87)		(1.32)	(3.96)		(1.25)	(3.41)		(1.97)	(3.76)		(0.26)	(3.38)	
Germany	2.97*	2.97***	0.78	-0.56	5.14**	2.41	3.76**	1.63*	0.19	3.33	3.46**	1.04	2.91	2.32**	0.42
	(1.74)	(3.25)		(-0.07)	(2.44)		(2.32)	(1.91)		(1.01)	(2.26)		(1.58)	(2.30)	
Ireland	6.24***	1.18	0.07	-3.12	-0.25	-0.25	7.27***	2.76**	0.37	6.08**	-0.16	-0.06	4.98	6.72***	1.65
	(3.04)	(1.28)		(-0.34)	(-0.18)		(3.63)	(2.52)		(2.16)	(-0.17)		(1.62)	(4.38)	
Japan	1.06	4.14***	2.97	7.22	7.40***	8.88	0.65	2.32***	0.94	0.00	5.94***	5.98	2.39	1.93***	0.61
	(0.72)	(4.07)		(1.05)	(3.71)		(0.44)	(2.89)		(0.00)	(3.85)		(1.21)	(2.74)	
Netherlands	2.16	4.04***	1.42	4.90	7.97***	5.71	2.23	1.24	0.09	6.07	5.61***	2.83	1.17	2.32**	0.40
	(1.33)	(3.77)		(0.65)	(4.16)		(1.53)	(1.51)		(1.45)	(3.34)		(0.75)	(2.24)	
Norway	3.26	5.44***	0.83	-2.81	8.09*	0.94	4.29**	4.18***	0.67	3.60	7.21***	1.07	2.92	3.19**	0.44
	(1.55)	(3.40)		(-0.23)	(1.95)		(2.48)	(3.47)		(1.00)	(2.74)		(1.27)	(2.42)	
NZ	1.42***	0.08	-0.03	-0.24	-0.28	-0.14	1.65***	0.33	0.07	1.33**	0.01	-0.06	1.52**	0.22	-0.03
	(3.03)	(0.25)		(-0.12)	(-0.43)		(3.73)	(1.37)		(1.97)	(0.02)		(2.51)	(0.64)	
Portugal	8.62***	2.21**	0.42	10.59	3.78**	1.28	8.49***	1.45	0.14	10.92***	1.86	0.19	7.70***	2.54**	0.56
	(5.37)	(2.48)		(1.56)	(2.31)		(5.34)	(1.40)		(2.72)	(1.29)		(4.66)	(2.18)	
Spain	10.80***	3.71***	1.31	16.70**	6.87***	4.67	10.13***	2.24**	0.44	17.32***	4.27***	1.77	7.37***	3.09**	0.85
	(6.08)	(3.73)		(2.24)	(3.29)		(6.03)	(2.20)		(4.83)	(2.79)		(4.05)	(2.51)	
Sweden	7.75***	2.89**	0.59	12.24*	-0.11	-0.26	6.97***	4.47***	1.52	10.27***	1.99	0.20	5.62***	4.24***	1.41
	(5.29)	(2.46)		(1.94)	(-0.04)		(5.31)	(4.29)		(4.04)	(1.15)		(3.58)	(3.08)	
Switzerland	-2.66	3.40**	0.65	-3.99	6.12**	2.13	-2.31	1.68*	0.12	-0.50	4.94**	1.49	-3.94**	0.69	-0.03
	(-1.49)	(2.39)		(-0.53)	(2.17)		(-1.39)	(1.66)		(-0.15)	(2.48)		(-2.15)	(0.59)	
UK	1.36	4.18***	1.44	11.04	6.88***	4.05	0.22	2.28**	0.38	5.64	5.89***	3.39	0.16	1.64	0.14
	(0.83)	(3.61)		(1.36)	(3.29)		(0.15)	(2.48)		(1.22)	(3.66)		(0.11)	(1.60)	
US	0.14	9.57***	3.41	4.80	18.28***	7.53	0.20	4.28**	1.05	0.59	13.49***	5.55	0.38	4.09*	0.84
	(0.09)	(3.45)		(0.53)	(3.14)		(0.17)	(2.46)		(0.21)	(3.22)		(0.24)	(1.75)	
Pooled	3.97**	2.68***	0.78	5.83	3.71***	1.18	3.84**	2.09***	0.63	–	–	–	–	–	–
	(2.19)	(7.53)		(0.61)	(4.60)		(2.41)	(7.28)		–	–	–	–	–	–

This table presents the in-sample over the full sample period (Panel A) as well as over various market conditions, namely financial crisis (Panel B), non-crisis period (Panel C), recession (Panel D), and expansion (Panel E). 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 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 FRED St. Louis website. The returns are annualized and in percentage. 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 period spans from 04 October 2005 to 29 December 2017. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Table 4: Out-of-sample Analysis

	$Ave.Intercept$	$Ave.\beta^F$	R^2_{OOS}	$Rst.R^2_{OOS}$	$MSPE-adj.$	ENC_{NEW}
Australia	5.36***	4.49***	1.23	1.10	3.38***	46.14**
Austria	16.02***	1.19	0.14	0.12	1.60*	2.56**
Canada	6.12***	0.00	-0.14	-0.25	-0.84	-1.09
France	3.88	5.97***	-0.35	0.22	2.34***	27.81**
Germany	2.79	3.62***	-0.64	0.11	1.02	7.32**
Ireland	5.73**	1.42	0.18	0.15	1.70**	3.01**
Japan	3.78*	5.04***	-0.20	-1.32	2.41***	47.25**
Netherlands	2.52	5.35***	-2.39	-0.79	0.60	6.08**
Norway	1.85	5.92***	0.92	1.08	3.10***	19.84**
NZ	1.41**	0.12	-0.03	-0.02	-0.25	-0.16
Portugal	7.91***	3.14***	-0.25	-0.03	1.01	7.97**
Spain	12.63***	4.60***	-0.28	0.19	1.72**	22.19**
Sweden	9.57***	2.17	1.18	0.90	3.36***	16.23**
Switzerland	-3.23	3.84**	-0.01	0.05	1.56*	8.69**
UK	2.25	4.96***	-1.25	-0.58	1.00	10.82**
US	0.99	11.67***	-3.10	0.25	2.07**	68.57**

This table reports the individual out-of-sample analysis. Using the first five years (2005-2010) as the initial estimation period, we recursively estimate the predictive regression in each market 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). The last four columns report Campbell and Thompson (2008) R^2_{OOS}, $Rst.R^2_{OOS}$, 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) $MSPE-adjusted$. For ENC_{NEW}, we use critical values of 1.280 and 2.085 for 5% and 10% confidence levels, given by Clark and McCracken (2001). The slope coefficients are scaled by 100. The sample period spans from 04 Oct 2005 to 29 Dec 2017. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Table 5: Economic Significance of Individual Intraday Time Series Momentum

	Strategy	Mean (%)	SD (%)	Skewness	Kurtosis	Sharpe	ρ	α (%)	ARatio
Australia	ITSM	2.971	5.823	0.047	3.075	0.510			
	AL	4.152	5.820	-0.084	3.077	0.713	-0.099	3.384	0.584
	BH	3.594	25.612	-0.026	3.019	0.140	0.019	2.956	0.508
Austria	ITSM	2.209	6.807	-0.112	3.107	0.324			
	AL	15.198	6.740	0.113	3.107	2.255***	-0.071	3.293	0.485
	BH	3.242	29.034	-0.001	3.020	0.112	0.077	2.150	0.317
Canada	ITSM	-1.668	4.227	-0.019	3.045	-0.395			
	AL	4.275	4.220	0.084	3.045	1.013***	-0.047	-1.466	-0.347
	BH	4.979	15.985	0.004	3.040	0.311	0.064	-1.751	-0.415
France	ITSM	5.149	5.920	0.008	3.018	0.870			
	AL	2.810	5.926	-0.009	3.018	0.474	-0.053	5.298***	0.896
	BH	4.836	25.805	0.012	3.023	0.187	0.048	5.095***	0.862
Germany	ITSM	4.105	5.591	0.053	3.051	0.734			
	AL	3.764	5.592	0.027	3.051	0.673	-0.031	4.222**	0.756
	BH	7.253	24.763	-0.005	3.017	0.293	0.053	4.019**	0.720
Ireland	ITSM	3.297	6.421	0.014	3.031	0.513			
	AL	4.435	6.418	-0.055	3.032	0.691	-0.036	3.455*	0.538
	BH	3.980	25.516	-0.033	3.031	0.156	-0.027	3.324	0.518
Japan	ITSM	4.416	6.142	-0.014	3.117	0.719			
	AL	3.279	6.145	0.113	3.116	0.534	-0.052	4.586**	0.748
	BH	12.865	31.756	-0.010	3.028	0.405	-0.027	4.483**	0.730
Netherlands	ITSM	2.378	5.412	0.016	3.025	0.439			
	AL	1.824	5.413	-0.027	3.025	0.337	-0.095	2.552	0.474
	BH	1.090	23.888	-0.007	3.030	0.046	-0.037	2.387	0.441
Norway	ITSM	7.328	7.529	0.008	3.053	0.973			
	AL	4.193	7.539	-0.036	3.053	0.556	-0.028	7.446***	0.990
	BH	5.724	21.902	-0.026	3.022	0.261*	0.024	7.280***	0.967
NZ	ITSM	0.495	1.513	0.036	3.022	0.327			
	AL	1.618	1.510	0.013	3.022	1.071	0.030	0.445	0.295
	BH	9.980	19.145	-0.021	3.028	0.521	0.071	0.439	0.291
Portugal	ITSM	3.133	5.305	-0.004	3.018	0.591			
	AL	8.792	5.280	-0.026	3.019	1.665**	-0.009	3.213*	0.606
	BH	-1.277	23.890	0.010	3.020	-0.053	0.067	3.152*	0.596
Spain	ITSM	3.323	5.784	0.008	3.016	0.575			
	AL	11.157	5.745	-0.006	3.017	1.942***	0.015	3.159*	0.546
	BH	9.208	27.886	0.026	3.026	0.330	0.123	3.088*	0.538
Sweden	ITSM	2.531	4.391	-0.016	3.017	0.576			
	AL	7.483	4.368	-0.008	3.018	1.713**	-0.057	2.958*	0.675
	BH	3.762	19.740	-0.003	3.009	0.191	0.009	2.523	0.575
Switzerland	ITSM	0.326	5.262	-0.037	3.038	0.062			
	AL	-1.503	5.261	-0.002	3.038	-0.286	-0.020	0.296	0.056
	BH	-1.716	22.534	-0.065	3.111	-0.076	0.087	0.361	0.069
UK	ITSM	2.605	5.134	0.014	3.018	0.507			
	AL	1.077	5.136	0.009	3.018	0.210	-0.047	2.656*	0.518
	BH	0.841	22.144	0.008	3.036	0.038	0.038	2.598*	0.506
US	ITSM	6.567	5.892	0.086	3.099	1.115			
	AL	0.033	5.907	-0.028	3.099	0.006**	-0.106	6.570**	1.122
	BH	7.465	19.411	-0.032	3.045	0.385	-0.045	6.669**	1.133

This table presents the performance of intraday time-series momentum (i.e. ITSM) along with two benchmark strategies, *Always-long* (i.e.AL) and *Buy-and-hold* (i.e.BH), for each of the 16 equity markets. ITSM 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 *Always-long* strategy takes always a long position in the last half hour every trading day and the *Buy-and-hold* strategy holds the asset from the beginning until the end of the sample period. We report the Mean, Standard Deviation (SD), Skewness, Kurtosis and the Sharpe ratio for each strategy and market. The table also presents the correlation (ρ) between the ITSM and the benchmark strategies returns. The α and appraisal ratio (ARatio) are based on the regression: $r_{I,t} = \alpha + \beta r_{benchmark,t} + \epsilon_t$, where $r_{I,t}$ and $r_{benchmark,t}$ are returns from ITSM and benchmark strategies, respectively. The appraisal ratio is computed as α/σ_ϵ where σ_ϵ is the standard error of the regression. Standard errors are adjusted using Newey and West (1987).We test the hypothesis that the Sharpe ratios of the ITSM and the AL or BH strategies are equal following Ledoit and Wolf (2008). We use Newey-West (1987) standard errors for the statistical significance of alpha. Mean, Standard Deviation (SD), Skewness, Kurtosis, Sharpe ratio, and α's are annualized. *, **, and *** denote significance at 10%, 5%, and 1% confidence levels, respectively. The sample period spans from 04 October 2005 to 29 December 2017.

Table 6: Correlation Matrix

	Australia	Austria	Canada	France	Germany	Ireland	Japan	Netherlands	Norway	NZ	Portugal	Spain	Sweden	Switzerland	UK	US
Australia	1.00															
Austria	-0.04	1.00														
Canada	0.04	0.08	1.00													
France	-0.01	0.37	0.04	1.00												
Germany	-0.02	0.35	0.08	0.78	1.00											
Ireland	-0.03	0.27	-0.03	0.39	0.34	1.00										
Japan	0.14	-0.08	-0.05	-0.04	-0.09	-0.05	1.00									
Netherlands	0.02	0.33	0.02	0.79	0.69	0.40	-0.02	1.00								
Norway	0.07	0.05	0.04	0.02	0.01	0.02	0.07	0.00	1.00							
NZ	0.19	0.01	0.01	0.01	0.01	-0.04	0.03	0.01	0.00	1.00						
Portugal	0.00	0.27	-0.02	0.44	0.39	0.27	0.02	0.45	0.06	0.03	1.00					
Spain	0.00	0.36	0.04	0.67	0.63	0.33	0.00	0.60	0.06	0.04	0.42	1.00				
Sweden	0.05	0.05	-0.05	0.10	0.10	0.02	-0.02	0.07	0.10	0.00	0.03	0.12	1.00			
Switzerland	0.04	0.09	0.02	0.15	0.17	0.06	-0.06	0.11	0.08	0.00	0.04	0.11	0.19	1.00		
UK	0.03	0.29	0.05	0.63	0.59	0.35	-0.01	0.67	0.02	-0.01	0.31	0.54	0.08	0.19	1.00	
US	-0.13	-0.01	0.26	0.07	0.09	-0.02	-0.02	0.04	-0.03	0.01	0.00	0.05	-0.01	-0.05	0.02	1.00

Reported are Pearson correlation coefficients between individual intraday time-series momentum strategy returns. The sample period spans from 04 October 2005 to 29 December 2017.

Table 7: Cross-country Relation of ITSM

	Panel A: Global Common Variation					**Panel B:** Predictability of r^F_{US}			
	α	β_t	β_{t+1}	β_{t-1}	$Adj.R^2$ (%)	α	β_{US}	β_{local}	$\Delta_{Adj.R^2}$ (%)
Australia	5.75***	18.30**	-17.58**	3.93	1.14	4.79***	**-2.48**	4.35***	0.07
	(3.16)	(2.03)	(-2.11)	(0.40)		(3.14)	(-1.46)	(3.90)	
Austria	0.3	96.69***	6.46	-18.76	12.39	14.90***	**4.70****	0.25	0.54
	(0.16)	(11.77)	(0.66)	(-1.60)		(6.24)	(2.38)	(0.17)	
Canada	-1.04	10.95	-14.23	4.48	0.97	4.14***	-0.63	-0.76	0.02
	(-0.90)	(1.17)	(-1.48)	(0.51)		(2.78)	(-0.45)	(-0.52)	
France	0.01	179.83***	-5.74	-1.2	52.9	3.10	**4.64*****	3.59***	0.65
	(0.01)	(23.22)	(-1.23)	(-0.18)		(1.64)	(3.09)	(3.76)	
Germany	-2.46**	147.24***	6.84	16.14	41.62	3.24*	**2.99****	1.89*	0.17
	(-2.24)	(16.26)	(1.33)	(1.36)		(1.80)	(2.05)	(1.94)	
Ireland	0.01	87.88***	1.11	6.94	10.42	5.89***	**6.77*****	-0.07	1.25
	(0.01)	(9.70)	(0.13)	(1.07)		(2.85)	(4.48)	(-0.07)	
Japan	5.14***	-2.66	19.22*	3.97	0.61	1.45	0.71	4.04***	0.12
	(2.71)	(-0.43)	(1.87)	(0.45)		(0.91)	(0.37)	(3.70)	
Netherlands	-2.52**	155.87***	-7.75	-5.86	47.38	2.21	**3.84****	2.89***	0.48
	(-2.16)	(23.78)	(-1.64)	(-1.41)		(1.33)	(2.43)	(2.82)	
Norway	6.06***	32.86***	11.4	-6.08	1.32	3.35	**13.58*****	2.68	3.85
	(3.02)	(2.97)	(1.20)	(-0.61)		(1.54)	(6.36)	(1.61)	
NZ	0.47	2.75	2.44	-2.95	0.51	1.33***	-0.35	0.14	0.01
	(0.95)	(1.59)	(1.32)	(-1.22)		(2.74)	(-0.79)	(0.44)	
Portugal	-0.19	88.03***	-11.82*	-4.95	17.44	9.25***	0.95	1.88**	-0.04
	(-0.13)	(11.18)	(-1.68)	(-0.93)		(5.58)	(0.77)	(2.00)	
Spain	-2.43*	154.91***	-0.26	-4.62	41.36	10.83***	**2.36**	3.16***	0.18
	(-1.98)	(27.86)	(-0.06)	(-0.95)		(5.82)	(1.60)	(3.19)	
Sweden	2.57*	25.95***	-0.41	-11.73*	2.62	7.82***	**4.51*****	2.03*	1.29
	(1.84)	(4.38)	(-0.08)	(-1.81)		(5.20)	(4.52)	(1.67)	
Switzerland	-0.88	42.95***	-3.42	4.46	4.23	-2.89	1.49	3.04**	0.06
	(-0.64)	(4.89)	(-0.54)	(0.72)		(-1.56)	(1.08)	(2.01)	
UK	-0.44	130.3***	2.55	4.39	36.5	1.62	**2.58****	3.52***	0.34
	(-0.35)	(22.66)	(0.55)	(1.03)		(0.96)	(2.17)	(2.99)	
US	5.69***	8.66	12.35	6.42	0.43	–	–	–	–
	(2.77)	(1.01)	(0.93)	(0.96)		–	–	–	–
Average	1.00	73.78	0.07	-0.34	–	–	–	–	–

Panel A reports the results of global the comovement analysis: $r_{I,i,t} = \alpha_i + \beta_t r_{I,g,t} + \beta_{t+1} r_{I,g,t+1} + \beta_{t-1} r_{I,g,t-1} + \epsilon_{i,t}$, where $r_{I,i,t}$ is the ITSM return for market i at time t, $r_{I,g,t}$ is the contemporaneous equally-weighted ITSM return of all markets excluding market i, $r_{I,g,t+1}$ is the equally-weighted ITSM return for all markets excluding market i at $t+1$, and $r_{I,g,t-1}$ is the equally-weighted ITSM return for all markets excluding market i at $t-1$. In Panel B, we study the predictive power of the US first half-hour return (r^F_{US}) on the last half-hour returns of other countries, after controlling for those countries' own first half-hour return. For most of the countries, we regress the following model: $r^L_{local,t} = \alpha + \beta_{local} r^F_{local,t} + \beta_{US} r^F_{US,t} + \epsilon_t$. For Australia, Japan, and New Zealand, whose markets close before the US market open on the same calendar day, we use the US first half-hour return from the previous day:$r^L_{local,t} = \alpha + \beta_{local} r^F_{local,t} + \beta_{US} r^F_{US,t-1} + \epsilon_t$. We also test the null hypothesis that there is no predictability of r^F_{US} using wild bootstrapped data, and report β_{US}s in bold if reject the null at 10% confidence level. The last column of Panel B ($\Delta_{Adj.R^2}$) gives the increase of the adjusted R^2 in Equation (2) after including r^F_{US}. The returns are annualized and in percentage, the Newey and West (1987) t values are reported in parentheses, the βs are scaled by 100. The sample period spans from 04 October 2005 to 29 December 2017. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Table 8: Investing Intraday Time Series Momentum Globally

	Type (1) GITSM						**Type (2) GITSM**						**Type (3) GITSM**					
	EW	VW	IV	MD	MV	MinV	EW	VW	IV	MD	MV	MinV	EW	VW	IV	MD	MV	MinV
							Panel A: Global Portfolio Performance											
AVE (%)	3.06***	4.75***	0.77	1.48***	2.02	0.43	2.78***	2.71***	1.50**	1.35**	0.45	1.47**	5.17***	5.71***	1.18*	1.90***	6.75***	0.62
	(4.15)	(3.22)	(1.51)	(2.79)	(1.11)	(0.93)	(3.83)	(2.88)	(2.32)	(2.11)	(0.45)	(2.28)	(5.47)	(3.65)	(1.91)	(3.23)	(2.94)	(1.37)
SD (%)	2.43	3.22	1.21	1.18	3.81	1.03	2.01	2.41	1.47	1.44	2.39	1.46	2.93	3.51	1.39	1.31	5.36	1.09
Skewness	0.01	0.10	0.01	0.03	-0.04	0.00	0.05	0.04	0.02	0.02	0.00	0.02	0.03	0.10	0.01	0.03	0.02	-0.01
Kurtosis	3.03	3.10	3.01	3.01	3.06	3.02	3.05	3.06	3.01	3.01	3.03	3.01	3.03	3.10	3.01	3.01	3.02	3.02
Sharpe	1.26	1.48	0.64	1.26	0.53	0.42	1.38	1.12	1.02	0.94	0.19	1.01	1.77	1.63	0.85	1.44	1.26	0.57
							Panel B: Spanning Alphas (GITSM vs ITSM)											
Australia	2.84***	4.75***	0.60	1.24**	2.13	0.33	2.43***	2.58***	1.06*	0.94	0.37	1.02*	4.59***	5.39***	1.06*	1.83***	7.11***	0.57
Austria	2.66***	4.62***	0.40	1.17**	1.35	0.30	2.59***	2.51**	1.10*	0.99	-0.24	1.10*	4.44***	5.17***	0.93	1.73***	6.85***	0.56
Canada	3.25***	5.13***	0.97*	1.82***	2.69	0.66	3.18***	3.33***	1.95***	1.90***	0.97	1.93***	4.73***	5.58***	1.21*	2.05***	7.16***	0.70
France	1.40***	3.69***	0.45	1.31***	1.09	0.34	1.93***	1.86**	1.19**	1.07*	-0.12	1.18**	3.82***	4.68***	0.95	1.76***	6.89***	0.56
Germany	1.74***	3.86***	0.60	1.39***	1.66	0.39	2.09***	1.98**	1.33**	1.20**	0.15	1.32**	3.91***	4.67***	1.01*	1.81***	7.01***	0.57
Ireland	2.44***	4.54***	0.76	1.48***	2.02	0.43	2.52***	2.46***	1.49**	1.35**	0.44	1.47**	4.29***	5.12***	1.09*	1.86***	7.05***	0.60
Japan	2.84***	4.26***	0.70	1.26***	2.08	0.32	2.30***	2.53***	1.15**	1.02*	0.41	1.12**	4.76***	5.43***	1.11*	1.91***	7.16***	0.61
Netherlands	2.27***	4.27***	0.82*	1.51***	2.15	0.45	2.38***	2.32**	1.55**	1.40**	0.55	1.52**	4.27***	5.02***	1.11*	1.87***	7.07***	0.60
Norway	2.42***	4.63***	0.57	1.08**	1.85	0.31	2.40***	2.38**	1.16*	1.06*	0.15	1.15*	4.62***	5.28***	1.13*	1.86***	5.63**	0.63
NZ	3.00***	4.71***	0.86**	1.55***	2.03	0.56**	2.67***	2.65***	1.54**	1.39**	0.47	1.52**	4.56***	5.19***	1.10*	1.88***	7.10***	0.62
Portugal	2.29***	4.43***	0.47	1.29***	1.49	0.32	2.41***	2.37**	1.24**	1.12*	-0.06	1.23**	4.32***	5.13***	0.97	1.76***	7.00***	0.55
Spain	2.05***	4.15***	0.48	1.33**	1.43	0.36	2.25***	2.19**	1.21**	1.09*	-0.06	1.20**	4.17***	4.96***	0.96	1.77***	6.86***	0.55
Sweden	2.73***	4.65***	0.28	0.83*	1.58	0.04	2.63***	2.59***	1.06*	0.96	-0.40	1.06*	4.46***	5.18***	0.88	1.64***	6.39***	0.53
Switzerland	3.02***	4.73***	0.62	1.30**	2.01	0.31	2.76***	2.69***	1.39**	1.26**	0.24	1.38**	4.56***	5.21***	1.05*	1.84***	7.19***	0.59
UK	2.22***	4.17***	0.87**	1.54***	2.20	0.47	2.34***	2.28**	1.59***	1.44**	0.62	1.57***	4.20***	5.00***	1.13*	1.89***	7.08***	0.61
US	2.58***	1.58***	0.70	1.31***	0.89	0.35	1.56***	0.72	1.28**	1.06*	0.09	1.25**	3.64***	1.79***	0.94	1.62***	6.68***	0.51
							Panel C: Spanning Alphas (ITSM vs GITSM)											
Australia	1.63	3.00	2.44	1.38	3.08	2.72	0.17	2.28	1.07	1.31	2.94	1.02	3.09	3.85*	2.90	2.79	3.07	2.91
Austria	-2.28	0.94	2.12	1.13	2.84	3.13*	-0.58	0.26	1.53	1.80	3.13*	1.65	0.69	1.77	2.89	2.48	3.16	3.38*
Canada	-2.71**	-3.54***	-3.26**	-4.00***	-3.22**	-3.22**	-4.62***	-4.74***	-3.86***	-3.99***	-3.07**	-3.87***	-2.56*	-3.35**	-3.15**	-3.55***	-3.02**	-3.09**
France	-0.77	1.81	-0.17	-0.46	0.30	1.49	1.13	2.42	-0.79	-0.38	1.42	-0.61	2.33	3.57*	0.96	0.66	1.48	1.76
Germany	-1.15	0.98	-0.83	-1.06	-0.05	0.62	0.46	1.50	-1.39	-1.04	0.53	-1.23	1.31	2.32	0.06	-0.13	0.77	0.73
Ireland	-0.79	2.09	-1.13	-2.32	-0.51	-0.33	1.00	1.85	-1.64	-1.36	-0.29	-1.52	1.35	2.77	-0.39	-0.56	-0.16	-0.01
Japan	3.37	2.42	2.18	-0.02	2.62	2.04	1.53	3.66*	0.02	0.30	2.51	-0.06	5.24**	5.17**	2.66	3.13	2.81	2.61
Netherlands	-2.80**	-0.35	-2.01	-2.07	-1.37	-0.70	-1.11	0.10	-2.40	-2.09	-0.77	-2.25	0.28	1.33	-1.13	-1.24	-0.56	-0.47
Norway	4.74*	6.91***	8.05***	6.93***	8.33***	8.24***	5.31**	6.16**	7.61***	7.77***	8.33***	7.66***	7.54***	7.55***	8.48***	8.40***	7.21***	8.46***
NZ	0.33	0.41	-0.64	-0.80	-0.20	-0.64**	0.14	0.36	-0.46	-0.44	-0.20	-0.47	0.45	0.44	-0.27	-0.34	-0.29	-0.31
Portugal	-0.51	1.80	1.18	0.75	1.93	2.20	0.78	1.70	0.98	1.24	2.25	1.10	1.84	2.80*	1.99	1.58	2.49	2.39
Spain	-1.98	0.55	0.42	0.30	1.20	1.80	-0.36	0.89	-0.12	0.22	1.69	0.03	1.12	2.25	1.31	1.04	1.59	1.88
Sweden	1.24	2.22	3.77**	2.46*	4.35***	4.07**	1.80	2.16	3.65**	3.77**	4.34***	3.70**	2.08	2.45	4.19***	3.84**	4.05**	4.44***
Switzerland	-1.66	-0.27	1.28	0.04	2.02	1.56	-0.79	-0.33	1.33	1.48	1.88	1.38	-0.47	0.30	1.81	1.88	2.39	2.01
UK	-1.87	-0.08	-2.06	-2.29	-1.25	-0.99	-0.48	0.58	-2.43*	-2.14	-0.97	-2.31*	0.54	1.67	-1.32	-1.43	-0.79	-0.73
US	5.22**	-1.18	1.81	0.82	0.96	1.83	2.10	1.60	1.01	0.77	1.85	0.99	3.84	-1.24	1.48	0.28	1.42	1.75

This table presents the performance of global intraday time-series momentum strategies (GTISM). Three types of GITSM are studied: (1) GITSM based on individual ITSMs; (2) GITSM based on regional ITSMs; (3) GITSM based on cross-sectional predictability of US first half-hour return. See text for a detailed description. Panel A reports the portfolio performance of each type of GITSM constructed using six teqhniques, namely, equally-weighted (EW), value-weighed (VW), inverse-variance (IV), maximum-diversification (MD), mean-variance (MV) and minimum-variance (MinV). The equally-weighted and value-weighted portfolios are based on the full sample period (04/10/2005 - 29/12/2017), whereas the first five years (04/10/2005 - 01/10/2010) are treated as the initial estimation period for the remaining techniques, in which we use an expanding window approach. Panel B reports the alphas of spanning regressions of GITSM against individual ITSM, while Panel C reports the alphas when the regressand and regressor are reversed. In parentheses, we report the Newey and West (1987) t-statistics for strategy returns that are annualized and in percentage. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, after Newey and West (1987) corrections.

Table 9: Factor Exposure of GITSM on Fama-French Pricing Models

	Panel A: Without TVC					**Panel B:** TVC included				
	CAPM	FF3	FF3+MOM	FF5	FF5+MOM	CAPM	FF3	FF3+MOM	FF5	FF5+MOM
Intercept	2.911***	2.897***	2.907***	2.973***	2.973***	-0.365	-0.387	-0.344	-0.149	-0.145
	(3.85)	(3.83)	(3.81)	(3.83)	(3.83)	(-0.41)	(-0.43)	(-0.38)	(-0.16)	(-0.16)
Market	0.011	0.008	0.008	0.007	0.007	-0.009	-0.002	-0.003	-0.009	-0.009
	(1.42)	(1.03)	(1.04)	(0.82)	(0.82)	(-1.34)	(-0.24)	(-0.35)	(-1.07)	(-1.07)
SMB		-0.004	-0.004	-0.007	-0.007		0.026	0.027	0.020	0.021
		(-0.34)	(-0.32)	(-0.57)	(-0.57)		(1.13)	(1.09)	(1.06)	(0.99)
HML		0.016	0.015	0.012	0.012		-0.019	-0.022	-0.026	-0.027
		(1.22)	(1.07)	(0.88)	(0.85)		(-1.45)	(-1.28)	(-1.37)	(-1.17)
RMW				-0.015	-0.015				-0.039	-0.038
				(-0.70)	(-0.69)				(-1.12)	(-1.23)
CMA				-0.004	-0.004				-0.028	-0.027
				(-0.15)	(-0.15)				(-1.01)	(-1.12)
MOM			-0.001		0.000			-0.006		-0.002
			(-0.18)		(-0.01)			(-0.45)		(-0.13)
TVC						1.187***	1.190***	1.190***	1.190***	1.190***
						(56.01)	(57.33)	(57.10)	(57.09)	(57.04)
$Adj.R^2(\%)$	0.44	0.47	0.43	0.43	0.38	73.23	73.35	73.35	73.39	73.38

Panel A reports the results of time-series regressions of Global Intraday Time-series Momentum (GITSM) against CAPM model, Fama-French global 3 factors model, Fama-French global 3 factors model plus the global momentum factor, Fama-French global 5 factors model, and Fama-French global 5 factors model plus the global momentum factor respectively. Panel B reports the regression results where the doubled GITSM return is regressed against the same factors in Panel A along with a time-varying factor (TVC). Multiplying the return of GITSM by 2 ensures the total dollar value invested in the strategy is $2 and facilitates the construction of TVC (see text for details). The returns are annualized and in percentage. Newey and West (1987) t values 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 10: Cross-sectional Sorting Analysis of Intraday Time-series Momentum

	Small	Medium	Large	Small	Medium	Large
	Panel A: Spread			Panel B: Volatility		
AVE(%)	2.67***	3.33***	3.23***	2.57***	3.02***	3.61***
	(3.24)	(3.47)	(3.07)	(3.10)	(3.11)	(2.97)
SD	2.61	3.07	3.54	2.67	3.05	3.64
Sharpe Ratio	1.02	1.09	0.91	0.96	0.99	0.99
Skewness	0.01	0.00	-0.01	0.05	0.02	-0.01
Kurtosis	3.02	3.02	3.03	3.04	3.02	3.01
	Panel C: ID			Panel D: Individualism		
AVE(%)	4.21***	3.75***	1.15	3.44***	3.19***	2.57***
	(4.27)	(3.90)	(1.17)	(3.01)	(3.83)	(2.69)
SD	3.07	3.03	3.15	3.63	2.67	2.80
Sharpe Ratio	1.37	1.24	0.37	0.95	1.19	0.92
Skewness	0.01	0.03	0.02	0.02	-0.02	0.05
Kurtosis	3.02	3.01	3.05	3.01	3.02	3.03

Table B.1: Individual ITSM in Local Currency

	Intercept	β^F	*Adj.*R^2 (%)
Australia	3.15***	4.76***	3.92
	(3.27)	(5.59)	
Austria	13.84***	0.61	-0.01
	(6.21)	(0.38)	
Canada	4.87***	2.00	0.24
	(3.54)	(1.10)	
France	0.67	5.93***	2.68
	(0.41)	(5.01)	
Germany	1.26	3.98***	1.22
	(0.82)	(3.45)	
Ireland	3.10*	1.63*	0.17
	(1.67)	(1.84)	
Japan	0.65	5.60***	3.70
	(0.49)	(4.28)	
Netherlands	-0.10	5.37***	2.32
	(-0.07)	(3.73)	
Norway	1.10	7.05***	1.70
	(0.48)	(4.24)	
NZ	0.09**	-0.01	-0.03
	(2.39)	(-0.75)	
Portugal	5.63***	3.33***	0.99
	(4.06)	(3.99)	
Spain	9.24***	4.24***	1.43
	(5.54)	(3.53)	
Sweden	7.62***	5.46***	3.20
	(5.75)	(6.58)	
Switzerland	1.24	4.17***	1.45
	(0.92)	(2.89)	
UK	-0.54	6.96***	3.26
	(-0.37)	(4.99)	
US	0.14	9.57***	3.41
	(0.09)	(3.45)	

In this table, we replicate the in-sample statistical analysis conducted in Panel A Table 3 but using data in local currency. Returns are annualized and in percentage. The Newey and West (1987) t-statistics are reported in parentheses. The sample period spans from 04 October 2005 to 29 December 2017. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Table B.2: Economic Significance of Individual Intraday Time Series Momentum

	Strategy	Mean (%)	SD (%)	Skewness	Kurtosis	Sharpe	ρ	α (%)	ARatio
Australia	ITSM	4.686	3.306	0.028	3.023	1.418			
	AL	2.857	3.314	0.012	3.023	0.862	0.010	4.657***	1.409
	BH	3.330	16.838	-0.028	3.016	0.198***	0.016	4.675***	1.415
Austria	ITSM	0.839	6.368	-0.135	3.134	0.132			
	AL	14.014	6.307	0.151	3.134	2.222***	-0.096	2.197	0.347
	BH	1.496	25.026	-0.008	3.020	0.060	0.078	0.809	0.128
Canada	ITSM	0.070	4.420	0.013	3.083	0.016			
	AL	5.046	4.408	0.112	3.082	1.145**	-0.070	0.425	0.096
	BH	4.508	17.814	-0.024	3.048	0.253	0.050	0.015	0.003
France	ITSM	2.827	5.036	-0.002	3.024	0.561			
	AL	0.756	5.039	0.000	3.024	0.150	-0.070	2.879*	0.573
	BH	2.977	22.175	0.007	3.019	0.134	0.043	2.798*	0.556
Germany	ITSM	2.677	4.931	0.059	3.067	0.543			
	AL	2.306	4.932	0.042	3.068	0.468	-0.036	2.759*	0.560
	BH	5.422	21.353	-0.003	3.018	0.254	0.049	2.615*	0.531
Ireland	ITSM	4.374	5.489	0.024	3.042	0.797			
	AL	1.262	5.496	-0.059	3.043	0.230	-0.060	4.450**	0.812
	BH	2.446	23.008	-0.033	3.032	0.106	-0.069	4.414**	0.806
Japan	ITSM	5.347	5.384	0.030	3.080	0.993			
	AL	2.437	5.392	0.070	3.079	0.452	-0.020	5.396***	1.003
	BH	10.366	24.526	-0.015	3.034	0.423	-0.021	5.395***	1.003
Netherlands	ITSM	1.118	4.514	0.036	3.030	0.248			
	AL	-0.075	4.516	-0.029	3.030	-0.017	-0.083	1.112	0.247
	BH	-0.670	20.473	-0.017	3.027	-0.033	-0.011	1.117	0.247
Norway	ITSM	11.330	7.599	0.011	3.075	1.491			
	AL	2.813	7.633	-0.073	3.074	0.369***	-0.077	11.546***	1.524
	BH	2.665	22.868	-0.044	3.024	0.117***	-0.021	11.349***	1.494
NZ	ITSM	-0.007	0.148	0.475	5.152	-0.051			
	AL	0.112	0.148	1.188	5.147	0.760**	0.163	-0.026	-0.177
	BH	10.997	10.709	-0.017	3.024	1.027**	0.032	-0.012	-0.083
Portugal	ITSM	3.241	4.300	0.006	3.024	0.754			
	AL	6.132	4.288	-0.019	3.025	1.430	0.019	3.125**	0.727
	BH	-2.541	20.258	0.007	3.019	-0.125**	0.063	3.275**	0.763
Spain	ITSM	2.863	5.166	0.003	3.014	0.554			
	AL	9.877	5.131	0.001	3.015	1.925***	-0.029	3.148*	0.610
	BH	7.044	23.982	0.024	3.024	0.294	0.110	2.696*	0.525
Sweden	ITSM	7.619	3.803	0.016	3.013	2.003			
	AL	7.183	3.808	-0.006	3.014	1.886	-0.066	8.091***	2.133
	BH	1.065	20.444	-0.012	3.017	0.052***	0.037	7.611***	2.003
Switzerland	ITSM	1.478	3.756	0.014	3.028	0.394			
	AL	2.301	3.754	0.012	3.028	0.613	-0.033	1.555	0.414
	BH	1.539	17.389	-0.026	3.024	0.088	0.042	1.464	0.390
UK	ITSM	2.412	4.372	0.010	3.018	0.552			
	AL	0.206	4.375	0.016	3.018	0.047	-0.078	2.428	0.557
	BH	0.548	18.214	-0.003	3.024	0.030	0.009	2.411	0.552
US	ITSM	6.611	5.897	0.086	3.099	1.121			
	AL	0.060	5.912	-0.028	3.099	0.010**	-0.107	6.617**	1.129
	BH	7.618	19.425	-0.032	3.045	0.392	-0.045	6.716**	1.140

This table presents the performance of intraday time-series momentum (i.e. ITSM) along with two benchmark strategies, *Always-long* (i.e.AL) and *Buy-and-hold* (i.e.BH), for each of the 16 equity markets using data based on local currencies. ITSM 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 *Always-long* strategy takes always a long position in the last half hour every trading day and the *Buy-and-hold* strategy holds the asset from the beginning until the end of the sample period. The Table reports the Mean, Standard Deviation (SD), Skewness, Kurtosis and the Sharpe ratio for each strategy and market. The table also presents the correlation (ρ) between the ITSM and the benchmark strategies returns. The α and appraisal ratio (ARatio) are based on the regression: $r_{I,t} = \alpha + \beta r_{benchmark,t} + \epsilon_t$, where $r_{I,t}$ and $r_{benchmark,t}$ are returns from ITSM and benchmark strategies, respectively. The appraisal ratio is computed as α/σ_ϵ where σ_ϵ is the standard error of the regression. Standard errors are adjusted using Newey and West (1987).We test the hypothesis that the Sharpe ratios of the ITSM and the AL or BH strategies are equal following Ledoit and Wolf (2008). We use Newey-West (1987) standard errors for the statistical significance of alpha. Mean, Standard Deviation (SD), Skewness, Kurtosis, Sharpe ratio, and α's are annualized. *, **, and *** denote significance at 10%, 5%, and 1% confidence levels, respectively. The sample period spans from 04 October 2005 to 29 December 2017.

Table B.3: Investing Intraday Time Series Momentum Globally – Rolling Approach

	Type (1) GITSM						**Type (2) GITSM**						**Type (3) GITSM**					
	EW	VW	IV	MD	MV	MinV	EW	VW	IV	MD	MV	MinV	EW	VW	IV	MD	MV	MinV
	Panel A: Global Portfolio Performance																	
AVE (%)	3.06***	4.75***	0.76	1.48***	2.84	0.48	2.78***	2.71***	1.54**	1.37**	-0.95	1.51**	5.17***	5.71***	1.13*	1.71***	4.64**	0.45
	(4.15)	(3.22)	(1.50)	(2.77)	(1.33)	(1.05)	(3.83)	(2.88)	(2.38)	(2.15)	(-0.78)	(2.34)	(5.47)	(3.65)	(1.86)	(2.88)	(2.15)	(1.00)
SD (%)	2.43	3.22	1.18	1.18	4.39	1.01	2.01	2.41	1.46	1.44	2.56	1.46	2.93	3.51	1.36	1.31	5.08	1.07
Skewness	0.01	0.10	0.02	0.04	-0.03	0.01	0.05	0.04	0.03	0.02	-0.06	0.03	0.03	0.10	0.02	0.03	0.04	-0.01
Kurtosis	3.03	3.10	3.02	3.01	3.05	3.01	3.05	3.06	3.01	3.01	3.12	3.01	3.03	3.10	3.01	3.01	3.02	3.01
Sharpe	1.26	1.48	0.64	1.25	0.65	0.48	1.38	1.12	1.05	0.95	-0.37	1.03	1.77	1.63	0.83	1.30	0.91	0.43
	Panel B: Spanning Alphas (GITSM vs ITSM)																	
Australia	2.84***	4.75***	0.58	1.22**	3.01	0.35	2.43***	2.58***	1.11*	0.97*	-0.99	1.07*	4.59***	5.39***	1.01*	1.64***	4.93**	0.41
Austria	2.66***	4.62***	0.39	1.18**	2.45	0.34	2.59***	2.51**	1.17*	1.01*	-1.50	1.15*	4.44***	5.17***	0.89	1.55**	4.74**	0.39
Canada	3.25***	5.13***	1.00**	1.85***	3.53*	0.76*	3.18***	3.33***	2.06***	1.96***	-0.15	2.04***	4.73***	5.58***	1.19*	1.89***	4.99**	0.56
France	1.40***	3.69***	0.45	1.30***	2.54	0.39	1.93***	1.86**	1.25**	1.09*	-1.38	1.23**	3.82***	4.68***	0.91	1.58***	4.80**	0.39
Germany	1.74***	3.86***	0.60	1.39***	2.74	0.44	2.09***	1.98**	1.39**	1.22**	-1.18	1.36**	3.91***	4.67***	0.96	1.62***	4.90**	0.40
Ireland	2.44***	4.54***	0.75	1.48***	2.84	0.48	2.52***	2.46***	1.53**	1.37**	-0.96	1.50**	4.29***	5.12***	1.04*	1.67***	4.98**	0.43
Japan	2.84***	4.26***	0.69	1.28**	2.81	0.38	2.30***	2.53***	1.20**	1.06*	-0.98	1.16**	4.76***	5.43***	1.06*	1.72***	5.03**	0.44
Netherlands	2.27***	4.27***	0.81*	1.51***	2.88	0.50	2.38***	2.32**	1.58***	1.41**	-0.88	1.55**	4.27***	5.02***	1.06*	1.68***	5.01**	0.43
Norway	2.42***	4.63***	0.52	0.99*	-0.13	0.30	2.40***	2.38**	1.19*	1.07*	-1.00	1.18*	4.62***	5.28***	1.06*	1.66***	4.25**	0.44
NZ	3.00***	4.71***	0.85**	1.54***	2.85	0.60**	2.67***	2.65***	1.58**	1.41**	-0.92	1.55**	4.56***	5.19***	1.05*	1.68***	5.02**	0.45
Portugal	2.29***	4.43***	0.48	1.29**	2.75	0.38	2.41***	2.37**	1.30**	1.14*	-1.35	1.28**	4.32***	5.13***	0.93	1.57***	4.85**	0.38
Spain	2.05***	4.15***	0.48	1.32**	2.68	0.41	2.25***	2.19**	1.27**	1.12*	-1.31	1.26**	4.17***	4.96***	0.92	1.58***	4.71**	0.38
Sweden	2.73***	4.65***	0.29	0.88*	2.41	0.12	2.63***	2.59***	1.15*	0.98	-1.69	1.13*	4.46***	5.18***	0.84	1.47***	4.35**	0.36
Switzerland	3.02***	4.73***	0.62	1.28**	2.87	0.37	2.76***	2.69***	1.45**	1.29**	-1.13	1.42**	4.56***	5.21***	1.00	1.66***	5.03**	0.42
UK	2.22***	4.17***	0.86**	1.54***	2.88	0.52	2.34***	2.28**	1.63***	1.46**	-0.83	1.59***	4.20***	5.00***	1.08*	1.69***	5.03**	0.44
US	2.58***	1.58***	0.67	1.30***	1.82	0.38	1.56***	0.72	1.28**	1.07*	-1.57	1.25**	3.64***	1.79***	0.87	1.41***	4.57**	0.32
	Panel C: Spanning Alphas (ITSM vs GITSM)																	
Australia	1.63	3.00	2.39	1.26	3.14	2.60	0.17	2.28	1.09	1.34	3.01	1.06	3.09	3.85*	2.89	2.81	2.91	2.93
Austria	-2.28	0.94	2.09	1.21	3.11*	3.04	-0.58	0.26	1.61	1.80	4.10**	1.71	0.69	1.77	2.91	2.69	3.18*	3.43*
Canada	-2.71**	-3.54***	-3.34**	-4.08***	-3.24**	-3.33***	-4.62***	-4.74***	-4.04***	-4.08***	-2.60**	-4.04***	-2.56*	-3.35**	-3.19**	-3.57***	-2.95**	-3.09**
France	-0.77	1.81	-0.13	-0.45	1.42	1.42	1.13	2.42	-0.66	-0.39	2.80	-0.52	2.33	3.57*	1.01	0.84	1.52	1.83
Germany	-1.15	0.98	-0.80	-1.03	0.71	0.57	0.46	1.50	-1.26	-1.03	1.70	-1.14	1.31	2.32	0.10	0.01	0.68	0.81
Ireland	-0.79	2.09	-1.13	-2.12	-0.23	-0.36	1.00	1.85	-1.57	-1.37	0.46	-1.47	1.35	2.77	-0.36	-0.47	-0.15	0.01
Japan	3.37	2.42	2.16	0.28	2.50	2.02	1.53	3.66*	-0.01	0.34	2.57	-0.04	5.24**	5.17**	2.67	3.04	2.63	2.59
Netherlands	-2.80**	-0.35	-1.99	-2.06	-0.69	-0.75	-1.11	0.10	-2.30	-2.10	0.36	-2.19	0.28	1.33	-1.08	-1.09	-0.57	-0.42
Norway	4.74*	6.91***	7.98***	6.65***	6.93***	8.11***	5.31**	6.16**	7.57***	7.74***	8.43***	7.62***	7.54***	7.55***	8.45***	8.38***	7.92***	8.42***
NZ	0.33	0.41	-0.63	-0.76	-0.20	-0.69**	0.14	0.36	-0.46	-0.44	-0.15	-0.47	0.45	0.44	-0.27	-0.33	-0.25	-0.27
Portugal	-0.51	1.80	1.25	0.77	2.50	2.18	0.78	1.70	1.07	1.24	3.15*	1.16	1.84	2.80*	2.03	1.75	2.37	2.47
Spain	-1.98	0.55	0.46	0.25	1.87	1.75	-0.36	0.89	0.00	0.23	2.74	0.13	1.12	2.25	1.35	1.16	1.53	1.95
Sweden	1.24	2.22	3.78**	2.65*	4.35***	4.02**	1.80	2.16	3.71**	3.78**	4.86***	3.74**	2.08	2.45	4.21***	3.95**	4.17***	4.46***
Switzerland	-1.66	-0.27	1.31	-0.02	2.09	1.49	-0.79	-0.33	1.40	1.49	2.30	1.44	-0.47	0.30	1.84	1.96	2.13	2.03
UK	-1.87	-0.08	-2.07	-2.26	-0.76	-1.05	-0.48	0.58	-2.36*	-2.16	-0.11	-2.27	0.54	1.67	-1.30	-1.32	-0.87	-0.70
US	5.22**	-1.18	1.73	0.73	1.02	1.72	2.10	1.60	0.80	0.66	2.66*	0.80	3.84	-1.24	1.41	0.35	1.49	1.77

This table presents the performance of global intraday time-series momentum strategies (GTISM) as in Table 8 constructed using a rolling window, instead of expanding window, approach.

Table B.4: Factor Exposure by Liquidity

	CAPM	FF3	FF3+MOM	FF5	FF5+MOM	CAPM	FF3	FF3+MOM	FF5	FF5+MOM	CAPM	FF3	FF3+MOM	FF5	FF5+MOM
Panel A: Liquidity (without TVC)															
	Low					Medium					High				
Intercept	3.955***	3.945***	3.936***	4.034***	4.024***	2.549**	2.536**	2.538**	2.426**	2.432**	2.304***	2.283***	2.323***	2.569***	2.573***
	(3.65)	(3.63)	(3.61)	(3.70)	(3.68)	(2.53)	(2.51)	(2.49)	(2.37)	(2.37)	(2.73)	(2.70)	(2.79)	(2.99)	(3.00)
Market	0.014	0.008	0.008	0.005	0.005	0.010	0.008	0.008	0.010	0.010	0.008	0.009	0.009	0.004	0.004
	(1.30)	(0.70)	(0.72)	(0.43)	(0.42)	(0.92)	(0.80)	(0.78)	(0.88)	(0.88)	(1.24)	(1.50)	(1.52)	(0.56)	(0.56)
SMB		-0.020	-0.021	-0.023	-0.024		-0.002	-0.002	-0.001	-0.001		0.011	0.012	0.004	0.005
		(-1.11)	(-1.12)	(-1.27)	(-1.32)		(-0.14)	(-0.14)	(-0.08)	(-0.04)		(0.40)	(0.42)	(0.18)	(0.19)
HML		0.024	0.025	0.030	0.032		0.013	0.013	0.019	0.017		0.010	0.007	-0.013	-0.013
		(1.18)	(1.17)	(1.32)	(1.39)		(0.78)	(0.76)	(0.93)	(0.82)		(0.82)	(0.42)	(-0.65)	(-0.58)
RMW				-0.005	-0.007				0.023	0.024				-0.069*	-0.068*
				(-0.16)	(-0.22)				(0.70)	(0.73)				(-1.70)	(-1.77)
CMA				-0.017	-0.019				0.006	0.008				-0.003	-0.002
				(-0.44)	(-0.51)				(0.18)	(0.22)				(-0.14)	(-0.11)
MOM			0.001		0.004			0.000		-0.002			-0.005		-0.001
			(0.12)		(0.34)			(-0.03)		(-0.29)			(-0.47)		(-0.12)
Adj.R^2(%)	0.398	0.582	0.539	0.542	0.505	0.187	0.145	0.100	0.106	0.064	0.210	0.205	0.198	0.849	0.806
Panel B: Liquidity (TVC included)															
	Low					Medium					High				
Intercept	2.901**	2.910**	2.998**	3.152**	3.174**	0.284	0.282	0.322	0.414	0.420	-0.993	-1.025	-0.991	-0.787	-0.782
	(2.31)	(2.31)	(2.33)	(2.36)	(2.37)	(0.25)	(0.25)	(0.28)	(0.36)	(0.36)	(-0.78)	(-0.81)	(-0.81)	(-0.64)	(-0.64)
Market	-0.003	0.001	0.000	-0.006	-0.006	-0.009*	-0.006	-0.007	-0.012	-0.012	0.000	0.007	0.006	0.004	0.004
	(-0.33)	(0.12)	(0.00)	(-0.58)	(-0.57)	(-1.68)	(-0.94)	(-1.04)	(-1.37)	(-1.37)	(-0.02)	(0.57)	(0.55)	(0.29)	(0.29)
SMB		0.009	0.012	0.005	0.007		0.008	0.009	0.006	0.007		0.032	0.033	0.026	0.026
		(0.42)	(0.50)	(0.25)	(0.34)		(0.43)	(0.48)	(0.33)	(0.35)		(1.12)	(1.09)	(1.05)	(0.99)
HML		-0.025	-0.032	-0.022	-0.028		-0.006	-0.009	0.005	0.004		-0.003	-0.006	-0.033	-0.034
		(-1.10)	(-1.20)	(-0.74)	(-0.83)		(-0.39)	(-0.61)	(0.30)	(0.21)		(-0.17)	(-0.25)	(-1.44)	(-1.20)
RMW				-0.028	-0.024				-0.001	0.000				-0.068	-0.068*
				(-0.65)	(-0.59)				(-0.04)	(0.00)				(-1.64)	(-1.76)
CMA				-0.040	-0.035				-0.041	-0.039				0.015	0.016
				(-1.29)	(-1.24)				(-1.31)	(-1.27)				(0.49)	(0.59)
MOM			-0.012		-0.008			-0.005		-0.002			-0.004		-0.002
			(-0.89)		(-0.67)			(-0.52)		(-0.23)			(-0.30)		(-0.14)
TVF	3.297***	3.304***	3.305***	3.304***	3.305***	2.896***	2.897***	2.897***	2.899***	2.899***	3.299***	3.303***	3.302***	3.291***	3.291***
	(67.13)	(71.71)	(71.97)	(70.94)	(71.34)	(57.91)	(57.67)	(57.67)	(57.57)	(57.60)	(38.16)	(39.29)	(39.62)	(41.20)	(41.21)
Adj.R^2(%)	71.514	71.532	71.545	71.551	71.548	72.994	72.978	72.972	72.991	72.980	51.425	51.509	51.494	51.647	51.626

In this table, we examine the Fama-French factor exposure of equally-weighted ITSM within groups by Corwin and Schultz (2012) High-Low liquidity. Panel A reports the regression results where the equally-weighted ITSM within low, medium, and high liquidity groups are regressed against the global market factor (CAPM), global Fama-French 3 factors (FF3), global Fama-French 3 factors plus the (cross-sectional) momentum factor (FF3+MOM), global Fama-French 5 factors (FF5), and global Fama-French 5 factors plus the momentum factor (FF5+MOM) respectively. In Panel B, we repeat the analyses with the time-varying factor (TVF, for details see text) constructed and included as an additional regressor. The returns are annualized and in percentage. Newey and West (1987) t values 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.5: Factor Exposure by Information Discreteness

	CAPM	FF3	FF3+MOM	FF5	FF5+MOM	CAPM	FF3	FF3+MOM	FF5	FF5+MOM	CAPM	FF3	FF3+MOM	FF5	FF5+MOM
Panel A: Information Discreteness (without TVC)															
	Small					Medium					Large				
Intercept	4.006***	3.993***	3.971***	3.960***	3.952***	3.109***	3.101***	3.121***	3.185***	3.192***	1.579	1.556	1.587	1.732*	1.732*
	(4.11)	(4.06)	(4.00)	(4.00)	(3.97)	(3.22)	(3.21)	(3.24)	(3.24)	(3.25)	(1.60)	(1.58)	(1.60)	(1.71)	(1.71)
Market	0.005	0.001	0.001	0.001	0.001	0.011	0.009	0.008	0.009	0.009	0.015	0.015	0.015	0.009	0.009
	(0.52)	(0.09)	(0.12)	(0.10)	(0.10)	(1.45)	(1.11)	(1.08)	(1.00)	(1.01)	(1.43)	(1.25)	(1.29)	(0.89)	(0.89)
SMB		-0.012	-0.013	-0.012	-0.013		-0.006	-0.006	-0.010	-0.009		0.007	0.008	0.003	0.003
		(-0.76)	(-0.82)	(-0.74)	(-0.80)		(-0.43)	(-0.39)	(-0.71)	(-0.67)		(0.42)	(0.47)	(0.21)	(0.21)
HML		0.021	0.023	0.027	0.029		0.012	0.010	-0.009	-0.011		0.015	0.012	0.024	0.023
		(1.55)	(1.56)	(1.42)	(1.51)		(0.66)	(0.55)	(-0.48)	(-0.54)		(0.88)	(0.60)	(1.22)	(1.15)
RMW				0.013	0.011				-0.042	-0.040				-0.010	-0.010
				(0.50)	(0.44)				(-1.52)	(-1.47)				(-0.36)	(-0.35)
CMA				-0.004	-0.006				0.028	0.030				-0.042	-0.042
				(-0.11)	(-0.17)				(1.14)	(1.22)				(-1.02)	(-1.09)
MOM			0.003		0.003			-0.003		-0.003			-0.004		0.000
			(0.30)		(0.32)			(-0.33)		(-0.31)			(-0.33)		(-0.01)
$Adj.R^2$(%)	0.033	0.134	0.097	0.071	0.033	0.303	0.275	0.237	0.500	0.461	0.544	0.521	0.490	0.595	0.550
Panel B: Information Discreteness (TVC included)															
	Small					Medium					Large				
Intercept	0.576	0.519	0.499	0.614	0.598	0.239	0.245	0.296	0.570	0.574	-0.496	-0.524	-0.396	-0.245	-0.209
	(0.43)	(0.38)	(0.37)	(0.45)	(0.44)	(0.22)	(0.22)	(0.27)	(0.51)	(0.51)	(-0.41)	(-0.43)	(-0.31)	(-0.19)	(-0.16)
Market	-0.011	-0.004	-0.004	-0.008	-0.008	-0.009	-0.006	-0.006	-0.014	-0.014	0.001	0.012	0.010	0.004	0.004
	(-0.92)	(-0.29)	(-0.27)	(-0.54)	(-0.54)	(-1.16)	(-0.63)	(-0.74)	(-1.39)	(-1.39)	(0.06)	(1.07)	(1.02)	(0.44)	(0.46)
SMB		0.035	0.035	0.032	0.031		0.010	0.011	0.004	0.004		0.047**	0.051**	0.040**	0.044**
		(1.06)	(0.99)	(1.03)	(0.93)		(0.45)	(0.49)	(0.21)	(0.22)		(2.50)	(2.55)	(2.25)	(2.35)
HML		0.004	0.006	0.004	0.008		-0.019	-0.023	-0.028	-0.028		-0.023	-0.033	-0.029	-0.038
		(0.21)	(0.26)	(0.16)	(0.29)		(-1.16)	(-1.36)	(-1.30)	(-1.21)		(-0.94)	(-1.11)	(-0.97)	(-1.08)
RMW				-0.010	-0.013				-0.055	-0.055				-0.042	-0.035
				(-0.27)	(-0.37)				(-1.49)	(-1.55)				(-1.12)	(-1.01)
CMA				-0.021	-0.025				-0.033	-0.032				-0.039	-0.029
				(-0.45)	(-0.58)				(-1.25)	(-1.18)				(-1.22)	(-1.02)
MOM			0.003		0.006			-0.007		-0.001			-0.018		-0.013
			(0.17)		(0.39)			(-0.67)		(-0.13)			(-1.15)		(-0.95)
TVF	3.288***	3.297***	3.297***	3.297***	3.297***	2.913***	2.917***	2.917***	2.918***	2.918***	3.390***	3.400***	3.402***	3.399***	3.401***
	(26.00)	(28.42)	(28.44)	(28.65)	(28.55)	(57.31)	(56.98)	(56.66)	(55.91)	(55.84)	(80.94)	(81.51)	(81.41)	(81.16)	(81.37)
$Adj.R^2$(%)	58.732	58.793	58.776	58.757	58.744	71.126	71.138	71.136	71.214	71.201	71.604	71.796	71.844	71.816	71.834

In this table, we examine the Fama-French factor exposure of equally-weighted ITSM within groups by information discreteness (Da et al. (2014)). Panel A reports the regression results where the equally-weighted ITSM within small, medium, and large information discreteness groups are regressed against the global market factor (CAPM), global Fama-French 3 factors (FF3), global Fama-French 3 factors plus the (cross-sectional) momentum factor (FF3+MOM), global Fama-French 5 factors (FF5), and global Fama-French 5 factors plus the momentum factor (FF5+MOM) respectively. In Panel B, we repeat the analyses with the time-varying factor (TVF, for details see text) constructed and included as an additional regressor. The returns are annualized and in percentage. Newey and West (1987) t values 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.