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Faculty of Social Sciences
Southampton Business School

Essays on Intraday Stock Return Predictability

by

Zeming Li
MSc

A thesis for the degree of
Doctor of Philosophy

May 2021

University of Southampton

Abstract

Faculty of Social Sciences
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Essays on Intraday Stock Return Predictability

by Zeming Li

The thrust of this thesis is to shed light on the intraday predictability of stock returns and its association with market microstructure and behavioural biases of traders. The first essay looks into an intraday effect of return continuation, namely intraday time series momentum (ITSM), in an international setting. Employing high-frequency trading data, we show that ITSM is economically sizeable and statistically significant both in- and out-of-sample in most of the 16 developed markets in our sample. To obtain a deeper understanding of the drivers behind the phenomenon, we propose four hypotheses based on existing theories of market microstructure and investor behaviour. We empirically test the hypotheses in both cross-sectional and time series dimensions, finding that ITSM is stronger when liquidity is low, volatility is high, and new information is discrete. The evidence suggests that the ITSM is driven by both market microstructure and behavioural factors.

In the second essay, we turn our attention to the intraday cross-sectional predictability of stock returns, again in an international setting. Portfolio sorts and Fama-Macbeth regressions show that the first half-hour return and the first half-hour volatility have strong cross-sectional predictability on the last half-hour return, both economically and statistically. Portfolios that exploit the predictability of these two intraday characteristics produce positive and statistically significant alphas when regressed against passive benchmarks, suggesting remarkable economic gains. A comparison of our cross-sectional portfolios and a strategy based on the intraday time series momentum (ITSM) shows that our strategies provide extra benefit to ITSM. This chapter contributes to the recent growing literature on intraday return predictability and asset pricing.

Finally, the third essay is concerned with the dynamic overnight-intraday return relationship and intraday investor heterogeneity. We find that there exists a significant reversal effect at the market open that converts to the momentum documented in Gao et al. (2018) at the market close. More importantly, we show that the significance of the opening reversal is almost entirely from days with negative overnight returns whereas that of the closing momentum is mainly from days with positive overnight return days.

The asymmetric overnight-intraday return relationship on the two types of days implies heterogeneity in intraday traders. A closer examination of the opening reversal shows that the effect is stronger on days with larger overnight volatility and trade size, and over periods of financial crisis, recessions, and greater uncertainty. Practically, we document strong economic significance of strategies that are based on the opening reversal.

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Declaration of Authorship

I declare that this thesis and the work presented in it is my own and has been generated by me as the result of my own original research.

I confirm that:

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To my parents.

Chapter 1

Introduction

Questions such as what drives the price dynamics of financial assets and, more practically, to what extent the performance of financial assets is predictable lie in the centre of financial economics studies. Traditionally, there are generally two bunches of models addressing this asset pricing issue. The first bunch of models are based on the concept of general equilibrium, i.e. the supply and demand of securities should be equal when the market is clear. The prototypical model of this kind is the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966). From this seminal model follow some significant developments in the equilibrium asset pricing literature, most notably, the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973) that generalises the CAPM to a multi-beta model in a continuous-time setting and the Consumption Capital Asset Pricing Model (CCAPM) of Breeden (1979) that streamlines the ICAPM to a single consumption beta model. In contrast, the second bunch of asset pricing models seek to solve the problem using the law of one price, or equivalently, the no-arbitrage principle. The most well-known of this kind is probably the Black and Scholes (1973) options pricing model, wherein options are priced relative to their underlying assets. Other examples also include the state preference theory of Arrow and Debreu (1954) and the term structure model of Heath et al. (1992).

Despite seemingly distinct standpoints of these two asset pricing approaches, the assumptions of both types of models are interlinked, and thus they can be understood under a unified framework. That is, one can always treat the price of an asset at time t as the expectation of its payoff, i.e. the price plus the dividend, at the future time T times a stochastic discount factor (Cochrane, 2005):

$$S_t = E_t^{\Pi}[\tilde{m}_T \tilde{x}_T], \tag{1.1}$$

where S_t is the price of the asset under evaluation at the current time t, Π is the probability measure under which the expectation is taken, $\tilde{m}_T$ is the stochastic discount factor at time T, and $\tilde{x}_T$ is the payoff at time T. The task then becomes to find the right specification for the discount factor $\tilde{m}$, and the probability measure Π. For example, one can price a risky cash flow by adjusting $\tilde{m}$ to distort either the expected payoff or the discount rate to reflect its riskiness, while stick with the true distribution of the payoff. Alternatively, one can reflect the riskiness in Π, by taking the expectation under a different probability measure from the true one. Often a risk-neutral probability measure is used such that the price of an asset is the expected price discounted by the risk free rate:

$$S_t = \frac{1}{1+r_f} E^{RN}[S_{t+1}]. \tag{1.2}$$

It can be shown directly from equation (1.2) that under this risk-neutral pricing framework, the discounted price process is a martingale,[1] which is the fundamental basis for the Efficient Market Hypothesis (Fama, 1970; Samuelson, 1965). In the case that investors are risk neutral or there is no aggregated risk, and the discounting is included in a drift term, the prices follow a random walk process. A well-known and important implication that follows is that asset prices on average are not predictable, thus a simple strategy that uses past price information cannot be profitable.

The empirical evidence against this theoretical implication, however, is extensive. For example, Conrad and Kaul (1988); Conrad et al. (1991); Fama (1965); French and Roll (1986); Jegadeesh (1990); Jegadeesh and Titman (1993, 1995); Lo and MacKinlay (1988, 1990); Mech (1993); Moskowitz et al. (2012) and Lim et al. (2018) show strong evidence that there exist short-term reversal in individual securities and long-term momentum in portfolio returns, that cannot be explained by the traditional asset pricing theories. How, then, can these empirical findings be reconciled with the idealised theoretical setup outlined above? One solution is to turn our attention to the underlying asset characteristics at the micro level including market microstructure effects and investor behavioural biases.

A common assumption assumed by the aforementioned asset pricing models is that the market is frictionless at the aggregate level, ignoring some critical micro factors, such as information diffusion processes, transaction costs, and inventory control of market makers, that have been shown to play a significant part in asset price formation, particularly in the short-run (Easley and O'Hara, 2003). To see this more explicitly, consider the following depiction of asset prices from the market microstructure perspective:

$$p_t = v_t + s_t, \tag{1.3}$$

where p_t is the observable price, v_t is the underlying efficient price that is not observable (Hasbrouck, 2002) but drives the observable price permanently in the long-run, and s_t is a random term, which includes market frictions, that drives the observable

[1] $\frac{S_t}{(1+r_f)^0} = E^{RN}[\frac{S_{t+1}}{(1+r_f)^1}]$.

price transiently in the short-run. s_t has zero mean and is uncorrelated with v_t. In the traditional asset pricing models, the permanent component v_t is a martingale and is determined by various macroeconomic (state) variables, whereas the transient component s_t is irrelevant in the long-run. The literature of market microstructure, however, considers how trading behaviour can affect and determine the observed price. For example, in asymmetric information models the permanent component v_t is affected not only by the public information but also by the market's assessment of the chances that a trade is initiated by information known by the trader but not the public (i.e. private information), whereas in behavioural models, the transient component s_t is determined not only by non-informational frictions but also by investor behavioural biases (Hasbrouck, 1996).

With the rise of computer-based high-frequency trading, understating the price dynamics from a more micro level is of particular importance. This type of high-frequency trading is normally characterised by small profit margin for each trade, and thus requires rapid and large turnover to cover fixed costs (Goldstein et al., 2014). Such heavy trading behaviour might radically affect the underlying characteristics of the market. For example, U.S. Securities and Exchange Commission notes that (2010, p. 3606): 'One of the most significant market structure developments in recent years is high frequency trading ('HFT').'

The current thesis, therefore, follows this route and studies stock price formation process and return predictability at a high-frequency level. Chapter 2 examines an effect of intraday stock return continuity introduced by Gao et al. (2018), namely intraday time series momentum (ITSM), in a global setting. Employing high-frequency data of SPY, the largest exchange-traded fund (ETF) in the world that tracks the S&P 500 index, Gao et al. (2018) show that the first half-hour return that is computed using the previous closing price at 16:00 and today's price at 10:00 processes strong predictability, both economically and statistically, on the last half-hour return on the same day. Chapter 2 first investigates this intraday effect in 16 developed countries and finds evidence of ITSM in most of the countries under various market conditions. A thorough out-of-sample test confirms the in-sample evidence of the existence of ITSM.

In order to grasp the economic mechanism that drives this intraday phenomena, furthermore, four hypotheses are established and empirically tested. Gao et al. (2018) conjecture that one of the biggest sources of this intraday momentum effect is the overnight accumulation of information. If this conjecture holds, we hypothesise that the strength of the ITSM effect should be affected by the liquidity provision at the market open (Bogousslavsky, 2016), the information arrival process, i.e. whether new information comes as a shock or is slowly perceived (Da et al., 2014), clarity of the economic implications for new information (Daniel and Titman, 1999; Zhang, 2006), and cultural differences (Chui et al., 2010). Our evidence from both the cross-section and time series shows that the ITSM effect is stronger when liquidity is low, volatility is high, and new information is discrete.

Chapter 3 turns to the intraday return predictability in the cross-section. While the cross-sectional return predictability has been studied extensively at lower frequencies (Ang and Bekaert, 2007; Fama and French, 1992, 1993, 2015; Goyal and Jegadeesh, 2018; Jiang and Yao, 2013; Mclean and Pontiff, 2016; Menzly and Ozbas, 2010; Nagel, 2005; Polk et al., 2006), less attention has been paid to higher frequencies, especially at the intraday level. With the rise of computer based trading and increasing availability of high frequency data, a deep understanding of how intraday information might be used for cross-sectional forecasting has aroused great interest of academics and practitioners. For example, Lou et al. (2019), and Bogousslavsky (2021) study the relationship between intraday information and traditional anomalies that have been observed in the cross-section at the monthly level. In contrast, Chapter 3 zooms further into the intraday cross-sectional predictability. That is, we use information from the intraday period to predict not the performance in the longer-run, but instead the cross-sectional performance within the trading day.

Restricting our attention to the first half-hour return and the last half-hour return, in Chapter 3 we explore the cross-sectional predictability of five intraday variables. First, we use the first half-hour return due to the strong evidence of its time series predictability documented in Chapter 2. Second, we explore the predictability of the first half-hour information discreteness that has been shown to explain the cross-sectional momentum at monthly frequency (Da et al., 2014). Third, inspired by the well-known U shape of the intraday volatility and liquidity and their cross-sectional predictability in the longer-run (Amihud and Mendelson, 1986; Ang et al., 2006; Bakshi and Kapadia, 2003; Chordia et al., 2001; Holmström and Tirole, 2001; Liu, 2006; O'Hara, 2003), we investigate the intraday predictability of first half-hour volatility and liquidity. Finally, we include also the previous day's last half-hour return given its significant cross-day continuity documented in the US market (Heston et al., 2010).

The main analysis of Chapter 3 starts with a cross-sectional portfolio sort, wherein we observe a monotonic pattern across groups sorted by the first half-hour return and volatility, whereas no such pattern is observed when we sort the countries by information discreteness, first half-hour liquidity, and previous day's last half-hour return. Next, we perform a Fama and MacBeth (1973) regression and confirm the cross-sectional sorting results. Economically, we show that long-short portfolios based on the first half-hour return and volatility, respectively, generate remarkable Sharpe ratios and economic gains. A spanning analysis shows that the profitability of these two portfolios do not subsume one another, implying further benefit of diversification. Indeed, a larger Sharpe ratio is achieved when we invest simultaneously the two portfolios that are based on the two intraday variables respectively. This strategy beats passive benchmarks under various portfolio weight schemes. Finally, we present evidence that the cross-sectional portfolio that invests in both intraday predictive variables outperforms a global strategy that invests in the intraday time series momentum of Gao et al. (2018), once a market timing component is striped off from the latter (Goyal and Jegadeesh, 2018).

In Chapter 4, we turn our attention back to the time series predictability of intraday returns but with a particular focus on the overnight-intraday relationship in the US market. We find that the overnight return is closely related to not only the last half-hour return on the following day, as documented in Gao et al. (2018), but also the first half-hour return on that day. Particularly, we show that there exists an intraday reversal at the market open that is statistically significant both in- and out-of-sample over the full sample period (2000 - 2017). Similar to the intraday momentum effect, the statistical significance of this intraday reversal effect is stronger during periods of financial crisis, economic recession, and high uncertainty. Moreover, we test the relationship between intraday reversal and microstructure variables, such as overnight volatility and trade size that serve as indicators of the occurrence of overnight information. We find that the intraday reversal effect is significantly stronger on days with high overnight volatility and large overnight trade size, implying that the effect is related to the arrival of overnight information. Economically, a portfolio based on the opening reversal yields an annualised return of 6.386%, which is significantly higher than that of the passive benchmarks employed in the study.

More interestingly, in Chapter 4, we discover that while both the intraday reversal and momentum are statistically significant over the full sample period, the reversal effect mainly presents on days with negative overnight returns, whereas the momentum effect mainly shows up on days with positive overnight returns. We conjecture that this might be due to the short selling restrictions faced by retail traders on days with negative overnight news. An emerging body of literature seeks to understand monthly anomalies using intraday information (Bogousslavsky, 2021; Lou et al., 2019), and states that most of the well established anomalies earn their premium either entirely from the overnight period or entirely from the intraday period, emphasising that heterogeneous clientele over the two periods might play a key role in explaining monthly anomalies. Our findings suggest that this clientele effect is also crucial to comprehend the intraday return dynamics.

With the increasing computational power and massive use of automatic trading algorithms, it is more crucial than ever for academics, practitioners, and regulators to understand the price and return dynamics at the micro level. This thesis, therefore, sheds light on this issue using international data. Focusing primarily on the two most critical time windows in a trading day, namely the first and the last half hours, the first essay explores time series stock return predictability in a global setting. In addition to simply identifying return patterns, it discusses the economic rationale behind the phenomenon based on existing market microstructure and behavioural theories. In contrast, the second essay reveals intraday return patterns in the international cross-section, which cannot be explained by existing asset pricing theories, providing empirical remarks for further theoretical development. Similarly, the third essay identifies significant intraday return predictability at the market open that calls for theoretical formulation. More importantly, the third essay also discloses different return behaviour conditional on overnight stock performance, suggesting potential effect of heterogeneous clientele on intraday return dynamics.

The remainder of the thesis is organised as follows. Chapter 2 studies intraday time series momentum in a global setting and provides economic explanations for the phenomenon. Chapter 3 explores intraday cross-sectional return predictability. Chapter 4 examines the dynamic relationship between overnight and intraday periods and introduces a time series reversal effect at the market open. Chapter 5 concludes the thesis.

Chapter 2

Intraday Time Series Momentum: Global Evidence and Links to Market Characteristics

This chapter studies intraday time-series momentum (ITSM) in an international setting by employing high-frequency data of 16 developed markets. We show that ITSM is economically sizeable and statistically significant both in- and out-of-sample in most countries. Based on existing theories of investor behaviour, we propose and test four hypotheses to reveal the source of ITSM profitability. We document both in the cross-sectional and time-series dimensions that ITSM is stronger when liquidity is low, volatility is high and new information is discrete. Overall, our analysis suggests that the ITSM is driven by both market microstructure and behavioural factors.

2.1 Introduction

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

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

In this chapter, we provide a cross-country study on intraday momentum based on the work of Gao et al. (2018). These authors provide strong evidence of intraday time series momentum (ITSM) where the first half-hour return of the trading day significantly predicts the last half-hour return in a selection of U.S. exchange-traded funds (ETFs) that track the U.S. market, various U.S. sectors, and emerging markets. We provide a global study on ITSM by employing international indices to determine the statistical and economic power of ITSM around the globe. We first show that ITSM is economically sizable and statistically significant in international stock markets. Then, we examine the potential sources of ITSM by testing four hypotheses proposed both in the market microstructure and behavioral academic literature. We find significant relationships between ITSM and market characteristics, such as the market liquidity, volatility, information discreteness, and the degree of individualism.

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

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

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

In addition to the market perception of new information, Da et al. (2014) propose the “frog-in-the-pan” hypothesis, highlighting the vital role of the information arrival process. In their hypothesis, investors under-react to information that arrives gradually to the market and over-react to information that comes as a surprise. Thus, our third hypothesis is that ITSM is stronger when the overnight information is digested smoothly and weaker when the market reacts swiftly with strong emotion. Finally, Chui et al.

(2010) show that the conventional momentum is stronger in countries with high individualistic cultures. Our last hypothesis addresses this cultural effect and states that ITSM is related to individualism.

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

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

The rest of the chapter is organised as follows. We describe the data in Section 2.2. In Section 2.3, we examine the pervasiveness of intraday time series momentum around the world both statistically and economically. We develop the hypotheses that relate ITSM to market characteristics in Section 2.4. In Section 2.5, we discuss hypothesis testing results. We conclude in Section 2.6.

2.2 Data and intraday returns

2.2.1 Data

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

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

based on the local currency, and consists of information on trading time, open price, high price, low price, and last price for every trading minute.

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

Finally, in order to study the cross-sectional and time series relation of market characteristics with ITSM returns, we take the perspective of the U.S. dollar investor, and hence we convert all local currency data into U.S. dollars. Specifically, we convert index prices based on the contemporaneous 1-minute exchange rate. While some scholars argue that using the U.S. dollar as the common numeraire might generate misleading conclusions on return predictability (Jordan et al., 2015), our approach is consistent with Lawrenz and Zorn (2017) and our results are robust to using local currencies, as shown in Tables A.6 and A.7 of Appendix A. We exclude Hong Kong and Singapore from our sample due to the lack of 1-minute foreign exchange data. Of the 16 remaining MSCI developed countries, the sample period varies from country to country due to data availability. Full details of the data, sample periods and trading hours used in this chapter are available in Table 2.1.

2.2.2 Calculation of the first and last half-hour returns

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

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

TABLE 2.1: Indices

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

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

$$r_t^F = \frac{p_{first30,t}}{p_{close,t-1}} - 1, \qquad r_t^L = \frac{p_{close,t}}{p_{last30,t}} - 1, \tag{2.1}$$

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 2.2 presents the summary statistics of the annualised first and last half-hour returns and reports the number of days, mean, standard deviation, skewness, and kurtosis. Excluding Spain and Sweden, the mean return for all markets in the first half hour is substantially higher and more volatile than in the last half hour. The high return during the first half hour may reflect the incorporation of overnight information in stock returns, while the high variability of the first half-hour returns may reflect the discrepancy in understanding this overnight information. The low variability in the last half-hour returns indicates less disagreement on the pricing of stocks. This is consistent with the hypothesis that traders who trade in the morning are more informed and have stronger information processing power while those who trade in the last half hour are followers who have less access to the information and are less informed as a result (Barclay and Hendershott, 2003; Gao et al., 2018). Most of the returns have a slightly negative skewness with a kurtosis around 3, indicating that these intraday returns are not as non-normal as found with daily returns.

2.3 Intraday return predictability around the world

2.3.1 Estimating the relation between first and last half-hour returns

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

$$r_t^L = \alpha + \beta^F r_t^F + \epsilon_t, \quad t = 1, \cdots, T, \tag{2.2}$$

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

Table 2.3 provides the in-sample estimation results of the predictive regression shown in equation (2.2) for each equity market, over the full sample period. The last row shows the results from a pooled regression where we run a panel model with country

TABLE 2.2: Summary statistics of the first and last half-hour returns

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

This table reports the summary statistics for the first and last half-hour returns of the 16 developed equity market indices. The first and last half-hour returns are defined in equation (2.1). The table reports the number of days (i.e., No. Days), mean, standard deviation (i.e., SD), skewness, and kurtosis for each equity market index. The sample periods for each market are reported in Table 2.1. For each market, we exclude a day if the first or the last half-hour return is not available. The mean, standard deviation, skewness and kurtosis are annualised. We also compute one sample t-statistic for the returns and account for autocorrelation and heteroskedasticity by Newey and West (1987) correction. *, **, and *** denote the 10%, 5%, and 1% significant levels, respectively.

dummies, clustering the standard errors by country. This model allows for the observations of the same country at different time points to be correlated. To control for the heteroskedastisity and autocorrelation, we adjust the standard errors using the Newey and West (1987) correction modified for a panel framework. In Table A.6 of Appendix A, we also report the results for the full sample based on local currency.

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

While we observe a significant intraday time series momentum effect in most of the countries, the evidence in Austria, Canada, Ireland, and New Zealand is rather weak and deserves further investigation. First, we examine whether the periodic institutional trading behavior that is documented in Murphy and Thirumalai (2017) and Etula et al. (2019) can explain this evidence. Our evidence is mixed and support Gao et al. (2018), who find that, on the U.S. market, institutional trading is more strongly associated with the predictability of the second last half-hour return on the last half-hour return, compared to that of the first half-hour return. We provide a detailed discussion in Section A.1 of Appendix A.

Second, we investigate the possibility that the weak evidence in Austria, Canada, Ireland, and New Zealand is due to that these four markets are led by other larger international markets in close proximity to them. Our motivation stems from Rapach et al. (2013), who document the strong cross-country predictability of the U.S. market on other international markets in a monthly setting. While a comprehensive study of intraday cross-country predictability is beyond the scope of this chapter, in Section A.2 of Appendix A we follow the approach of Rapach et al. (2013) and perform a pair-wise examination of the first-last half-hour relation. Our evidence does not suggest significant predictability of the U.S. market on the Canadian market, despite the fact that they are in the same timezone. Similarly, the first half-hour return of the U.K. does not appear to significantly predict the last half-hour return of Ireland. However, we find strong cross-market predictability of the U.S. market on the European markets, confirming the dominating role of the U.S. market (Rapach et al., 2013).

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

TABLE 2.3: In-sample evidence of intraday time series momentum

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

This table presents the in-sample regression results over the full sample period. In the individual country-based regressions, we regress the last half-hour return against the first half-hour return: $r_t^L = \alpha + \beta^F r_t^F + \epsilon_t$. In the pooled panel regressions, we regress the last half-hour return against the first half-hour return and country dummy variables: $r_{i,t}^L = \alpha + \beta^F r_{i,t}^F + \sum_{j=2}^{16} \beta_j D_{j,t} + \epsilon_{i,t}$. Note that the first half-hour return includes the overnight return in order to take into account the impact of information released overnight. The Newey and West (1987) t-statistics are reported in parentheses. In the pooled regression, we also cluster the standard errors by country. The slope coefficients are scaled by 100. The sample periods for each market are shown in Table 2.1. In the pooled regression we use only days on which all the markets have available data. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

2.3.2 Intraday time series momentum under various conditions

We now investigate the relation between the first and last half-hour returns under the following market conditions: the financial and non-financial crisis periods and the business cycle. We follow Gao et al. (2018) and set the financial crisis period from December 2, 2007 to June 30, 2009, while the OECD recession and expansion indicators are sourced from the St. Louis FRED website.[3] Panels A and B of Table 2.4 show that the predictability of the first half hour on the last half-hour return is economically stronger during the financial crisis compared to the non-crisis period; 12 out of 16 markets exhibit larger slope coefficients during financial crisis, while the magnitude of the adjusted R^2s is much larger compared to the one in the non-crisis period. Among the 16 markets, the predictive power of the first half hour is more pronounced in the U.S. stock market, which has a (scaled) coefficient of the first half hour equal to 18.28 during the financial crisis, four times larger than the corresponding one observed when we exclude the financial crisis period from our full sample period (the coefficient is equal to 4.24). In the pooled regression, we find a stronger positive relation between the first and the last half-hour returns during the financial crisis period relative to the non-crisis period; the coefficients of the first half-hour returns are 3.71 and 2.09, for the financial and non-financial crisis periods, respectively. Note that both coefficients are statistically distinguishable from zero. Similarly, the adjusted R^2 is equal to 1.18% during financial crisis; this is almost two times larger than the one observed in the non-crisis period (i.e., 0.63%). Panels C and D show that the predictive ability of the first half hour on the last half-hour return is stronger during recessions compared to expansions, with an average slope and adjusted R^2 equal to 4.04 (2.57) and 1.67% (0.65%) for the recession (expansion) periods.[4] The ITSM exhibits larger slope coefficients in 12 out of 16 markets during recession compared to expansion periods.

Collectively, Table 2.4 provides strong evidence that the positive relation between the first half hour and the last half-hour return is more pronounced during the financial crisis and recession periods. Our findings extend the evidence shown in Gao et al. (2018) for the U.S. stock market to a comprehensive set of countries around the world.

2.3.3 Out-of-sample predictability

Up to this point, we have examined the in-sample predictability of the first half hour on the last half-hour return, which is based on the entire sample period. In this subsection, we formally examine the out-of-sample (OOS) predictive power of the first half-hour

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

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

TABLE 2.4: Intraday time series momentum in different market conditions

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

This table presents the in-sample regression results under various market conditions, namely financial crisis (Panel A), non-crisis period (Panel B), recession (Panel C), and expansion (Panel D). In the individual country-based regressions, we regress the last half-hour return against the first half-hour return: $r_t^L = \alpha + \beta^F r_t^F + \epsilon_t$. In the pooled panel regressions, we regress the last half-hour return against the first half-hour return and country dummy variables: $r_{i,t}^L = \alpha + \beta^F r_{i,t}^F + \sum_{j=2}^{16} \beta_j D_{j,t} + \epsilon_{i,t}$. Note that the first half-hour return includes the overnight return in order to take into account the impact of information released overnight. The financial crisis period spans form 2 December 2007 to 30 June 2009 (Gao et al., 2018). Recession indicators are sourced from St. Louis FRED website. The returns are annualised and in percentages. The Newey and West (1987) t-statistics are reported in parentheses. In the pooled regression, we also cluster the standard errors by country. The slope coefficients are scaled by 100. The sample periods for each market are shown in Table 2.1. In the pooled regression we use only days on which all the markets have available data. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

return on the last half-hour return for each individual stock market index. This enables us to assess the parameter instability over time in the predictive regressions (Ashley et al., 1980; Welch and Goyal, 2008).

Based on an expanding window approach, we use the first five years of our sample for each market as the initial estimation period and recursively regress equation (2.2) on each market by adding one day at a time. Then we evaluate the OOS performance of our predictive model by comparing it with that of a simple historical mean model via three statistics.

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

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T}(r_t^L - \hat{r}_t^L)^2}{\sum_{t=1}^{T}(r_t^L - \bar{r}_t^L)^2}, \tag{2.3}$$

where T is the number of observations in the out-of-sample period, r_t^L is the realized value of the last half-hour return at time t, $\bar{r}_t^L$ is the value estimated by using historical mean of the last half-hour return with data until time $t-1$, and $\hat{r}_t^L$ is the estimated value from the predictive regression using information available up to time $t-1$. This statistic compares the mean squared prediction error (MSPE) of our predictive model with that of the historical mean model; a positive value implies that the predictive model (equation (2.2)) outperforms the historical mean model.

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

$$\hat{f}_t = (r_t^L - \bar{r}_t^L)^2 - [(r_t^L - \hat{r}_t^L)^2 - (\bar{r}_t^L - \hat{r}_t^L)^2], \tag{2.4}$$

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

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

[5]This statistic is also employed by Barroso and Maio (2019); 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 the 5% and 10% significance levels, respectively.

the predictive model:

$$ENC_{NEW} = \frac{\sum_{t=1}^{T}[(r_t^L - \bar{r}_t^L)^2 - (r_t^L - \hat{r}_t^L)(r_t^L - \bar{r}_t^L)]}{T^{-1}\sum_{t=1}^{T}(r_t^L - \hat{r}_t^L)^2}. \quad (2.5)$$

Table 2.5 provides the three OOS statistics along with the average recursive regression coefficients for each country. As shown in the table, the average slope coefficient is positive for all countries and significant for 10 countries. Eleven out of 16 countries exhibit positive R^2_{OOS}, while the Clark and West (2007) MSPE-adjusted rejects the null ($R^2_{OOS} \leq 0$) in 12 markets. Interestingly, we observe a negative R^2_{OOS} in Germany, along with a MSPE-adjusted that is significant at the 1% level, which indicates that the MSPEs for the predictive model are significantly less than that of the historical mean model in this market.[6] The last column of Table 2.5 reports results of the forecast encompassing test. The null hypothesis (the historical mean forecasts encompass the predictive forecasts) is rejected for 12 out of 16 countries, implying that the first half-hour return provides additional predictive information relative to the simple historical mean of the last half-hour return in those markets. Overall, our OOS analysis provides strong evidence of OOS predictability in the first half-hour return on the last hour-hour return in most countries.

2.3.4 The profitability of ITSM

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

For the ITSM strategy, we consider the sign of the first half-hour return as the trading/-timing signal: if the first half-hour yields a positive return, we take a long position in the last half-hour on the same day; if the first half-hour yields a negative return, we

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

TABLE 2.5: Out-of-sample analysis

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

This table reports the individual out-of-sample analysis results. For each market, we use the first five years as the initial estimation period and recursively perform the predictive regression by adding one day at a time. The intercept and slope coefficients are averaged from individual regressions. The stars next to them are assigned based on average Newey and West (1987) t-statistics (unreported). For each country, we also report Campbell and Thompson (2008) R^2_{OOS}, Clark and West (2007) MSPE-adjusted, and Clark and McCracken (2001) ENC_{NEW} respectively. We apply Newey and West (1987) corrections in computing the Clark and West (2007) MSPE-adjusted, which is an one-tailed (upper-tail) t-statistic. For ENC_{NEW}, we use critical values of 1.280 and 2.085 for the 5% and 10% significance levels, given by Clark and McCracken (2001). The slope coefficients are scaled by 100. The sample periods are reported in Table 2.1. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

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:

$$r_{I,t} = \begin{cases} r_t^L, & \text{if } r_t^F > 0; \\ -r_t^L, & \text{if } r_t^F \leq 0, \end{cases} \tag{2.6}$$

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

TABLE 2.6: Profitability of individual intraday time series momentum

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

This table presents the performance of intraday time series momentum (i.e. ITSM) and the buy-and-hold benchmark for each of the 16 equity markets. The ITSM strategy opens a long (short) position at the beginning of the last half hour if the return during the first half hour on the same trading day is positive (negative), and closes the positions at the market close. The buy-and-hold benchmark strategy opens a long position at the beginning of our sample and hold it throughout the sample period. We report the mean, standard deviation (SD), skewness, kurtosis, and the Sharpe ratio (SR) of the two strategies for each market. *, **, and *** denote 10%, 5%, and 1% significance levels after Newey and West (1987) correction, respectively. The sample periods are reported in Table 2.1.

Table 2.6 provides the mean, standard deviation (SD), skewness, kurtosis, and the Sharpe ratio of the ITSM strategy, and the buy-and-hold benchmark for each of the 16 equity markets. Over the full sample period, the ITSM strategy exhibits positive average annualised returns in all countries. Thirteen out of 16 countries show a statistically significant ITSM strategy return, of which 11 are significant at the 5% level following the Newey and West (1987) correction. We also observe a positive Sharpe ratio for the ITSM strategy in all countries, ranging from 0.02 for Canada to 1.24 for the U.K. The skewness of the ITSM return is positive in 9 out of 16 markets, suggesting a low crash risk. In contrast, 15 out of 16 countries exhibit a positive buy-and-hold strategy return, of which only two show statistical significance at the 5% level. In addition, the standard deviation of the benchmark strategy is significantly greater than that of the ITSM strategy (4 to 10 times higher) in all countries, resulting in a trivial Sharpe ratio compared to the ITSM. While the Sharpe ratio of the buy-and-hold strategy varies from -0.02 to 0.68, for example, it is smaller than its ITSM counterpart in 12 countries. We find that the results in Table A.7 of Appendix A remain intact when the sample is based on local currencies.

2.4 Intraday time series momentum and market characteristics: Hypothesis development

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

2.4.1 Liquidity provision and market impact

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

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

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

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

2.4.2 Limited attention and inattentive "frogs"

Studies show that attention is a scarce cognitive resource of investors and the strategic allocation of it can affect asset prices (Peng and Xiong, 2006). While Hirshleifer et al. (2009) show investors have an upper attention threshold and can be overwhelmed by huge amounts of information, Da et al. (2014) propose the "frog-in-the-pan" (FIP) hypothesis in which there exits a lower attention threshold that is required for investors to respond to the news. Da et al. (2014) posit that investors are inclined to be inattentive and under-react to small amounts of information arriving continuously. This underreaction can be adjusted later in time causing momentum. They document that the cross-sectional momentum is stronger when the information in the formation period arrives continuously. Similarly, Lim et al. (2018) test this hypothesis on the time series momentum of Moskowitz et al. (2012) and find that the time series momentum performs better in the group of stocks in which the information arrives gently and continuously in the formation period.

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

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

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

2.4.3 Self-attribution bias

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

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

2.4.4 Cultural differences

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

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

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

2.5 Intraday time series momentum and market characteristics: Empirical tests

2.5.1 Estimating market characteristic variables

2.5.1.1 Intraday liquidity

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

$$\begin{aligned}
S &= \frac{2(e^{\alpha}-1)}{1+e^{\alpha}} \\
\alpha &= \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}} \\
\beta &= \sum_{j=0}^{1}\left[\ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2, \quad \gamma = \left[\ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2,
\end{aligned} \tag{2.7}$$

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

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

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

2.5.1.2 Information discreteness

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

$$ID_t = sign(r_t^F) \times (\%neg_t - \%pos_t), \tag{2.8}$$

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

To see how ID measures the information incorporation process, consider the first half-hour returns from two days on the same market, r_k^F and r_s^F, triggered by equally effective overnight information, ϕ_k^O and ϕ_s^O, which lead to an upward price movement.[10] Now suppose ϕ_k^O is smoothly incorporated into the price while ϕ_s^O is absorbed by a few sudden price movements. This can be translated into that r_k^F has a higher proportion of positive minutely returns than does r_s^F. Collectively:

$$\begin{aligned}
&\phi_k^O = \phi_s^O \\
&r_k^F = r_s^F > 0 \\
&0 \leq p_s < p_k \leq 1,
\end{aligned} \tag{2.9}$$

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

$$1 - 2p_k = ID_k < ID_s = 1 - 2p_s. \tag{2.10}$$

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

2.5.1.3 Information uncertainty and individualism

For estimating the information uncertainty, we follow Zhang (2006) and use stock return volatility as a proxy. Intuitively, the more ambiguous the market is about news, the larger the volatility of stock returns. In particular, we estimate stock return volatility by computing the standard deviation of minute returns in the first half hour for each country. While the volatility of returns contains the uncertainty of information, it accounts for the variation in the information itself. The high-frequency nature of our

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

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

study effectively mitigates this problem, given that the intrinsic value of an asset is believed to change less in thirty minutes than in weeks or months.

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

2.5.1.4 Descriptive statistics of characteristic variables

Table 2.7 reports the summary statistics of our estimates for liquidity, information discreteness, and volatility for each country. It also reports the Hofstede (2001) Individual Index numbers for each country. Due to the high frequency nature of our study and data quality, we observe extreme outliers in the estimates. To address this issue, we winsorize our estimates in the time series using the 5th and 95th percentiles, that is, we set any value below the 5th percentile to the 5th percentile and any value above 95th percentile to the 95th percentile.[12]

Table 2.8 presents the Pearson correlation coefficients among all characteristic variables but individualism, which is constant over time. Generally, we do not observe a strong correlation between characteristic variables. For example, the correlation between Spread and Volatility ranges from 0.16 in New Zealand to 0.52 in both Germany and U.S. In addition, the correlation between ID and the other two characteristic variables is virtually neglectable, ranging from -0.07 to 0.08.

2.5.2 Hypothesis testing in the cross-section

2.5.2.1 Fama-MacBeth regressions

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

$$r_{I,i,t} = \alpha_t + \beta_t^C Char_{i,t} + \epsilon_{i,t}, \tag{2.11}$$

where $r_{I,i,t}$ is the ITSM return for country i at time t, and $Char_{i,t}$ is the characteristic variable for country i at time t. We perform this analysis with each of our characteristic variables, namely, liquidity, ID, volatility, and individualism, which are standardized

[12] Regarding the sorting analyses presented below, we report the results using pre-winsorized data in Tables A.8 and A.9 of Appendix A. Our main conclusion remains largely unchanged.

TABLE 2.7: Characteristic variable estimates

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

For each country, we report the number of observations (No.Obs), standard deviation (SD), skewness (Skew), and kurtosis (Kurt) of the estimated characteristic variables with missing values excluded. Spread is the first half-hour liquidity estimated from Equation (2.7); ID is the first-half hour information discreteness estimated from Equation (2.8); Volatility is the standard deviation of minutely return in the first half hour. Individualism is the Hofstede (2001) individualism index and is constant over time. To address the issue of outliers, Spread, ID, and Volatility are winsorized in the time series using the 5th and 95th percentiles. The sample periods are reported in Table 2.1.

TABLE 2.8: Correlation of characteristic variables

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

This table reports pair-wise Pearson correlation coefficients of Spread, ID, and Volatility for each country. Spread is the first half-hour liquidity estimated from equation (2.7); ID is the first-half hour information discreteness estimated from equation (2.8); Volatility is the standard deviation of minutely return in the first half hour. To address the issue of outliers, Spread, ID, and Volatility are winsorized in the time series using the 5th and 95th percentiles. The sample periods are reported in Table 2.1.

across markets at every time t. Next, we conduct the following multivariate cross-sectional regressions at each day t:

$$r_{I,i,t} = \alpha_t + \boldsymbol{\beta}_t^{C\prime} \boldsymbol{C}_{i,t} + \epsilon_{i,t}, \tag{2.12}$$

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

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

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

Table 2.9 reports the average annualised coefficients of the Fama and MacBeth (1973) regressions, which correspond to the average profit of a long–short trading strategy over time; the corresponding t-statistics are estimated using Newey and West (1987) standard errors. Table 2.9 shows that liquidity, information discreteness, and individualism exhibit a significant cross-sectional relationship with ITSM return. For example, the annualised average ITSM return of a long-short strategy based on the Spread, ID, and individualism is equal to 1.19%, -1.92%, and 0.89%, associated with Newey and West (1987) t-statistics of 2.37, -3.01, and 2.24, respectively. The statistical significance of the Spread and ID remains intact, when we regress ITSM returns against all variables collectively, while individualism remains marginally significant at a 10% significance level. Our evidence suggests that the ITSM return is higher in markets with lower liquidity, smaller information discreteness, and higher individualism, endorsing Hypotheses 1, 2, and 4.

In contrast, although the sign of the coefficient of volatility is consistent with our Hypothesis 3 (i.e., the higher the volatility, the larger the ITSM return), it is not statistically

TABLE 2.9: Fama-MacBeth regression analysis

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

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

significant in the univariate regressions or in the multivariate Fama-Macbeth regressions.

2.5.2.2 Cross-sectional sorting analysis

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

The clear monotonic cross-group pattern in portfolio returns shown in Panels A and B of Table 2.10 largely confirm our Fama-MacBeth regression results and support Hypotheses 1 and 2. For example, when we sort the countries by the first half-hour High-Low spread, we observe a monotonic increase in the ITSM portfolio returns from 2.67% to 5.43% as liquidity shrinks (Panel A). The significance levels of the portfolio returns also increase from the 5% significance level in the small spread (liquid) group to the 1% significance level in the medium and large spread (illiquid) groups. A long-short portfolio that takes a long position in the large spread group and a short position in the small spread group enjoys an annualised average return of 2.76%, which is significant at the 5% level. This evidence is consistent with Hypothesis 1 that ITSM is stronger in markets with low liquidity.

TABLE 2.10: Intraday time series momentum and market characteristics: Cross-market sorting

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

This table presents the results for the cross-market sorting analysis that tests the hypotheses introduced in Section 2.4. At 10:00 am New York time each day, we sort in ascending order the markets based on the characteristic variables computed from the first half hour of the same calendar day. The markets are then split into three groups. Within each group, we form an equally weighted portfolio of ITSM and report the average return, standard deviation, Sharpe ratio, Skewness, and Kurtosis of the portfolio. All numbers are annualised. We also present results for a strategy that takes a long position in the large group and a short position in the small group (L - S). In parentheses, we report the *t*-statistics for the portfolio returns that are corrected for autocorrelation and heteroskedasticity through Newey and West (1987) correction. *, **, *** denote 10%, 5%, 1% significance levels. The sample period spans from 04 January 2000 to 29 December 2017.

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

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

Finally, Panel D provides the results when we sort ITSM country returns by individualism. The large individualism group exhibits a ITSM portfolio return of 5.04%, which is greater than that of both the small and medium individualism groups (3.82% and

3.78%, respectively), however this difference is not statistically significant. A long-short ITSM strategy yields a return of 1.22% with no statistical significance, in contrast to the Fama and MacBeth (1973) analysis, which suggests a significant relationship between ITSM and individualism. Note that the difference between the slope coefficients of the Fama and MacBeth (1973) regressions and the cross-sectional analysis is that the former represent portfolio returns with specific characteristics combined linearly, while the later represent portfolio returns based on a non-parametric ranking of the characteristic values (Back et al., 2013).

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

2.5.3 Time series sorting analysis

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

For each market, we sort all trading days by the characteristic variables and split them into three groups similar to the cross-market sorting. In each group, we first perform the predictive regression and then form the equally-weighted ITSM portfolio as in the cross-market sorting analysis. We report the slope coefficients and portfolio returns, in Panels A and B of Table 2.11, respectively.

As shown in Panel A of Table 2.11, the estimated slope coefficients exhibit a clear cross-group pattern in both magnitude and significance for liquidity and ID, echoing our cross-market findings shown in the previous section. For example, 10 out of 16 countries show a positive and significant slope coefficient in the large Spread (illiquid) group, in contrast to 7 and 9 in the small (liquid) and medium Spread groups. Moreover, in 10 countries, the large Spread group exhibits the largest slope coefficient across groups. In addition, when we sort the days by ID, we observe 11 countries with a positive and significant slope coefficient in the small group, 7 of which are significant at the 1% level. In contrast, two countries in the large ID group have a slope coefficient that is significant at the 1% level. Panel B of Table 2.11 provides portfolio returns for each group. In 11 out of 16 countries, the most illiquid group enjoys the largest ITSM

TABLE 2.11: Intraday time series momentum and market characteristics: time series sorting

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

This table presents the time series sorting analysis results. For each market, we sort all trading days by the characteristic variables and split into three groups using a similar approach as in the cross-market sorting. Within each group, we first perform the predictive regression and report the slope coefficient estimates in Panel A. Then we form an equally weighted portfolio within each group and report the portfolio returns in Panel B. *, **, *** denote 10%, 5%, 1% significance levels after the Newey and West (1987) correction. The slope coefficients are scaled by 100. Returns are annualised and in percentage. The sample periods are reported in Table 2.1.

portfolio return across groups. Similarly, 12 out 16 countries show the strongest portfolio performance in the small ID group compared to that of the medium and large ID groups.

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

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

2.6 Conclusion

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

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

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

Chapter 3

Intraday Cross-sectional Predictability: Evidence From Around the Globe

We explore the intraday cross-sectional predictability of stock markets in an international setting. By studying 13 developed markets, we show that the first half-hour return and the first half-hour volatility have strong cross-sectional predictability on the last half-hour return, both statistically and economically. Portfolios that combine the two intraday characteristics produce positive and statistically significant alphas when regressed against passive benchmarks, suggesting remarkable economic gains. A comparison of our cross-sectional portfolios and a strategy based on the intraday time series momentum (ITSM) of Gao et al. (2018) shows that our strategies provide extra benefit to ITSM. Our research contributes to the recent growing literature on intraday return predictability and asset pricing.

3.1 Introduction

Stock return predictability constitutes an important topic that has been extensively investigated by financial economists. There are two strands of literature on the stock return predictability. The first one is related to the time-series predictability of the aggregate market returns. A number of academic studies examine the predictive power of economic indicators, financial ratios, accounting variables, sentiment and historical average returns on future asset returns.[1] The second strand is related to the cross-sectional

[1]See e.g. Campbell (1987); Campbell and Vuolteenaho (2004); Fama (1981, 1984); Fama and Schwert (1977); Geske and Roll (1983); Huang et al. (2020); Jiang et al. (2019); Lim et al. (2018); Moskowitz et al. (2012); Shiller (1979); Stulz (1986); Welch and Goyal (2008).

predictability of asset characteristics on returns at the firm level and find evidence of a large number of equity market anomalies.[2] This extensive body of academic studies and the references therein have investigated the stock return predictability in a framework at lower frequency.

The fast development of machine-based trading and the improving transparency and availability of high-frequency data has stimulated the interest of academics to investigate the stock return predictability in an intraday setting. While there exists a number of academic studies that investigate the time-series intraday predictability of aggregate market returns,[3] there is less knowledge on the cross-sectional intraday predictability on asset returns. Our paper aims to fill this gap.

We restrict our attention to the first half hour after the market open and the last half hour before the close for several reasons. First, it is well known that there exists a U-shape in the intraday stock return, volume, and volatility (Brock and Kleidon, 1992; Chung et al., 1999; Harris, 1986; Wood et al., 1985), implying the speciality of these two periods in a trading day. Second, institutional investors put emphasis on the close of the market (Cushing and Madhavan, 2000; Gao et al., 2018) and some traders trade only in the periods of market open and close (Xu, 2017). Third, larger volatility of the last half-hour return makes its predictability economically exploitable, leading to a thorough investigation from a practical viewpoint. Fourth, our study employs international stock indices whose markets have very different settings. While the US market operates from 09:30 to 16:00, for example, the UK market operates from 08:00 to 16:30. Therefore, focusing only on the first and last half hours enables a meaningful cross-sectional study using international data.

We employ high-frequency data of 13 international stock market indices. Due to data availability, we construct characteristics based only on price and market data and end up with five market signals in total. We use the first half-hour return and sentiment (proxied by the information discreteness (ID) (Da et al., 2014)), which have been found good intraday time-series predictors on equity returns (Gao et al., 2018; Renault, 2017, respectively). We also employ the first half-hour liquidity and volatility following the long documented academic evidence on the cross-sectional predictability of these two variables in the dispersion of stock returns in lower frequency setting.[4] The last variable we employ is the one-day lagged last half-hour return, following Heston et al. (2010) who reveal a striking cross-sectional pattern in which half-hour returns from previous

[2]See Harvey et al. (2016) and Hou et al. (2020).

[3]Matías and Reboredo (2012) apply a number of linear and non-linear forecasting models to the S&P 500 index and find that non-linear models possess stronger intraday predictive power. Sun et al. (2016) and Renault (2017) predict the ETF of S&P500 (SPY) intraday returns based on the lagged half-hour investor sentiment. Gao et al. (2018) show that the first half-hour return of the SPY can statistically and economically predict its last half-hour return on the same day.

[4]See Amihud and Mendelson (1986); Chordia et al. (2001); Holmström and Tirole (2001); Liu (2006); O'Hara (2003) for the liquidity and Ang et al. (2006); Bakshi and Kapadia (2003) for the volatility

days strongly predict the corresponding half-hour returns on current day, with the one-day lagged returns having the strongest predictability.[5]

Our main analysis proceeds in four steps steps. First, we look for cross-sectional patterns in country equity markets. We observe strong monotonic cross-sectional patterns in portfolio returns when the first half-hour return and the volatility are used as signals. We find no evidence of cross-sectional patterns in the last half hour portfolio market returns, when ID, liquidity, and one-day lagged last half-hour return are used as signals. Fama-MacBeth (Fama and MacBeth, 1973) regressions also confirm that the average factor returns associated with exposure to the first half-hour return and volatility are statistically significantly different from zero.

Second, having confirmed that the first half-hour return and volatility are statistically significant cross-sectional intraday predictors on equity market returns, we construct long-short portfolios using these two variables as signals. We show that a long-short portfolio that goes long in the last half hour for markets with large first half-hour returns and short for those with small first half-hour returns (ICSM thereafter) generates an average return of 4.25% per year that is statistically significant at 1% level, with an annualized Sharpe ratio equal to 1.10. Similarly, a long-short portfolio that buys indices with large first half-hour volatility and sells indices with small first half-hour volatility (VOL thereafter) yields an average last-half hour return of 3.00% per year, which is significant at 1% level and is associated with a Sharpe ratio of 0.84.

Third, a spanning regression analysis of ICSM against VOL and vice versa shows that ICSM and VOL capture different sources of profitability and can not be subsumed by each other. This suggests potential economic benefits when combining these two portfolios. We document that long-only and long-short portfolios that combine the first half-hour return and volatility signals possess higher Sharpe ratios than the corresponding portfolios that are based solely on either the first half-hour return or volatility. In addition, we compare these portfolios to two passive benchmarks. The first benchmark is an always-long strategy that takes a long position in the last half hour of all market indices everyday. The second benchmark is a buy-and-hold strategy that takes a long position in the market indices at the beginning of the investment and holds it throughout the whole sample period. Spanning analysis of our portfolios against these two benchmarks suggests that they add value to the passive benchmarks. Our analysis is robust to alternative portfolio weighting schemes.

Finally, we investigate the relationship between ICSM and VOL, and the intraday time series (ITSM) momentum proposed by Gao et al. (2018). Using high-frequency data of SPY and other US domiciled ETFs, Gao et al. (2018) show that there exists an intraday time series pattern where the return in the first half hour positively predicts the return

[5]For instance, returns from 10:00am to 10:30am on day $t-1$, $t-2$, ... up to $t-60$ have been shown to positively predict the return of 10:00am-10:30am interval on day t.

in the last half hour on the same day. Following the methodology in Goyal and Jegadeesh (2018), we show that a global strategy that invests equally in the country ITSM benefits substantially from a time-varying component that helps the strategy to time the market. After controlling for this time-varying component, our analysis suggests the performance of ITSM can be replicated by a combination of the ICSM and a market timing strategy. Moreover, an equally-weighted strategy that simultaneously invests in ICSM and VOL generates a spanning alpha of 1.80% that is significant at 1% level when regressed against the ITSM strategy.

Our study adds to the growing literature on intraday asset pricing and predictability but differs from the existing literature in the following ways. First, we employ a collection of major developed markets and investigate the cross-sectional intraday predictability of price and market characteristics on international equity market returns. Second, instead of focusing on the impact of intraday information on mid- to long-term asset returns (Heston et al., 2010; Jiang et al., 2021; Lou et al., 2019), we look into the cross-sectional predictability of intraday characteristics on the last half-hour return on the same day. This paper sheds light on the intraday cross-sectional variation of stock market returns in an international setting.

The remainder of this paper is organised as follows. Section 3.2 describes the international indices used in this study. Section 3.3 reveals the intraday cross-sectional predictability of the first half-hour return and the intraday volatility on the last half-hour return. Section 3.4 examines the economic significance of investing the two intraday factors. Section 3.5 evaluates the relationship between our intraday cross-sectional strategies and the intraday time-series momentum of Gao et al. (2018). Section 3.6 concludes the paper.

3.2 Data

We collect 1-minute quote data from the Thomson Reuters Tick History (TRTH) database of stock market indices[6] and restrict our analysis to developed markets classified by the MSCI.[7,8] 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, high price, low price and last price for every trading minute.

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

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

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

In order to process the high-frequency dataset, we broadly follow the data-cleaning steps outlined in Barndorff-Nielsen et al. (2009) and Hollstein et al. (2020), with a few additions. First, we exclude Belgium, Denmark, Finland, Israel and Italy since TRTH does not provide liquid data for these countries for a long enough period for our study.[9] Second, we further exclude Australia, Hong Kong, Japan, New Zealand, and Singapore due to the time different issue. To be specific, our cross-sectional analysis requires feasibility of investing in the last half hour of all markets at the time that information from the first half hour of all markets becomes available. For example, the US is lagged behind all other countries in the sample, thus opens the latest. However, the New Zealand Stock Exchange, which is located in Wellington, is 16 hours ahead of New York Stock Exchange, meaning that the local time at the New Zealand Stock Exchange is 02:00 am on the next calendar day ($t + 1$) when the New York Stock Exchange hits 10:00 am on day t. This fact makes it impossible to invest in New Zealand based on the first half-hour information from US on the same day. The same problem applies to Australia, Hong Kong, Japan and Singapore as well. Third, 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 3.1 we report all market trading hours for each market studied.[10] Fourth, 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 better study the intraday return predictability in the international cross-section, we take the perspective of US dollar investor, and hence we convert all local currency data into US dollars.[11] Specifically, we convert index prices based on the contemporaneous 1-minute exchange rate. Table 3.1 tabulates the list of the 13 developed stock market indices employed in this study along with their RICs and trading hours.

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

[10]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.

[11]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).

TABLE 3.1: Indices

	Index	RIC	Trading Hours (local time)
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
Netherlands	AEX Amsterdam Index	.AEX	09:00 - 17:30
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.

3.3 Intraday Predictability in the Cross-section of Market Indices

3.3.1 Cross-sectional sorting analysis

We start our analysis by looking for intraday monotonic cross-sectional patterns in country equity markets using the following five characteristics:

- *First half-hour return*: Gao et al. (2018) study the US ETFs and find the first half-hour return possesses strong intraday predictability on the last half-hour return before market close. Following Gao et al. (2018), we compute the first half-hour return every day using previous close price to capture the overnight information[12]:
$$r_t^F = \frac{p_{first30,t}}{p_{close,t-1}} - 1, \tag{3.1}$$
where $p_{first30,t}$ 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 $t-1$.

- *Information discreteness*: Da et al. (2014) propose the 'frog-in-the-pan' hypothesis in which investors overreact to discretely arrived information whilst underreact to continuously arrived information. Similar to Da et al. (2014), we capture this

[12] Komarov (2017) conduct a similar examination in which he splits a trading day into 13 half hours and studies the intraday predictive power of each interval. Since our sample covers a range of international markets whose trading hours varies from market to market, we focus only on the first half hour, which is likely to have strongest intraday predictability, as suggested by the well documented intraday U shape of returns, volatility, and volume.

discreteness of information in the first half hour as:

$$ID_{i,t} = sign(r^F_{i,t}) \times (\%neg_{i,t} - \%pos_{i,t}), \tag{3.2}$$

where $r^F_{i,t}$ is the first half-hour return for country i on day t, $\%neg_{i,t}$ and $\%pos_{i,t}$ are the percentage of minutes associated with a negative and positive return within the first 30 minutes, respectively, for country i on day t.

- *Market liquidity*: We define the intraday liquidity in the first half hour every day for each market by computing the High-Low liquidity measure of Corwin and Schultz (2012):

$$\begin{aligned} S &= \frac{2(e^\alpha - 1)}{1 + e^\alpha} \\ \alpha &= \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \\ \beta &= \sum_{j=0}^{1} \left[\ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2, \quad \gamma = \left[\ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2, \end{aligned} \tag{3.3}$$

  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 $t+1$.

- *Market volatility*: The market volatility is defined as the standard deviation of the one minute returns in the first half hour after market open.

- *One-day lagged last half-hour return*: Heston et al. (2010) investigate the short-term return predictability in the cross-section of the US individual stocks and find that one-day lagged half-hour returns have the strongest predictability.

We sort the 13 market indices at 10:00am New York time each day into 3 groups by the sorting characteristics and invest in the last half hour return.

Table 3.2 presents the cross-sectional sorting results. We observe monotonic cross-sectional patterns across groups when we sort the indices by the first half-hour return and the intraday volatility. For instance, the annualized return for the small, medium and large first half-hour return groups is equal to 2.62%(marginally significant at the 10% level) , 6.47% (statistically significant at the 1% level) and 8.96% (statistically significant at the 1% level), respectively. Similarly, the annualized return for the small, medium and large volatility groups is equal to 4.63%(statistically significant at the 1% level) , 5.59% (statistically significant at the 1% level) and 8.44% (statistically significant at 1% level), respectively. In contrast, we do not observe monotonic cross-sectional patterns when we sort the indices by the information discreteness, liquidity (Spread), and the one-day lagged last half-hour return.

TABLE 3.2: Cross-sectional Sorting Analysis

	Small	Medium	Large	L-S	Small	Medium	Large	L-S	Small	Medium	Large	L-S
	First half-hour return				Information discreteness				Spread			
AVE(%)	2.62*	6.47***	8.96***	6.34***	5.81***	6.65***	5.62***	-0.18	6.16***	5.78***	6.66***	0.50
	(1.71)	(6.16)	(7.94)	(3.91)	(5.43)	(6.06)	(3.87)	(-0.13)	(4.68)	(5.66)	(5.94)	(0.37)
SD	6.44	3.97	4.18	6.84	4.07	4.25	6.04	6.06	5.20	3.85	4.31	5.35
Sharpe Ratio	0.41	1.63	2.14	0.93	1.43	1.56	0.93	-0.03	1.18	1.50	1.54	0.09
Skewness	-1.66	-0.01	0.00	1.43	0.01	-0.16	-1.90	-1.92	-1.04	0.01	0.00	0.97
Kurtosis	7.87	3.02	3.04	7.01	3.03	3.25	9.18	9.28	5.42	3.04	3.03	5.23
	Volatility				Lagged last half-hour return							
AVE(%)	4.63***	5.59***	8.44***	3.80***	6.42***	5.03***	6.99***	0.57				
	(4.50)	(4.88)	(7.06)	(3.64)	(5.87)	(4.57)	(5.63)	(0.50)				
SD	3.95	4.51	4.62	4.54	4.27	4.49	4.61	4.98				
Sharpe Ratio	1.17	1.24	1.82	0.84	1.50	1.12	1.52	0.11				
Skewness	-0.44	-0.56	-0.01	0.28	0.00	-0.58	-0.28	-0.23				
Kurtosis	3.84	4.24	3.03	3.47	3.04	4.24	3.52	3.43				

This table reports the results for the cross-sectional sorting analysis. we sort all the 13 indices at 10:00am New York time each day into 3 groups by the sorting variables and invest in the last half hour. We also form a long-short portfolio that takes a long position in the large group and a short position in the short group. For each portfolio, we report the mean, standard deviation, Sharp ratio, skewness, and kurtosis of the returns. Newey and West (1987) adjusted t-statistics for the portfolio returns are also reported in parentheses. The sample period spans from the 04 January 2000 to 29 December 2017.

Finally, a portfolio that takes a long position in the top first half-hour return group and a short position in the bottom group yields an average return of 6.34% per year. Accordingly, a portfolio that buys the top volatility group and sells the bottom volatility group gives an average return of 3.80% per annum.

3.3.2 Fama-Macbeth regressions

In addition to the portfolio sorting analysis shown in the previous section, we run Fama-Macbeth regressions to further investigate the cross sectional relationship between the characteristics and the last half-hour return of the international stock market indices. Specifically, we fit the following cross-sectional regression model on each day:

$$r^L_{i,t} = \alpha_t + \beta^V_t r^V_{i,t} + \epsilon_{i,t}, \tag{3.4}$$

where $r^L_{i,t}$ is the last half-hour return for country i on day t and $r^V_{i,t}$ is the intraday variable for country i on day t. We consider the first half-hour returns, information discreteness, intraday liquidity, intraday volatility, and one-day lagged last half-hour returns. Each characteristic is standardized by subtracting the cross-sectional mean and by dividing the cross-sectional standard deviation.

We estimate Equation (3.4) each day using as independent variable each characteristic. Columns (1) - (5) of Table 3.3 present the estimated slopes of the FM regressions which represent the annualized average factor premia that have exposure to each of the characteristic variables; the corresponding t-statistics are estimated using Newey and West (1987) standard errors. Our evidence suggests that the average factor premia with exposure to the first half-hour return and volatility are equal to 2.83% and 2.06% per annum respectively, both statistically significant at 1% level. On the contrary the average factor premia with exposure to the rest characteristic variables are not statistically distinguishable from zero.

Furthermore, we perform a multivariate cross-sectional regression at each time t where the last half-hour return is regressed against all the characteristic variables collectively:

$$r^L_{i,t} = \alpha_t + \boldsymbol{\beta}^{V\prime}_t \boldsymbol{V}_{i,t} + \epsilon_{i,t}, \tag{3.5}$$

where $\boldsymbol{V}_{i,t}$ is a 5-D vector of intraday variables for country i at t.

Column (6) of Table 3.3 presents the results. The average factor premium with exposure to the first half-hour return is equal to 2.22% per year and remains statistically significant at 1% level. In contrast, the premia with exposure to the rest characteristic variables are statistically insignificant, including the first half-hour volatility which has been found significant in the univariate FM regression.

Overall, our empirical evidence confirms the strong cross-sectional predictability of the first half-hour return and intraday volatility on the last half-hour return based on the univariate Fama-MacBeth regressions, while the significance of the first half-hour volatility is submumed by that of the first half-hour return in the multivairate Fama-MacBeth regression. The rest variables remain insignificant in both univariate and multivariate Fama-MacBeth regressions.

TABLE 3.3: Fama-Macbeth Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
α	6.07***	6.01***	6.06***	6.05***	5.91***	5.31***
	(6.35)	(6.20)	(6.33)	(6.31)	(6.06)	(5.20)
β^F	2.83***					2.22***
	(3.97)					(2.89)
β^{ID}		-0.32				-0.56
		(-0.48)				(-0.73)
β^{LIQ}			-0.10			6.67
			(-0.19)			(0.97)
β^{VOL}				2.06***		1.07
				(4.36)		(1.10)
β^L					-0.17	0.60
					(-0.28)	(0.85)
$Adj.R^2$ (%)	5.62	1.41	1.43	3.44	5.48	16.38

This table performs cross-sectional regressions and reports the serial average of the coefficients and the corresponding Newey and West (1987) t-statistics (in parentheses). Columns (1) to (5) report the results for regressing last half-hour return against an intraday variable, namely, first half-hour return, information discreteness Da et al. (2014), liquidity, volatility, and the previous last half-hour return. Column (6) reports the results for multivariate regressions where the last half-hour return is regressed against all intraday variables collectively. The slope coefficients are annualised and in percentage. The sample period spans from the 04 January 2000 to 29 December 2017.

3.4 Economic Significance

3.4.1 Intraday cross-sectional momentum and intraday volatility portfolios

In this section, we evaluate the economic significance of exploiting the intraday cross-sectional predictability of the first half-hour return and volatility. To this end, we evaluate the performance of two portfolios using the first half-hour return and volatility as signals. We refer to the first portfolio as intraday cross-sectional momentum (ICSM) and the second portfolio as Intraday Volatility (VOL).

To construct these portfolios, we follow Goyal and Jegadeesh (2018). In particular, we first compute on each day t the cross-sectional mean of the signal, $\bar{F}_t$. Then we take a long (short) position in the last half hour of Market i if $F_{i,t} \geq \bar{F}_t$ ($F_{i,t} < \bar{F}_t$). Our construction produces a zero-cost long-short strategy that invests equally amongst the long and short portfolios and within each portfolio. Mathematically, the two portfolios can be denoted as:

$$r_t^{ICSM} = \frac{1}{N^+} \sum_{r_{i,t}^F \geq \bar{r}_t^F} r_{i,t}^L - \frac{1}{N^-} \sum_{r_{i,t}^F < \bar{r}_t^F} r_{i,t}^L, \tag{3.6}$$

$$r_t^{VOL} = \frac{1}{N^+} \sum_{VOL_{i,t} \geq \overline{VOL_t}} r_{i,t}^L - \frac{1}{N^-} \sum_{VOL_{i,t} < \overline{VOL_t}} r_{i,t}^L, \tag{3.7}$$

where N^+ (N^-) is the number of indices whose first half-hour return is greater than or equal to (less than) the cross-sectional mean of the corresponding factor.

Panels A and B of Table 3.4 summarise the portfolio performance for the two strategies. For both strategies, we observe a positive return for both long and short portfolios with the long portfolio exhibiting superior performance. As a result, the long-short ICSM strategy enjoys an average annualised return of 4.25% while the long-short VOL strategy produces an average annualised return of 3.00%, with the Shape ratio being 1.10 and 0.84 for ICSM and VOL, respectively. Both long-short portfolios have a positive skewness, suggesting larger chance of higher-than-average returns.

TABLE 3.4: Portfolio Performance

	AVE Ret (%)	NW t-stat	SD	Sharpe Ratio	Skewness	Kurtosis
	Panel A: Intraday Cross-sectional Momentum Portfolios					
Short	3.99***	(3.99)	3.89	1.03	-0.12	3.13
Long	8.25***	(7.69)	3.82	2.16	0.00	3.03
ICSM	4.25***	(4.39)	3.88	1.10	0.10	3.13
	Panel B: Intraday Volatility Portfolios					
Short	4.70***	(4.89)	3.47	1.35	-0.15	3.20
Long	7.83***	(6.46)	4.71	1.66	-0.26	3.43
VOL	3.00***	(3.25)	3.57	0.84	0.14	3.17

This table reports the performance of the intraday cross-sectional momentum strategy (ICSM) and the intraday volatility strategy (VOL). For a given portfolio we report the annualised average return (AVE Ret), the Newey and West (1987) t statistic of the return, annualised standard deviation, Sharpe ratio, Skewness, and Kurtosis. The sample consists of 13 markets and spans over a period from 04 January 2000 to 29 December 2017.

3.4.2 Investing in ICSM and VOL

We now turn our attention to the economic significance of investing ICSM and VOL simultaneously. First, we investigate statistically the economic gain of combining ICSM and VOL. Specifically, we perform spanning regressions where ICSM is regressed against VOL and vice versa. As shown in Table 3.5, a significant (at 1% level) alpha of 4.06% per year appears when we regress ICSM against VOL. Conversely, when we regress VOL against ICSM, the annualised alpha is 2.76% and is significant at 1%. Our evidence suggests that neither ICSM subsumes VOL nor VOL subsumes ICSM. Put differently, this implies that a strategy that combines these two portfolios should provide extra economic gains.

TABLE 3.5: Spanning Analysis between ICSM and VOL

	Alpha	ICSM	VOL	$Adj.R^2$ (%)
ICSM	4.06***	–	6.42	0.34
	(4.21)		(0.68)	
VOL	2.76***	5.64	–	0.34
	(3.02)	(0.67)		

This table reports the results of spanning regressions between ICSM and VOL. We first regress ICSM against VOL and then VOL against ICSM. ICSM and VOL are long-short portfolios that are constructed following Equations (3.6) and (3.7), respectively. Newey and West (1987) t statistics are reported in parentheses. The sample consists of 13 markets and spans over a period from 04 January 2000 to 29 December 2017.

Next, we adopt four portfolio construction techniques , namely, equal-weight (EW), maximum-diversification (MD), minimum-variance (MinV), and inverse-variance (IV), and invest in ICSM and VOL simultaneously. In the EW, we equally allocate our wealth between ICSM and VOL. This strategy does not require estimation of return or risk, and thus is estimation risk free. For the MD portfolio, we maximise the diversification ratio (Choueifaty and Coignard, 2008):

$$\max_{w} \frac{w^T \sigma}{\sqrt{w^T \Sigma w}}, \quad s.t. \mathbf{1}^T w = 1. \tag{3.8}$$

where w is a two-dimensional vector of portfolio weights and σ is the vector of standard deviations of ICSM and VOL. The numerator is the portfolio volatility ignoring the correlation between ICSM and VOL, whereas the denominator is the portfolio volatility that takes into account this correlation. The MinV strategy minimises the variance of the portfolio:

$$\min_{w} w^T \Sigma w, \quad s.t. \mathbf{1}^T w = 1. \tag{3.9}$$

Finally, to implement the inverse-variance, we follow the approach of Kirby and Ostdiek (2012) and calculate the weight invested in strategy i based the following formula:

$$w_{i,t} = \frac{(1/\hat{\sigma}^2_{i,t})}{(1/\hat{\sigma}^2_{ISCM,t} + 1/\hat{\sigma}^2_{VOL,t})}. \tag{3.10}$$

Note that while ICSM and VOL can be a long-short strategy themselves, at the combined portfolio construction level, we restrict the weights assigned to the two strategies to be non-negative for all construction techniques, i.e. for either of the strategies i, $w_i \geq 0$.

For all portfolio weighting schemes, we employ an expanding window approach that uses the first five years of our sample period (04 January 2000 to 03 January 2005) as the initial estimation period. In addition to the four portfolios that invest in the long-short ICSM and VOL, we also examine an implementation in which we invest only in the long positions of ICSM and VOL.

Table 3.6 reports the portfolio performance of our combined strategies. Since all the combined strategies, apart from EW, require an initial estimation period, which is set to five years in our study, we report again the performance of ICSM and VOL but over the period from 04 January 2005 to 29 December 2017 to form a more direct comparison. As shown in the table, all the combined portfolios provide extra economic gains. When we invest in the long-short ICSM and VOL, the combined portfolios yield equal or slightly greater average returns. More importantly, the Sharpe ratio of the combined portfolios ranges from 1.25 to 1.26, greater than that of ICSM (0.81) and VOL (0.90). Similarly, when we invest in the long-only ICSM and VOL, the Sharpe ratio of the combined portfolios ranges from 1.75 to 1.82, which is larger than that of ICSM (1.73) and VOL (1.72).

Finally, we study the economic value added from our strategies to two passive benchmarks. The first benchmark is an always-long strategy that equally invests in the last 30 minutes of all markets and clears all positions at the market close each day. The second benchmark is a buy-and-hold strategy that enters the markets at the beginning of our sample period with a long position and holds it throughout the full sample period.

We perform a mean-variance spanning test of our strategies against the two passive benchmarks. Specifically, we regress each of the portfolios against the two passive benchmarks and report the alphas in Table 3.7. As shown in the table, all strategies show a significant alpha against the benchmarks. In particular, portfolios that invest in long-short ICSM, VOL or both have a significant alpha ranging from 2.09% (VOL) to 2.70% (ICSM) when regressed against the always-long benchmark, and a significant alpha ranging from 1.12% (MinV) to 1.38% (VOL) when regressed against the buy-and-hold benchmark. Moreover, portfolios that invest in long-only ICSM, VOL or both have a significant alpha ranging from 2.78% (VOL) to 2.86% (ICSM) when regressed

TABLE 3.6: Investing in ICSM and VOL

	AVE Ret (%)	NW t-stat	SD (%)	Sharpe Ratio	Skewness	Kurtosis
	Panel A: Combining ICSM and VOL – Long-short					
ICSM	2.86***	(2.97)	3.51	0.81	0.02	3.03
VOL	2.88***	(2.90)	3.21	0.90	0.03	3.03
EW	2.88***	(4.06)	2.31	1.25	0.04	3.03
MD	2.89***	(4.07)	2.30	1.25	0.04	3.03
MinV	2.89***	(4.08)	2.30	1.26	0.04	3.03
IV	2.89***	(4.08)	2.30	1.26	0.04	3.03
	Panel B: Combining ICSM and VOL – Long-only					
ICSM	6.52***	(5.21)	3.78	1.73	-0.01	3.04
VOL	7.17***	(5.38)	4.18	1.72	-0.02	3.03
EW	6.80***	(5.46)	3.73	1.82	-0.02	3.03
MD	6.73***	(5.41)	3.71	1.81	-0.01	3.03
MinV	6.49***	(5.18)	3.71	1.75	-0.01	3.03
IV	6.67***	(5.37)	3.70	1.80	-0.01	3.03

This table reports the performance for portfolios that invest simultaneously in ICSM and VOL. For a given portfolio we report the annualised average return (AVE Ret), the Newey and West (1987) t statistic of the return, annualised standard deviation, Sharpe ratio, Skewness, and Kurtosis. The constituents of the combined portfolios reported in Panel A are long-short portfolios of ICSM and VOL, whereas that in Panel B are long-only ICSM and VOL. We report results for four weigting schemes, namyly, equal-weight (EW), maximum-diversification (MD), minimum-variance (MinV), and inverse-variance (IV). For the MD, MinV, and IV portfolios, we use the first five years of our sample period (04 January 2000 to 03 January 2005) as the initial estimation period and invest in the period from 04 January 2005 to 29 December 2017. Short-selling is prohibited in the portfolio constructions. To facilitate a more direct comparison, we also report results for ICSM, VOL, and EW portfolios over the period from 04 January 2005 to 29 December 2017.

against the always-long benchmark, and a significant alpha ranging from 5.89% (MinV) to 6.51% (VOL) when regressed against the buy-and-hold benchmark.

To sum up, it is attested by our evidence that investing in ICSM and VOL strategies, and portfolios that combine the two strategies, produces remarkable economic gains and adds value to the passive benchmarks.

TABLE 3.7: Spanning Alphas Against Passive Benchmarks

	ICSM	VOL	EW	MD	MinV	IV
	Panel A: Portfolio vs Always-long					
Long-short	2.70***	2.09**	2.39***	2.38***	2.37***	2.38***
	(2.74)	(1.99)	(3.23)	(3.22)	(3.21)	(3.21)
Long-only	2.86***	2.78***	2.83***	2.83***	2.84***	2.83***
	(2.97)	(2.77)	(3.98)	(3.99)	(3.99)	(3.99)
	Panel B: Portfolio vs Buy-and-hold					
Long-short	1.35***	1.38**	1.27***	1.23***	1.12**	1.20***
	(2.60)	(2.15)	(3.00)	(2.97)	(2.47)	(2.90)
Long-only	6.03***	6.51***	6.17***	6.12***	5.89***	6.06***
	(5.25)	(5.37)	(5.51)	(5.47)	(5.20)	(5.41)

This table reports the spanning alphas when we regress the two intraday factors and portfolios constructed based on them against two passive benchmarks. The portfolios that combine ICSM and VOL are constructed using equal-weight (EW), maximum-diversification (MD), minimum-variance (MinV), and inverse-variance (IV) weighting schemes. The benchmark employed in Panel A is an always-long strategy, which is an equal-weight strategy that constantly takes a long position in the last half hour of all markets each day. The benchmark employed in Panel B is a buy-and-hold strategy, which is an equal-weight strategy that enters all markets at the beginning of the sample and holds the position throughout. In each panel, we first report results for portfolios that are constructed based on long-short ICSM and VOL, and then for portfolios that are constructed based on long-only ICSM and VOL. The sample consists of 13 markets and spans over a period from 04 January 2000 to 29 December 2017, while the first five years of our sample period (04 January 2000 to 03 January 2005) is preserved as the initial estimation period.

3.5 Intraday Factor Porfolios vs Intraday Time-series Momentum

3.5.1 Intraday time-series momentum

An analogous phenomenon that also reflects the intraday return continuity is the intraday time-series momentum (ITSM) introduced by Gao et al. (2018). In ITSM, it is stated that the first half-hour return of an asset alone positively predicts the last hour-hour return of that asset on the same day.[13] Li et al. (2021) find strong evidence of ITSM in

[13] Similar to our ICSM, the first half-hour return in ITSM is computed from the previous market close to incorporate overnight information.

a collection of international markets. In this section we investigate the relationship between this time-series intraday pattern and our ICSM and VOL portfolios. In particular, we ask the following questions: Does ITSM subsume our ICSM and VOL portfolios? Do these portfolios add value to ITSM? To answer these questions, we first construct the ITSM portfolio.

The ITSM strategy simply invests, equally, in the ITSM in all individual markets. On each day t, we first compute the individual ITSM return for Market i as $sign(r^F_{i,t}) \times r^L_{i,t}$, and then take the cross-sectional average of the 13 market returns:

$$r_t^{ITSM} = \frac{1}{N}\sum_{i=1}^{N}[sign(r^F_{i,t}) \times r^L_{i,t}], \tag{3.11}$$

where $N = 13$ in our study. Note, while both $r^F_{i,t}$ and $r^L_{i,t}$ are on day t, this is an ex ante strategy since the former comes available before the latter.

TABLE 3.8: ITSM Portfolio Performance

	AVE Ret (%)	NW t-stat	SD (%)	Sharpe Ratio	Skewness	Kurtosis
Austria	2.47*	(1.68)	6.22	0.40	-0.08	3.09
Canada	0.07	(0.06)	4.38	0.02	-0.07	3.13
France	7.18***	(5.02)	5.90	1.22	0.02	3.02
Germany	6.33***	(3.69)	7.38	0.86	0.06	3.08
Ireland	2.41	(0.82)	12.61	0.19	-1.37	9.01
Netherlands	5.87***	(4.15)	5.59	1.05	0.02	3.02
Norway	5.92***	(3.47)	6.96	0.85	0.02	3.05
Portugal	2.66**	(2.22)	5.12	0.52	0.00	3.02
Spain	4.61***	(3.51)	5.65	0.81	0.01	3.02
Sweden	3.03**	(2.19)	4.41	0.69	-0.01	3.02
Switzerland	2.21*	(1.65)	5.69	0.39	0.00	3.03
UK	6.51***	(4.96)	5.27	1.24	0.04	3.03
US	6.19***	(3.45)	5.54	1.12	0.07	3.08
ITSM	4.21***	(5.66)	3.13	1.35	-0.16	3.34
TVC	3.09***	(5.36)	2.58	1.20	-0.34	3.70

This table reports the portfolio performance for ITSM in each market and for an equal-weight ITSM strategy that invests in all the markets. In the last row, we also report the performance of the time-varying component that is incorporated in the ITSM strategy construction. For a given portfolio we report the annualised average return (AVE Ret), the Newey and West (1987) t statistic of the return, annualised standard deviation, Sharpe ratio, Skewness, and Kurtosis. The sample consists of 13 markets and spans over a period from 04 January 2000 to 29 December 2017.

Table 3.8 presents the performance of the ITSM strategy along with that of the constituent individual ITSM portfolios. The ITSM strategy shows an average return of 4.21 % per year, associated with a Shape ratio of 1.35.

3.5.2 Market-timing component in ITSM

While the ITSM strategy seemingly exhibits comparable performance, one must take into account the hidden discrepancy in the portfolio construction of ITSM and our long-short factor portfolios to form a truly meaningful comparison.

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 of 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.

The global ITSM strategy possesses similar construction features. Suppose on a given day t that 10 of the 13 indices in the sample generate buy signals while the remaining 3 generate sell signals. In this example, the wealth one needs to invest in the long leg is by construction higher than that in the short leg. The reason is we are equally weighting all the 13 indices across the long and short legs rather than weighting within the long and short portfolios separately. As a result, we end up with a net long position in the 10 indices that give buy signals. Over time, this net position varies and can be either net long or net short depending on the number of assets in the long and short legs. Put differently, the ITSM possesses a time-varying component through which it times the market.

We follow Goyal and Jegadeesh (2018) and construct the time-varying component as follows:[14]

$$TVC_t = EWM_t \times NPM_t, \tag{3.12}$$

where EWM_t is the equally-weighted last half-hour return across the 13 country indices, i.e. $EWM_t = \frac{1}{13} \times \sum_{i=1}^{13} r_{i,t}^L$, 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. $NPM_t = (\frac{N^+}{13} - \frac{N^-}{13})$. N^+ (N^-) 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 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.

[14]Consistent with Goyal and Jegadeesh (2018), we multiply the net position by an equal-weight market portfolio. This is because the unconditional probability of an asset goes into long/short portfolio is 0.5, so that the net position between the long and short legs on average invests in the whole market.

The last row of Table 3.8 reports the performance of TVC. With an average return of 3.09% per annum and a Sharpe ratio of 1.20, TVC appears as the major contributor to the profitability of the ITSM strategy.

3.5.3 Intraday factor portfolios vs ITSM

Now we examine the relationship between intraday factor portfolios and ITSM strategy through the mean-variance spanning analysis. First, we regress the ITSM strategy against its most close analogue, ICSM, and the time-varying component. As shown by the first row of Table 3.9, the spanning alpha is not significantly different from 0, implying no economic value added by ITSM to a mixture of ICSM and TVC. Since TVC is just a market timing component, our evidence suggests that one can achieve the economic performance of ITSM by simply holding a combination of ICSM and a market timing strategy.

Then we regress the long-short VOL portfolio against ITSM and report the result in the second row of Table 3.9. The regression exhibits an alpha of 2.71 that is strongly significant at 1% level, implying remarkable economic benefit of holding the VOL portfolio. Similarly, regressing the portfolio that invests equally in ICSM and VOL produces an alpha of 1.80 that is significant at 1% level.

Overall, our analysis suggests that the strategy that invests in the ITSM of Gao et al. (2018) can be subsumed by a combination of ICSM and a market timing strategy. Moreover, both VOL alone and a strategy that invests simultaneously in VOL and ICSM add remarkable economic value to the ITSM strategy.

3.6 Conclusion

The cross-sectional variation in asset returns has long been one of the focal points of the asset pricing literature. While relevant studies in mid- to long-term predictability of asset return have been extensive, research focusing on the intraday cross-sectional return variation is still scant. Our paper fills this gap by examining the cross-sectional predictability of the last half-hour return prior to market close.

Employing international data that covers a collection of 13 developed markets, we start our examination by investigating the predictability of five candidate intraday variables on the last half-hour return. Through a sorting analysis, we show that first half-hour return and volatility strongly predict the last half-hour return in the international cross-section. Our results are confirmed by Fama-Macbeth regressions. We show further that

TABLE 3.9: Intraday Factor Portfolios vs ITSM

	Alpha	ITSM	ICSM	TVC	$Adj.R^2$ (%)
ITSM	-0.04		16.27***	111.46***	86.49
	(-0.16)		(3.52)	(18.26)	
VOL	2.71***	6.75			0.27
	(3.02)	(0.87)			
EW	1.80***	42.22***			20.46
	(3.11)	(6.39)			

This table presents the estimates for the spanning regressions through which we evaluate the intraday factor portfolios with the ITSM strategy. In the first row, we regress ITSM against ICSM and TVC. In the second row, we regress the VOL against ITSM. In the last row, we regress the long-short equal-weight strategy introduced in Section (3.4) against ITSM. All returns are annualised and in percentage, the slope coefficients are scaled by 100. Newey and West (1987) t-statistic are in parentheses. The sample consists of 13 markets and spans over a period from 04 January 2000 to 29 December 2017.

practical portfolios that invest in the two predictive intraday factors generate considerable economic gains and improve the return-risk trade-off of a mean-variance investor that holds passive benchmarks.

Comparing our intraday cross-sectional strategies to a strategy based on the intraday time-series momentum (ITSM) Gao et al. (2018), we find that the strategy that invests equally in ITSM around the globe can be imitated by our intraday cross-sectional strategy and a timing strategy. Optimally combining the two intraday cross-sectional strategies that are based on the two intraday factors respectively provides additional economic gains to the ITSM strategy.

Chapter 4

Dynamic Overnight-intraday Relationship in Stock Returns

Studying minutely SPY trading records over the 2000-2017 period, we investigate the dynamic relationship between overnight and intraday returns. We show that there exists a time series reversal at the market open that converts to a momentum at the close. While we observe strong evidence for both intraday phenomena over the full sample period, the significance of the opening reversal and the closing momentum are mainly from days with negative and positive overnight returns, respectively, implying heterogeneity in intraday traders. A careful examination of the opening reversal suggests that the effect is stronger during the financial crisis, recession, and high uncertainty periods, and is related to market microstructure characteristics, such as overnight volatility and trade size. Trading strategies based on the opening reversal economically dominate passive benchmarks, and is robust across 10 alternative ETFs.

4.1 Introduction

Stock return patterns such as momentum and reversal are well established and studied extensively in the academic literature (Asness et al., 2013; De Bondt and Thaler, 1985; Jegadeesh, 1990; Jegadeesh and Titman, 1993, 1995, 2001; Lehmann, 1990; Moskowitz and Grinblatt, 1999; Moskowitz et al., 2012). Recently, an emerging body of literature pays attention to the relationship between intraday return patterns and investor heterogeneity. For example, Lou et al. (2019) divide a day (24 hours) into the overnight and intraday periods and find return persistence in the two periods respectively. They further document a reversal effect across the two periods, which they call a 'tug-of-war' between overnight and intraday traders who alternately dominate the market. Akbas et al. (2019) state that this tug of war is more intense for months with higher frequency of positive overnight returns followed by negative intraday returns. Further decomposing the open-to-close returns, Bogousslavsky (2021) find evidence that the documented intraday pattern are closely related to clientele effects within the trading hours. All of these studies use firm-level data and investigate the issue from a cross-sectional perspective. In the time series, Gao et al. (2018) introduce a momentum effect in which the first half-hour return positively predicts the return in the last 30 trading minutes. However, the authors do not draw significant attention to the relationship between the intraday pattern and investor clientele effect.[1]

In this study, we investigate the dynamic relationship between overnight and intraday returns from a time series perspective. We show that at the aggregated market level, there exists a time series short-term reversal effect at the market open (i.e. opening reversal) that converts to the intraday momentum of Gao et al. (2018) at the market close (i.e. closing momentum). In between, the overnight return does not possess predictability on intraday returns. Despite this, both effects are statistically significant over the full sample and we further show that the significance of the opening reversal is mainly from the days with *negative* overnight returns, whereas for the closing momentum, it is mainly from the days with *positive* overnight returns. We believe that this conditional overnight-intraday relationship might be caused by the short selling constraints faced by retail investors.

Using 18 years of minutely trading data of SPY, we start our examination by recursively performing a standard univariate predictive regression, in which we regress the intraday returns against the overnight return. In order to study the dynamic and accumulative effect of the overnight return on intraday returns, we adopt two approaches to compute the intraday returns. In the first approach we start from computing the return for the 9:30 - 10:00 interval and *move* one minute ahead at a time, such that we end up with a time series of half-hour returns for each trading day. In the second approach, we also start with the 9:30 - 10:00 interval but instead *expand* one minute a time, such that we have a time series of expanding intraday returns for each day. By regressing each intraday interval on the overnight return respectively, we are able to identify the dynamic of the overnight-intraday return relationship within a day. Our results show that there exists a strong reversal effect at the market open that is the most pronounced in the first half hour and lasts less than an hour. This opening reversal converts to an equally strong momentum just before the market close, which is consistent with the findings of Gao et al. (2018). In between, the overnight return does not possess any statistically significant predictability on the intraday returns. Our findings supplement

[1]In the main analysis of Gao et al. (2018), the first half-hour return is computed from the previous closing price. However, in the robustness check, the authors show that the intraday predictability is mainly from the night instead of the period from 9:30 am to 10:00 am. In the paper, the authors make an attempt to investigate the relationship between the predictability of the first half-hour return on the last half-hour return and institutional trading and find that the former is virtually unaffected by the latter.

that of Gao et al. (2018) and suggest that an information shock from the night can cause two opposing effects at the open and the close respectively.

However, a further examination reveals the distinct nature of the two intraday effects apart from, obviously, the opposing direction of returns. By repeating the above analysis on two subsamples divided by the sign of the overnight return, we disclose that the statistical significance of the opening reversal is mainly from negative overnight return days whereas that of the closing momentum is mainly from positive overnight return days. In other words, while both effects are strongly significant over the full sample period, they are intrinsically hinged on the direction of price movement over the night. One possible explanation is that, on good news days (i.e. positive overnight return days), the overnight professional traders are joined by some intraday retail investors from the other end of the tug of war, whereas on bad news days (i.e. negative overnight return days) the selling pressure is mainly generated by the professional traders due to the short selling constraints faced by their retail counterparts.[2]

Next, we focus only on the opening reversal to assess its statistical significance both in- and out-of-sample. The first half-hour return is computed using the open price at 09:30 am and the last price at 10:00 am while the overnight return is computed using the last price at 04:00 pm previous trading day and the open price at 09:30 am. With a slope coefficient of -8.81 (scaled by 100) and a Newey and West (1987) t-statistic of -3.78, our predictive analysis evidences that the overnight return has strong negative predictability on the return in the following first half hour, providing first support of the validation of aforementioned theory at intraday level. Taking into account the instability issue of linear predictive regressions (Welch and Goyal, 2008), we conduct an out-of-sample (OOS) analysis by recursively fitting the model using information up to the previous observation and compute Campbell and Thompson (2008) R^2_{OOS} and its McCracken (2007) OOS-F statistic. The OOS analysis confirms the negative predictability of the overnight-return drawn from the in-sample analysis, given the remarkable R^2_{OOS} of 2.41% that is significant at 1% level (McCracken (2007) OOS-F statistic of 78.26).

We further assess the intraday reversal over periods with greater uncertainty. Specifically, we compare the predictability of the overnight return during financial crisis and non-crisis periods, recessions and expansions. We find that the predictability is generally greater and more significant during financial crisis and recessions. This finding leads us directly testing the relation between the intraday reversal and economic uncertainty measured by VIX index. We split our sample into two groups based on the VIX index value, and we study the intraday reversal on trading days with low and high uncertainty, respectively. The analysis further confirms our statement that the intraday reversal appears to be stronger on uncertain days. This might be explained by the fact

[2]Normally retail investors can only sell stocks they have whereas professional traders have greater flexibility to short sell. See, for example, Barber and Odean (2008).

that on days with greater uncertainty, both the frequency and influence of the information released are presumably at a high level. As a consequence, it is more plausible for a large liquidity shock to be present at the open. Therefore, stronger intraday reversal, predicted by the models of Duffie (2010) and Bogousslavsky (2016), is observed.

Return volatility and trade size are normally considered to reflect informativeness of the transactions (Boudoukh et al., 2019). We therefore investigate the relation between intraday reversal and these two variables at micro level. Stronger reversal effect on days with higher volatility and larger trade size is expect to be observed. First, we calculate the overnight return volatility, based on which our sample is divided into two groups. Again, we then run the predictive analysis within each group. The group with higher overnight volatility exhibits stronger reversal effect with a slope of -11.13, Newey and West (1987) t-statistic of -4.38, and an adjusted R^2 of 4.21 %. Next, we repeat the same analysis within groups classified by the average overnight trade size, which is computed by firstly dividing volume with number of trades in each minute there is trading occurred and then taking the average across minutes. Consistent with our expectation, the intraday reversal effect is stronger on days with larger average overnight trade size, showing a slope coefficient of -11.52, Newey and West (1987) t-statistic of -4.10, and an adjusted R^2 of 4.45 %.

In addition to the strong statistical evidence, we also illustrate that the intraday reversal has superior economic performance. To evaluate the economic significance, we investigate the performance of the intraday reversal in a market timing and mean-variance setting. For the market timing strategy, we long (short) SPY in the first half hour if the previous overnight return was negative (positive) and borrow (lend) at the risk free rate (US one month T-bill rate). We compare this timing strategy with two passive benchmarks. The first passive strategy is *Always-long* in which we borrow at the risk free rate and hold a long position in SPY over the first half hour on every day. The second passive strategy is *Buy-and-hold* in which we borrow at the risk free rate and hold long a position in SPY throughout the whole sample period. Our analysis shows that the intraday reversal market timing strategy significantly outperforms the two passive benchmarks. Spanning regression we observe alphas of 6.23% and 6.21% against *Always-long* and *Buy-and-hold* respectively, both are significant at 1% confidence level after Newey and West (1987) corrections.

Next, we investigate the economic value added to a mean-variance investor, with a relative risk aversion of five, who convert her belief from random walk to the intraday reversal. Let the investor, after conversion, determines the optimal weights in SPY and risk free asset using the estimated return and standard deviation from the predictive regression. We compare the performance of such a mean-variance portfolio with another portfolio in which the weights are calculated using historical mean of the return and standard deviation. Results show that the portfolio based on the predictive regression yields an average return of 5.326% per year with a Sharpe ratio of 0.877, whereas the benchmark portfolio produces an annualised average return of only 1.492% and a Sharpe ratio of 0.555. The certainty equivalent return (CER) is 3.094%.

We argue that there are two possible explanations for the time series reversal at the market open. First, in the dynamic theoretical model of Duffie (2010), only a subset of traders are able to absorb a sudden liquidity shock at any given time point. The costs of trading, such as processing information and searching for counterparties, among others, prevent some investors from being always attentive. For this reason, the market is thinner than that one would have expected. The thin market results in a limited capacity of contemporaneous available traders to absorb a short-term liquidity shock. As a result, a price concession is required by liquidity providers to absorb the shock. For instance, the execution price should be low enough at a supply shock so that the liquidity providers would be willing to buy, with the expectation of a future appreciation. The magnitude of this price concession gets smaller as more capital gradually becomes available, and consequently, a reversal occurs. We posit that the situation at the market open is very similar to the theoretical justification provided in the model of Duffie (2010). The first reason is the low liquidity, high uncertainty, and high risk associated with participating in the overnight trading, where only a limited number of investors (mostly professional and quasi-professional) play a role in the after hour market (Barclay and Hendershott, 2003). This makes the overnight market much thinner than the intraday market, hence, the price impact of liquidity shocks will be amplified. The second reason is that information asymmetry declines over time (Easley and O'Hara, 1992), and the likelihood of informed liquidity shocks is the highest at the market open. The empirical work by Barclay and Hendershott (2003) suggests that the trades in the pre-open session and post-close are more likely to convey information than the trades during the intraday session. Higher probability of informed trading implies higher probability of supply or demand shocks which are predicted to be followed by a reversal effect according to the model of Duffie (2010).

Second, the designated specialist plays a significant role at the market open. The specialist has the priority to observe the limit order book, in which the pre-open orders are submitted, and set the opening price of the day. Further, the specialist can participate in the opening auction and provide liquidity. In a study of market opening auction process in NYSE, Madhavan and Panchapagesan (2015) states that the specialist tend to hold the position from opening auction for only a short period of time. The authors further provide empirical evidence that shows the specialist's opening purchases (sales) are normally followed by positive (negative) ex post returns in the period of 9:30 am to 10:00 am. Intuitively, purchases of the specialist at market open imply sales from her counterparties, informed traders. If the Duffie (2010) model discussed above holds, the overnight return should be most likely negative due to the selling pressure at the opening auction and slow moving capital of the liquidity providers. Therefore, the following positive return in the empirical analysis of Madhavan and Panchapagesan (2015) entails a reversal at the open of the market.

One of the main contributions of this research is that we empirically test what happens immediately after the overnight information accumulation. We claim that the reversal effect at the open revealed by us together with the momentum effect at the close revealed by Gao et al. (2018) present the intraday return dynamics at two most critical time points of a trading day after the accumulation of information over the night. More importantly, we show that these two effects are hinged on the sign of the overnight return, implying investor heterogeneity around market open on the positive and negative overnight return days.

Based on the work of Duffie (2010), Bogousslavsky (2016) provides a theoretical model in which a liquidity shock can generate specific return autocorrelation patterns. A simplistic description of the mechanism is that, after a liquidity shock, a reversal will occur in the first phase due to the slow-moving capital and a momentum will follow in the second phase due to the unloading of the liquidity providers who absorbed the liquidity shock in the first phase. Using intraday SPY data, Gao et al. (2018) empirically document a strong intraday time series momentum between the return from previous close to 10:00 am in the following morning and the last half-hour return. In the robustness check, the paper shows the momentum effect is mainly from the overnight, during which information is accumulated. Put the models of Duffie (2010) and Bogousslavsky (2016) into intraday scale, we argue, while the intraday time series momentum by Gao et al. (2018) emphasises the second phase of the whole process, our reversal effect at the open tells the prequel of the intraday time series momentum. Put in other words, our empirical findings may reflect the return dynamics in the first phase of the model when there is a supply or demand shock induced by overnight accumulated information.

Our research, by studying the dynamic relationship between overnight and intraday returns, contributes to the literature on intraday predictability, and literature on investor heterogeneity. It also adds value to the field of empirical asset price in micro scale, particular the empirical study of overnight and pre-open trading mechanism. Furthermore, this research provides benefits directly to the investment management industry, the hedge fund asset managers in particular. Finally, long-term infrequent traders can also benefit from our study and make optimal decision on the timing to place orders based on the overnight performance.

The remainder proceeds as follows: Section 4.2 describes and summarises the data. Section 4.3 investigates dynamic overnight-intraday return relationship. Section 4.4 explores in detail the statistical significance of the opening reversal under various market conditions. Section 4.5 evaluates the economic significance of intraday reversal effect in market timing and mean-variance portfolio respectively. Section 4.6 examines the robustness of intraday reversal effect using 10 alternative ETFs that cover a wide range of assets. Section 4.7 concludes the chapter.

4.2 Data

The primary data employed in this study is minutely trading data of SPY, which is the largest actively traded ETF in the world, tracking the S&P 500 index. The data is retrieved from Thomson Reuters Tick History (TRTH) database, spanning through an 18-year period from the 3rd of January 2000 to the 29th of December 2017. The data set provides information on trading date, trading time, open price, last price, high price, low price, trading volume, number of trades, bid price, and ask price for every 1 minute interval.

Outliers and extreme values can be an issue in the calculation of returns.[3] We therefore filter out these errors by removing any observations that are above (below) 1.2 (0.8) times of the maximum (minimum) price that is computed from the contemporaneous daily data of SPY from Thomson Reuters Datastream. We use multipliers of 1.2 and 0.8 to allow for intraday fluctuation.

To examine the dynamic relationship between overnight and intraday returns, we calculate the overnight return and intraday half-hour returns for a 30-minute window that moves one minute a time from 09:30 – 10:00 to 15:30 – 16:00 New York time. The use of 30-minute interval is conventional in relevant intraday research (Gao et al., 2018; Heston et al., 2010; Komarov, 2017; Mcinish and Wood, 1992). To be more specific, we calculate overnight simple return of day t, r_t^O, using the previous closing price, which is the last price at 16:00 New York time on day $t-1$, and the opening price at 09:30 on day t. For the intraday returns, we denote a given 30-minute interval by the timestamp of its last minute, τ, and compute its return using the opening and closing prices of that interval (e.g. $r^I_{10:00,t}$ denotes the half-hour return from 09:30 to 10:00 on day t):

$$r_t^O = \frac{open_{09:30,t}}{last_{04:00,t-1}} - 1, \qquad r^I_{\tau,t} = \frac{last_{\tau,t}}{open_{\tau,t}} - 1. \tag{4.1}$$

In the case that the price needed is missing, we search for the nearest available observation with a five-minute radius. For example, if the last price at 04:00 pm is missing, we use the last price in the last five-minute interval on that day; if the open price at 09:30 am is missing, we use the first open price in the first five-minute interval on that day; if the last price at 10:00 am is missing, we search for the nearest available last price within the interval 09:55 am to 10:05 am, starting with the price at 09:59 am.

[3] For example, the last price can suddenly become zero at some time point, which is obviously an error.

Our procedure leads us to a total sample size of 4412 days. For simplicity, we report only the descriptive statistics for the overnight, first half-hour, and last half-hour returns in Table 4.1. As documented in the previous literature (Andersen and Bollerslev, 1997; Gao et al., 2018; Jain and Joh, 1988; Xu, 2017), as well as shown by the analysis in the following sections, these three periods are the most critical periods in a day, characterised with high liquidity and volatility. On average, SPY has an annualised overnight return of 3.82%, which is higher than that during the first half hour (-0.46%) and the last half hour (1.08%). Associated with the higher return, a higher standard deviation is observed over the night. The annualised overnight return standard deviation is 10.24% whereas that for the first (last) half hour is 5.75% (5.60%). Returns in both the overnight period and the intraday periods have a skewness near 0 and a non-excess kurtosis closing to 3, implying symmetric distributions with similar shape to a normal distribution. In addition, the magnitude of the first order autocorrelations are very close to 0.

TABLE 4.1: Descriptive Statistics

	No.Days	Avg ret (%)	Std dev (%)	Skewness	Kurtosis	AR(1)
r^O	4292	3.82*	10.24	-0.04	3.05	-0.09
		(1.92)				
$r^I_{10:00}$	4292	-0.46	5.75	0.02	3.05	-0.01
		(-0.37)				
$r^I_{16:00}$	4292	1.08	5.60	-0.01	3.09	-0.14
		(-0.93)				

This table reports number of observations, annualised average return, annualised standard deviation, annualised skewness, annualised kurtosis, and first order autocorrelation for overnight, first half-hour, and last half-hour returns, which are computed as in Equation (4.1). Newey and West (1987) t-statistics of average returns are reported in parentheses. *, **, and *** denote confidence levels of 10%, 5%, and 1%. The sample period spans from 03 Jan 2000 to 29 Dec 2017.

4.3 Overnight-intraday Relationship

Previous literature has documented important implications of investor heterogeneity for asset prices (Campbell, 2017; Cochrane, 2005; Constantinides and Duffie, 1996; Gârleanu and Panageas, 2015; Harrison and Kreps, 1978; He and Krishnamurthy, 2013). Recently, Akbas et al. (2019) and Lou et al. (2019) study intraday patterns in the cross-section of stock returns, suggesting that there exists a momentum effect in the overnight and intraday periods, respectively, and a reversal effect across the two periods. They attribute this 'tug of war', as coined in their studies, between the overnight and intraday traders to that the two types of traders have heterogeneous demands and alternately dominate the market during overnight and intraday periods.

Implicitly, this reasoning assumes homogeneity in the intraday traders. While the after hour market is more likely to be dominated by the professional traders due to the low liquidity and high risk (Barclay and Hendershott, 2003, 2004), however, it remains unclear whether it is safe to assume homogeneity among the intraday traders. For example, Berkman et al. (2012) analyse intraday trading data of retail investors and conclude that the retail trading intensity is significantly higher in the first one hour after market open than in the rest of the day. Bogousslavsky (2021) presents evidence that a group of anomalies gain returns from different time period within a day. Moreover, the intraday momentum documented by Gao et al. (2018) implies the possibility of that traders who trade in the last half hour are on the same side of the tug of war with the overnight traders. In this section, therefore, we conduct a closer investigation of the dynamic relationship between the overnight and intraday returns from a time series perspective.

4.3.1 Dynamic overnight-intraday relationship

The conventional methodology in relevant studies is to compute intraday returns from a fixed interval. For example, Gao et al. (2018), Heston et al. (2010) and Li et al. (2021) compute intraday returns in a 30-minute interval, whereas Xu (2017) uses a 2-hour interval. Akbas et al. (2019) and Lou et al. (2019) employ the whole six-and-a-half-hour trading period as the intraday interval. Instead of focusing on the relationship between the overnight return and the intraday return from a specific interval, we attempt to explore how this relationship dynamically varies within the day. To this end, we employ both rolling and expanding approaches when compute the intraday returns.

For the rolling approach, we first compute intraday returns from the 09:30 - 10:00 interval on each day, and perform a predictive regression whereby we regress the intraday returns against the overnight returns. Then we compute the intraday returns from the 09:31 – 10:01 interval and regress it against the same time series of overnight returns. We repeat this process by moving the return interval one minute ahead at a time until we reach the interval of 15:30 – 16:00. For the expanding approach, we perform similar computations with expanding windows instead of rolling windows. That is, we first compute intraday returns from the 09:30 - 10:00 interval for the first regression analysis as in the rolling approach. Then for the second regression analysis, we use the intraday return from the 09:30 - 10:31 interval instead. We repeat this process by adding one minute at a time to the intraday interval until we end up with the interval of 09:30 – 16:00, i.e. the whole daytime trading period.

Mathematically, we estimate the following predictive models for the expanding and rolling approaches respectively:

$$r^I_{\tau,t} = \alpha_\tau + \beta_\tau \times r^O_t + \epsilon_{\tau,t}, \quad t = 1, \cdots, T, \tag{4.2}$$

where $\tau = 10:00, \cdots, 16:00$. For each τ, $r^I_{\tau,t}$ denotes the intraday return from the interval that ends at time τ on day t, r^O_t is the overnight return on day t, and T is the total number of days in our sample.

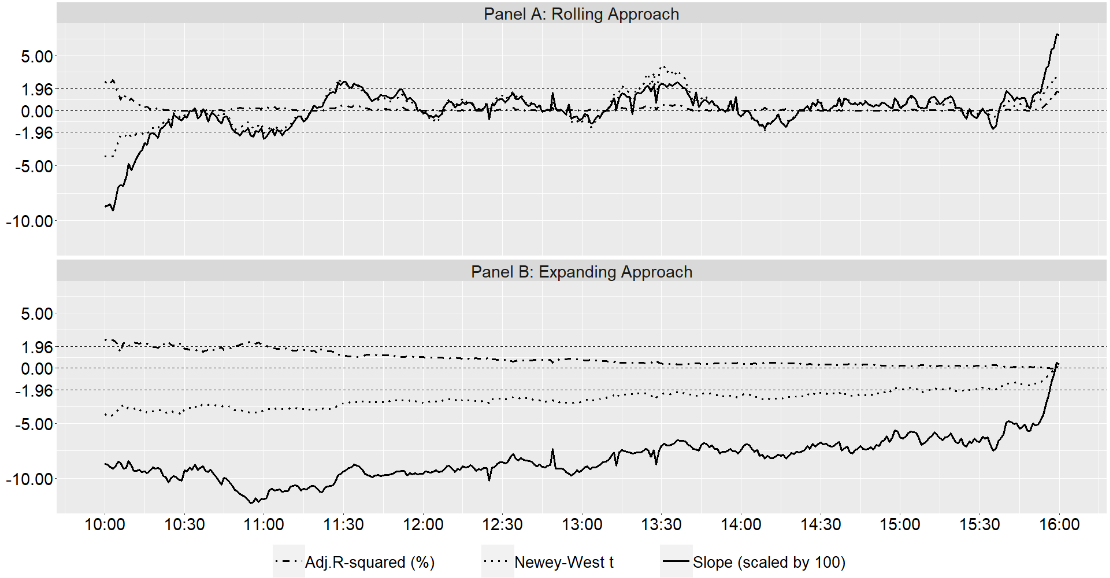


FIGURE 4.1: Dynamic O-I Relationship

This figure shows the dynamic relationship between overnight and intraday returns. We regress the predictive models described in Equation 4.2 whereby intraday returns are computed from various intraday intervals. Panel A plots the estimated slope coefficients, $Adj.R^2$s, and Newey and West (1987) t-statistics from the regressions where the intraday returns are computed from the rolling intervals starting from the first thirty minutes after the market open. Panel B plots the same statistics for the regressions where the intraday returns are computed from the expanding intervals. The horizontal axis shows the end time of the return intervals (i.e. τ in Equation 4.2). The sample period spans from 03 Jan 2000 to 29 Dec 2017.

Panel A of Figure 4.1 depicts the slope coefficients, adjusted R^2s, and Newey and West (1987) t-statistics from the regressions for the rolling approach. We observe a slope coefficient (scaled by 100) around -10 and an associated Newey and West (1987) t-statistic of nearly -5 at the beginning of the day, suggesting a strong reversal effect. All the three statistics plunge up before market close, implying an equally strong momentum effect that is consistent with Gao et al. (2018), who find pronounced positive predictability of the overnight return on the returns at the end of the day. Indeed, except the periods proceeding the open and prior to the close, the slope coefficient fluctuates around zero while the $Adj.R^2$ exhibits a U shape, suggesting the explanatory of the overnight return is the highest at the open and the close but infinitesimal during the rest of the day.

Panel B of Figure 4.1 plots the same statistics but for the expanding approach. Again, this figure confirms the strong intraday reversal effect at the market open. With a gradual diminution, this reversal effect generally remains statistically significant at 5% confidence level until we expand the intraday return interval to 15:30. Not surprisingly, once we expand the intraday return interval to the last thirty minutes of the trading day, the slope coefficient plunges up and the $Adj.R^2$ decreases to virtually zero.

The findings discussed above put a question mark on the homogeneity assumption of intraday traders and suggest the reversal effect between overnight and intraday return is mainly from the reversal at the market open. One possible explanation for this pattern is that the traders with divergent demand from that of the overnight traders are densely distributed and heavily trade in the period immediately after the market open, whereas the traders who trade in the period immediately before the market close might have similar demand to that of the overnight traders.

4.3.2 Reversal, momentum, and retail trading

Unlike professional traders, retail investors face difficulties short selling stocks (Barber and Odean, 2008). Analysing individual US stocks, Berkman et al. (2012) document significant tendency for positive overnight returns to reverse in the following daytime for stocks with high attention and low institutional holdings. The authors hypothesise that this short-term reversal is due to the high opening price that results from the buying pressure of the retail traders who herd, at the market open, into attention-grabbing stocks. Therefore, we now turn our attention to the overnight-intraday relationship conditional on the overnight market performance.

We divide our sample into two subsamples based on the sign of the overnight return and then regress the overnight return on rolling and expanding intraday returns, respectively. That is, we repeat the analysis in Figure 4.1 using days with negative (1968 days) and positive (2286 days) overnight returns.[4]

As depicted in Figure 4.2, the inverse-S shape of the slope coefficient generally remains for both types of days. Surprisingly, however, Panel A of Figure 4.2 shows that the opening reversal is merely weakly significant, whereas the closing momentum is strong on the days with positive overnight returns. In contrast, Panel B of Figure 4.2 shows the opposite for the days with negative overnight returns, that is, the opening reversal is remarkable while the closing momentum is week.

Table 4.2 reports in detail the estimation of the end points in Panel A and B of Figure 4.2, i.e., the opening reversal and the closing momentum for positive and negative overnight return days. On the positive overnight return days, the opening reversal almost vanishes, whereas the closing momentum exhibits a remarkable slope coefficient of 12.65 (scaled by 100) that is associated with a Newey and West (1987) t-statistic of 3.27 and an adjusted R^2 of 2.96%. The opposite intraday pattern can be observed on the negative overnight return days, namely, the slope coefficient for the reversal increases

[4]There are 38 days with zero overnight return, we delete these days from our sample.

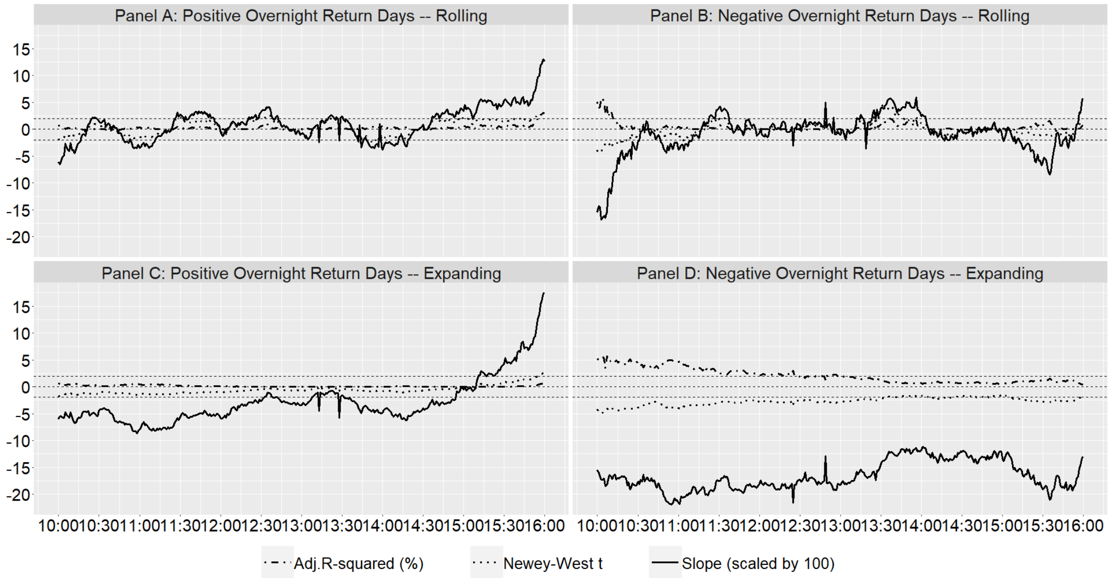


FIGURE 4.2: Conditional O-I Relationship

This figure reproduces the analysis in Figure 4.1 with sub-samples that are conditional on the sign of overnight returns. Panel A depicts the dynamic OI relationship on positive overnight return days with returns computed using the rolling approach described early this section. Panel B depicts the dynamic OI relationship on negative overnight return days with returns computed using the rolling approach described early this section. Panel C depicts the dynamic OI relationship on positive overnight return days with returns computed using the expanding approach described early this section. Panel D depicts the dynamic OI relationship on negative overnight return days with returns computed using the expanding approach described early this section. From top to bottom, the three horizontal dashed lines mark values of 1.96, 0, and, -1.96. The sample period spans from 03 Jan 2000 to 29 Dec 2017.

virtually three time in absolute magnitude and becomes strongly significant, as evidenced by a Newey and West (1987) t-statistic of -4.14. Moreover, the adjusted R^2 of 5.10% for the opening reversal on negative overnight return days is considerable and impressive in the relevant literature.[5] In contrast, the closing momentum is statistically significant only at 10% level.

Our empirical evidence from the aggregated market is inconsistent with Berkman et al. (2012), implying that the opening reversal might be a result of the selling pressure from the institutional traders whereas the closing momentum might rather be related to the herding of retail traders. This finding is somewhat in line with Gao et al. (2018) who do not find conclusive evidence on the effect of institutional traders on intraday momentum.

The revealed difference in the overnight-intraday relationship for the days with negative and positive overnight returns also explains to some extent the insignificant predictability of the 'pure first half-hour return' on the last half-hour return in Gao et al.

[5]For example, the R^2 reported by Gao et al. (2018) is 1.6% and is considered remarkable.

TABLE 4.2: Conditional Intraday Reversal & Momentum

	Positive r^O		Negative r^O	
	Reversal	Momentum	Reversal	Momentum
Intercept	1.88	-10.26***	-10.86***	0.12
	(0.59)	(-2.79)	(-2.85)	(0.04)
β	-6.03*	12.65***	-15.43***	5.78*
	(-1.84)	(3.27)	(-4.14)	(1.63)
$Adj.R^2$ (%)	0.64	2.96	5.10	0.71

This table reports the predictive regression results for the opening reversal and closing momentum for days with positive and negative overnight returns, respectively. For the opening reversal (closing momentum), we regress the first (last) half-hour return on the overnight return. β is the slope coefficient of the overnight return. Slope coefficients are scale by 100. Sample spans from 03 Jan 2000 to 29 Dec 2017. Newey and West (1987) robust t-statistics are in parentheses. *, **, and *** denote confidence level of 10%, 5%, and 1%.

(2018). In the robustness of Gao et al. (2018), the authors show that while the overnight returns ($r_{4:00pm-9:30am}$) is responsible for most of the predictability in intraday momentum, the pure first half-hour return ($r_{9:30am-10:00am}$) has no predictability. This is intuitively contradict to the opening reversal. Put in other words, if the overnight return negatively predicts the first half-hour return and positively predicts the last half-hour return, then shouldn't there exist a reversal effect between the first and last half-hour returns? Our findings suggest that this is not the case due to that the opening reversal and closing momentum are strongest on different days, depending on the overnight return.

4.4 Market Intraday Reversal

While the closing momentum has been studied in detail by Gao et al. (2018) on the US market and Li et al. (2021) on international stock markets, less attention has been paid to the opening reversal discovered in the previous section. In this section, we focus our attention on the opening reversal and investigate its association with various market conditions and micro-characteristics.

But first of all, why is there such an intraday reversal? Gao et al. (2018) document strong evidence of market intraday momentum in which the overnight return positively predicts the last half-hour return.[6] The authors argue the infrequent rebalancing model

[6]In the paper, the authors start their examination with the first half-hour return that is computed using previous closing price and the price 30 minutes after the market open, i.e. the overnight return is incorporated into the 'first half-hour return'. In their robustness section, the authors confirm the predictability

of Bogousslavsky (2016) could be one possible explanation of the empirical finding. In that model, everything starts from an initial liquidity shock, by absorbing which traders hold an excess position relative to their normal weight in their optimal portfolio. This excess position arouses the desire to unload thus create another liquidity shock that Gao et al. (2018) believe to happen in the last half hour, when the market is deep and ideal for avoiding overnight risks. If this reasoning holds, perhaps the most reasonable time in a day for the initial liquidity shock to occur is the market open given the considerable amount of news released and accumulated overnight.

4.4.1 In-sample evidence

We start our analysis by reproducing the in-sample statistical results, i.e. we fit a univariate OLS regression model using the first half-hour return against the overnight return:

$$r_{10:00,t} = \alpha + \beta \times r_t^O + \epsilon_t, \quad t = 1, \cdots, T, \tag{4.3}$$

where $r_{10:00,t}$ is the first half-hour return at day t, r_t^O is the overnight return from day $t-1$ to t, and T is the total number of trading days in our sample.

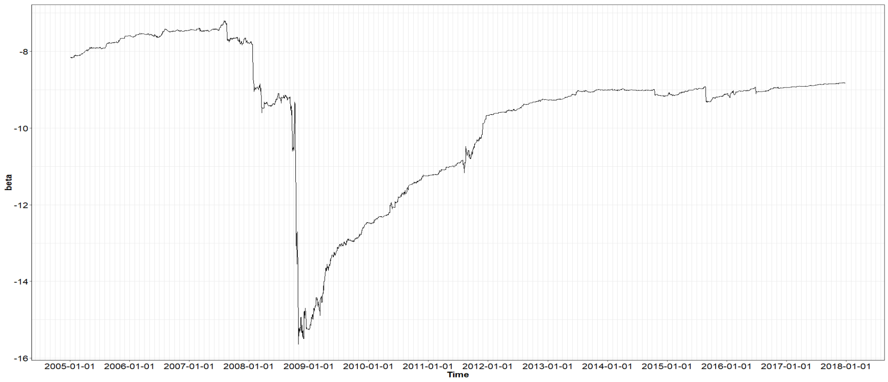
The first column of Table 4.3 reports in-sample predictability. The in-sample predictive regression reveals a negative slope coefficient of -8.81 (scaled by 100) and a Newey and West (1987) t-statistic of -3.78. The strong statistical significance is associated with an adjusted R^2 of 2.44%.[7] The statistics are indeed the first points of the lines shown in Figure 4.1.

To study the evolution of the predictor, we recursively estimate the predictive regression (Equation (4.3)) over the period from 2005 to 2017. The first five years are reserved as the initial estimation period. Figure 4.3 plots the time series of β, Newey and West (1987) t-statistic of the slope coefficient, and adjusted R^2 respectively in Panel A, B, and C. As shown in the figure, through the whole period of 2005-2017, the value of slope coefficient remains negative and considerably large in magnitude. The Newey and West (1987) t-statistic plotted in Panel B indicates the slope coefficient is significant at 1% confidence level throughout the full sample period. During the year of 2008, however, both the slope coefficient and the t-statistic are almost doubled in absolute term and gradually converge back to a level that is slightly stronger than in the pre-crisis period. Same pattern can be observed for the adjusted R^2 shown in Panel C.

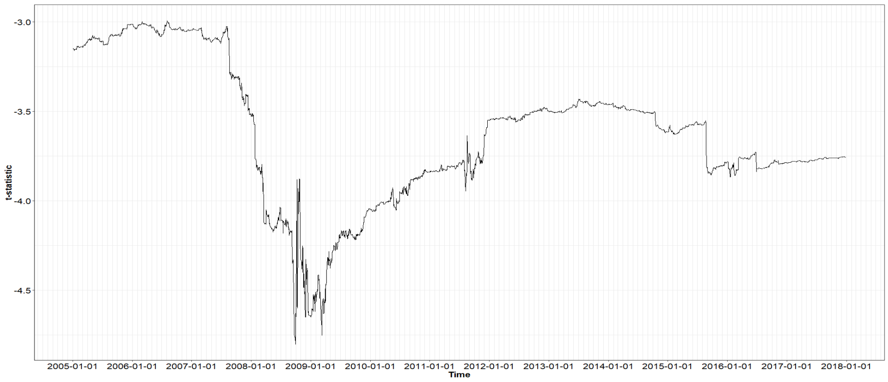
of the first half-hour return is mainly from the overnight period not the first thirty-minute period after market open.

[7] In the study of intraday time series momentum by Gao et al. (2018), an R^2 of 1.6% is considered remarkable given the high frequency nature of the study. Campbell and Thompson (2008) explain analytically how a small predictive R^2 can generate significant economic benefit for investors.

Panel A: Time series of β



Panel B: Time series of Newey and West (1987) t-statistic



Panel C: Time series of Adjusted R^2 (%)

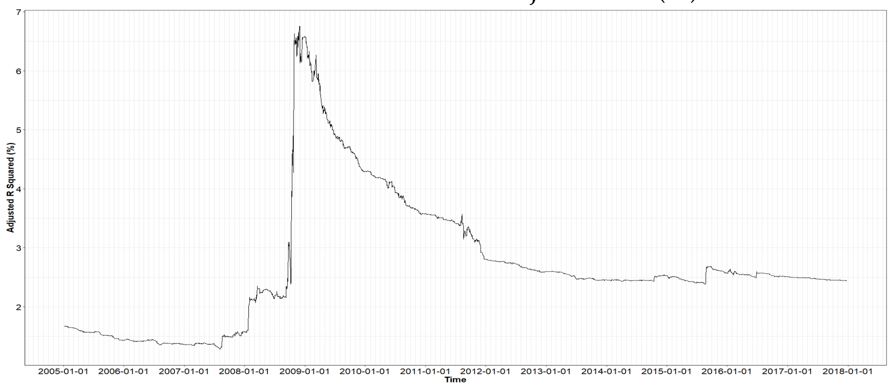


FIGURE 4.3: Time Series of Key Estimates.

This figure depicts the time series of β, Newey and West (1987) t-statistic of the slope coefficient, and adjusted R^2 respectively in Panel A, B, and C. The predictive regression is recursively estimated on an expanding window basis. While full sample spans from 03 Jan 2000 to 29 Dec 2017, we use the first five-year period as the initial estimation period.

TABLE 4.3: Intraday Reversal Predictability

	In-sample	Out-of-sample
Intercept	-0.13	-0.77
	(-0.10)	(-0.42)
β	-8.81***	-9.47***
	(-3.78)	(-3.64)
$Adj.R^2$ (%)	2.44	-
$OOSR^2$ (%)	-	2.41
MESF	-	78.26***
MSPE-adj	-	2.23**
ENC	-	108.11**

This table reports the intraday reversal predictability. For the in-sample analysis, we perform the predictive regression over the full sample. For the out-of-sample analysis, we recursively run the predictive regression on an daily expanding window basis where the first five years are used as the initial estimation period. Reported estimates and corresponding significance in the out-of-sample analysis are averaged from individual estimation regressions. The OOS R^2 is calculated as in Campbell and Thompson (2008). We also report McCracken (2007) OOS-F statistic. Intercepts are annualised and in percentage. Slope coefficients are scale by 100. Sample spans from 03 Jan 2000 to 29 Dec 2017. Newey and West (1987) robust t-statistics are in parentheses. *, **, and *** denote confidence level of 10%, 5%, and 1%.

4.4.2 Out-of-sample evidence

As argued by Welch and Goyal (2008), the in-sample predictability of linear models suffers from problems such as instability. Conditional on the significance shown in the in-sample analysis, therefore, it is necessary to formally examine the out-of-sample (OOS) predictability. Specifically, we compare the OOS predictability of an unrestricted model (Equation (4.3)) and that of a restricted model ($r_{10:00,t} = \alpha + \epsilon_t$) through four statistics. Based on each model, $r_{10:00,t}$ is recursively estimated using data up to time $t-1$. The first 5 years are reserved as the initial estimation period.

The first OOS statistic is the well-known Campbell and Thompson (2008) R^2_{OOS} that examines whether the our predictive model is better than a simple historical average model. The specification of R^2_{OOS} subtracts the ratio of the mean standard prediction error (MSPE) of the unrestricted and the MSPE of the restricted model from 1. Since the unrestricted model nests the the restricted model and estimates an additional parameter, it is expected to have have a larger MEPS than that of the restricted model in a finite sample if the extra regressor has no predictability (Clark and West, 2006). Let T_{OOS} denote the total number of observations in the out-of-sample period (3167 in our case), and $\hat{r}_{10:00,t}$ ($\bar{r}_{10:00,t}$) denote the estimation from the unrestricted (restricted) model at time t, the R^2_{OOS} is computed as follows:

$$R^2_{OOS} = 1 - \frac{MSPE_u}{MSPE_r} \tag{4.4}$$

where,

$$MSPE_u = \frac{\sum_{t=1}^{T_{OOS}} (r_{10:00,t} - \hat{r}_{10:00,t})^2}{T_{OOS}} \tag{4.5}$$

$$MSPE_r = \frac{\sum_{t=1}^{T_{OOS}} (r_{10:00,t} - \bar{r}_{10:00,t})^2}{T_{OOS}} \tag{4.6}$$

If the overnight return does not have any predctive power on the first half-hour return, a negative R^2_{OOS} is expected. In contrast, if the overnight return does predict the first half-hour return, a non-negative R^2_{OOS} is expected. This R^2_{OOS} is also used by many other scholars (Ferreira and Santa-Clara, 2011; Gao et al., 2018; Neely et al., 2014; Rapach et al., 2010).

The second OOS statistic we compute is the McCracken (2007) MESF, which enables us to answer the question how significantly the overnight reversal outperforms the historical average in terms of the OOS predictability. By computing this statistic, we conduct a one-tailed null hypothesis test in which the null is that the unrestricted model has same OOS predictability as the restricted model, and the alternative is that the unrestricted model has superior OOS predictability than the restricted. The statistic is also used by Rapach and Wohar (2006) and Barroso and Maio (2019) among others, and is computed as follows:[8]

$$MSEF = T_{OOS}\frac{MSPE_r - MSPE_u}{MSPE_u} \tag{4.7}$$

The third OOS statistic is the Clark and West (2007) MSPE-adjusted, which tests the same null hypothesis as does the McCracken (2007) MESF. To obtain the statistic, we first define:

$$\hat{f}_t = (r_{10:00,t} - \bar{r}_{10:00,t})^2 - [(r_{10:00,t} - \hat{r}_{10:00,t})^2 - (\bar{r}_{10:00,t} - \hat{r}_{10:00,t})^2] \tag{4.8}$$

and then regress $\hat{f}_t$ against a constant. The Clark and West (2007) MSPE-adjusted is the student-t statistic of the constant.

[8]The asymptotic distribution of the McCracken (2007) MESF depends on two parameters. The first is the number of additional predictors, k_2, in the unrestricted model, which is 1 in our case. The second is $\pi = \lim_{P,R\to\infty} P/R$, where R and P are the numbers of the in- and our-of-sample observations. In our case $\hat{\pi} = P/R = 3167/1161 = 2.73$. Since McCracken (2007) only provides critical values with π up to 2, we use the critical values when $\pi = 2$ and $k_2 = 1$, provided in Table 4 in McCracken (2007). That is, the critical values for confidence levels of 1%, 5% and 10% are 0.616, 1.518, and 3.951 respectively. Given our MSEF statistic in Table 4.3 is much larger than the critical values, the choice of π is unlikely to affect our conclusion.

Finally, the Clark and McCracken (2001) ENC statistic is computed to test the null that the unrestricted model does not add predictability to the restricted model. The statistic is computed as follows:[9]

$$MSEF = \frac{\sum_{t=1}^{T_{OOS}}[(r_{10:00,t} - \bar{r}_{10:00,t})^2 - (r_{10:00,t} - \hat{r}_{10:00,t})(r_{10:00,t} - \bar{r}_{10:00,t})]}{MSPE_u} \tag{4.9}$$

The second column of Table 4.3 reports the result of out-of-sample analysis. The intercept and slope estimates along with the Newey and West (1987) t-statistics reported are averaged from the individual recursive regressions. As shown in the table, the averaged intercept and slope coefficient are roughly as same large as that of the in-sample analysis. The out-of-sample analysis yields a positive R^2_{OOS} of 2.41% that is reasonable large. Moreover, the McCracken (2007) MSEF of 78.26 is magnificent and significant at 1% level. Clark and West (2007) MSPE-adj and Clark and McCracken (2001) ENC are both significant at 5% confidence level with values of 2.23 and 108.11 respectively.[10] Our out-of-sample analysis strongly supports the in-sample implication that the overnight return is a powerful predictor for the first half hour return.

4.4.3 Financial crisis, business cycle, and uncertainty

The sudden amplification of predictability around the financial crisis shown in Figure 4.3 suggests the intraday reversal behaves distinctively over this period. We therefore study how the performance of intraday reversal varies within crisis and non-crisis periods by fitting the predictive regressions over the two periods respectively. Consistent with Gao et al. (2018), we define the crisis period as from 02 December 2007 to 30 June 2009. Panel A in Table 4.4 presents the analysis results. The first column in Panel A performs the predictive regression over the financial crisis period whereas the second column performs the predictive regression over the sample period with crisis excluded. Though intraday reversal effect significantly appears in both periods, the negative relation between overnight and first half-hour returns is much more pronounced over crisis period with a slope coefficient of -18.46, which is more than 4 times larger than that over non-crisis period (-4.33) in terms of absolute magnitude. The Newey and West (1987) t-statistic over the crisis is -3.85, which is also larger than that of non-crisis period (-2.87) in absolute term. Moreover, a strikingly large adjusted R^2 of 10.29% is observed over the crisis phase while that of non-crisis period fells to only 0.58%.

[9] Similar to footnote 8, the asymptotic distribution of the ENC statistic depends on the value of π and k_2. Clark and McCracken (2001) give critical values with π up to 5. We use the critical values when $\pi = 3$ in our analysis, that is, 1.609 and 2.685 for confidence levels of 10% and 5% respectively. Again, since our statistic is far larger than the critical values, our conclusion is unlikely be affected by the choice of π.

[10] Although Clark and McCracken (2001) only gave critical values up to 5% confidence level, it is reasonably safe to believe our statistic is significant at 1% level due to the statistic is almost 38 times greater than the critical value of 5% level, which is 2.685.

We then investigate the intraday reversal performance during recessions and expansions. Similar analyses are conducted by splitting our sample into two subgroups based on recession indicators that are obtained from from FRED St. Louis website.[11] Panel B of Table 4.4 summarises the results. As we expected, the predictive regression during recessions produces large negative slope coefficient of -12.31 (scaled by 100) with a considerable Newey and West (1987) t-statistic of -4.12. The adjusted R^2 is 4.92%. In contrast, there is no significance shown in the expansion periods and the adjusted R^2 is merely 0.08%.

TABLE 4.4: Intraday Reversal and Uncertainty

	Panel A: Financial Crisis		**Panel B:** Business Cycle		**Panel C:** VIX	
	Financial Crisis	Non Financial Crisis	Recession	Expansion	Low Uncertainty	High Uncertainty
Intercept	-10.22	0.48	-1.94	0.73	3.19***	-4.50**
	(-1.43)	(0.41)	(-0.95)	(0.48)	(3.09)	(-2.02)
β	-18.46***	-4.33***	-12.31***	-2.05	0.94	-10.34***
	(-3.85)	(-2.87)	(-4.12)	(-1.11)	(0.66)	(-4.11)
$Adj.R^2$ (%)	10.29	0.58	4.92	0.08	-0.02	3.46

Panel A reports predictive regression results over financial crisis and non-crisis periods. We split our sample into financial crisis and non crisis periods. Following Gao et al. (2018), the crisis period is defined as from 02 December 2007 to 30 June 2009. Panel B repeats similar analysis over economic recession and expansion periods which are defined using recession indicators retrieved from FRED St. Louis website. Panel C divides our sample into three groups based on the VIX index and perform the predictive regression within each group. Intercepts are annualised and in percentage. Slope coefficients are scale by 100. Sample spans from 03 Jan 2000 to 29 Dec 2017. Newey and West (1987) robust t-statistics are in parentheses. *, **, and *** denote confidence level of 10%, 5%, and 1%.

The findings are not surprising. We argue the intraday reversal might be attributed to the liquidity shock at the market open which is largely due to the accumulation of information overnight. Presumably, during periods with greater uncertainty, such as financial crises and economic recessions, more information will be released at a higher frequency. Therefore, one should expect to observe stronger intraday reversal effect during these periods.

Above findings and hypothesis lead us naturally to investigating the relation between the intraday reversal and market uncertainty. Panel C of Table 4.4 divides our sample into two subgroups based on the value of the VIX index, which is generally considered as a gauge of market uncertainty. Consistent with our hypothesis, the statistical predictability vanishes during low uncertainty days while pronounced predictability is observed during high uncertainty days. The slope during low uncertainty days is 0.94 with a Newey and West (1987) t-statistic of 0.66. In contrast, during high uncertainty days, the analysis gives a substantial negative slope coefficient of -10.34 with a Newey and West (1987) t-statistic of -4.11. The adjusted R^2 is 3.46 during days with high VIX value and -0.02 during days with low VIX value.

[11] https://fred.stlouisfed.org/

4.4.4 Overnight volatility and trade size

The extraordinarily strong predictability shown in financial crisis, recessions, and periods with high uncertainty raises naturally the question how the intraday reversal is related with intraday level indicators that reflect information arrival and accumulation.

Applying textual analysis, Boudoukh et al. (2019) study the relation between fundamental information and firm-level volatility during overnight and intraday day. They claim that the news consisting fundamental information accounts for 49.6% of the overnight volatility and this figure is even larger when there are multiple types of news occur (termed complex news days in the study). Therefore, we split our sample into two groups based on the overnight return volatility, and perform the predictive regression analysis within each group. If the intraday reversal is caused by the arrival and accumulation of information overnight, a stronger reversal at the open is expected in the group with higher overnight volatility.

TABLE 4.5: Overnight Volatility and Trade Size

	Panel A: Overnight volatility		**Panel B:** Trade size	
	High	Low	Large	Small
Intercept	1.40	-2.59*	0.07	-0.68
	(0.62)	(-1.95)	(0.03)	(-0.44)
β	-11.13***	3.06*	-11.52***	-1.66
	(-4.38)	(1.69)	(-4.10)	(-0.75)
$Adj.R^2$ (%)	4.21	0.16	4.45	0.03

In Panel A, the sample is split into two groups based on overnight return volatility. In Panel B, the sample is split into two groups based on average overnight trade size. The trade size is calculated as volume over number of trades. The predictive regression is then performed within each group. Intercepts are annualised and in percentage. Slope coefficients are scale by 100. Sample spans from 03 Jan 2000 to 29 Dec 2017. Newey and West (1987) robust t-statistics are in parentheses. *, **, and *** denote confidence level of 10%, 5%, and 1%.

Panel A of Table 4.5 reports the predictive regression results on high and low overnight return volatility days. As expected, the intraday reversal on high overnight volatility days has a negative slope of -11.13 with a Newey and West (1987) t-statistic of -4.38 and an adjusted R^2 of 4.21%. Interestingly, on days with low overnight volatility, not only we do not observe reversal at the market open, the slope coefficient of the predictive regression is positive and slightly significant at 10% level. The adjusted R^2, however, is merely 0.16%.

Market microstructure literature suggests that informed traders value trading speed more than the trading costs or price impact. Therefore large trades are usually seen as initiated by informed traders (Gao et al., 2018). We next examine how the intraday reversal is affected by average overnight trade size. Panel B of Table 4.5 divides the sample into two groups based on the average overnight trade size. That is, we divide minutely volume by the number of trades per minute and take the average across time over the night, then we group the sample based on this value. As it shown in the table, trading days with large average overnight trade size have much stronger intraday reversal effect with a slope coefficient of -11.52 that is significant at 1% confidence level whereas the predictive analysis on days with small trade size shows an insignificant slope of -1.66.

4.5 Economic Significance

4.5.1 Sign-based market timing

We turn now our attention to the economic significance of the opening reversal by considering the profitability of a sign-based timing strategy based on the opening reversal reversal.[12] Specifically, we buy (sell) SPY and borrow (lend) at the risk free rate simultaneously at 09:30 am if the overnight return is positive (negative) and clear all position in SPY at 10:00 am. We stay out of the market if the overnight return is 0.[13] The mathematical notation of the strategy return on day t is as follows:

$$r_{ZCIR,t} = \begin{cases} r_{10:00,t} - r_{f,t}, & \text{if } r_t^O > 0; \\ -r_{10:00,t} + r_{f,t}, & \text{if } r_t^O < 0 \\ 0, & \text{if } r_t^O = 0. \end{cases} \tag{4.10}$$

where $r_{ZCIR,t}$ is the zero-cost intraday reversal strategy return on day t, $r_{10:00,t}$ is the first half hour return on day t, r_t^O is the overnight return from day $t-1$ to day t, and $r_{f,t}$ is the US one month t-bill rate on day t.

Following Gao et al. (2018), two simple passive strategies are used as the benchmarks. The first benchmark is *Always-long* strategy in which we borrow at the risk free rate and buy SPY at 9:30 am every trading day and clear all position in SPY at 10:00 am. The second benchmark is *Buy-and-hold* in which we buy SPY and borrow at the risk free rate at the beginning of our sample and hold the position throughout the sample period. To compare the strategy performance, we exclude a day if either the reversal or benchmark return is not available.

[12] To make it more realistic, we construct a self-financed strategy. Performance of the strategy without investing in risk free asset is shown in Appendix B Table B.1.

[13] In our sample, there are only 38 days with 0 overnight return.

TABLE 4.6: Economic Significance

	μ (%)	σ (%)	Skewness	Kurtosis	SRatio	$\rho_{IR,AL}$	α_{AL} (%)	$\rho_{IR,BH}$	α_{BH} (%)	Utility (%)
	Panel A: Sign-based zero-cost market timing									
Intraday reversal	6.386***	5.725	0.078	3.047	1.115	0.023	6.43***	-0.025	6.41***	5.566
	(4.41)						(4.35)		(4.40)	
Always-long	-1.895	5.749	0.018	3.048	-0.330	-	-	-	-	-2.721
	(-1.51)									
Buy-and-hold	3.753	18.951	0.004	3.035	0.198	-	-	-	-	-5.225
	(0.97)									
	Panel B: Mean-variance strategy									
Intraday reversal	5.326***	6.070	0.186	3.181	0.877	-	-	-	-	4.405
	(3.22)									
Historical average	1.492**	2.688	-0.038	3.080	0.555	-	-	-	-	1.311
	(2.22)									

This table examines the economic significance of the intraday reversal effect. Panel A compares zero-cost market timing performance of intraday reversal strategy and two zero-cost benchmarks, *Always-long* and *Buy-and-hold*. In the intraday reversal strategy, we buy (sell) SPY and borrow (lend) at the risk free rate simultaneously at 09:30 am if the overnight return is positive (negative) and clear all positions in SPY at 10:00 am. We stay out of the market if the overnight return is 0. In the *Always-long* strategy, we borrow at the risk free rate and buy SPY in the first half hour every day. In the *Buy-and-hold* strategy, we buy SPY and borrow at the risk free rate at the beginning of our sample and hold the position throughout the sample period. The table firstly reports average realised strategy return (μ), realised standard deviation (σ), skewness, kurtosis, and Sharpe ratio. We also reports the correlation coefficients (ρ) between the zero-cost intraday reversal and the zero-cost benchmarks. The alphas are obtained from the mean-variance spanning regressions: $r_{ZCIR,t} = \alpha_a + \beta_a r_{Always-long,t} + \epsilon_{a,t}$ and $r_{ZCIR,t} = \alpha_b + \beta_b r_{Buy-and-hold,t} + \epsilon_{b,t}$ where $r_{ZCIR,t}$ is the market timing return of the zero-cost intraday reversal strategy at time t. We also report the utility of each strategy which is calculated as: $U = \mu - \frac{\gamma}{2}\sigma^2$, where μ is the realised strategy return, γ is the risk aversion coefficient and is set to 5, and σ is the standard deviation of realised returns. Panel B compares the performance of (1) a mean-variance portfolio that invests in SPY and risk free asset using estimated value of $r_{10:00}$ and $\sigma_{10:00}$, which are estimated from the predictive regression, and that of (2) a mean-variance portfolio that invests in same assets but estimates $r_{10:00}$ and $\sigma_{10:00}$ using historical average. Consistent with Gao et al. (2018) and to make it more realistic, we constrain the weights on SPY between -0.5 to 1.5. Newey and West (1987) t-statistics are reported in parentheses and all figures are annualised. The sample period spans from 03 Jan 2000 to 29 Dec 2017. *. **, and *** denote significant levels at 10%, 5% and 1% respectively.

The first five columns of Panel A in Table 4.6 compare the zero-cost intraday reversal and the benchmark performance. Intraday reversal strategy has the largest annulised average return of 6.176% with a Newey and West (1987) t-statistic of 4.27 and the lowest standard deviation of 5.721%. As a result, the strategy yields the largest annualised Sharp ratio of 1.097. In contrast, the annualised average returns of *Always-long* and *Buy-and-hold* are -1.895% and 3.754% with no statistical significance shown in either case. Accordingly, the Sharpe ratios of the two benchmarks are -0.330 and 0.198 respectively, which are not comparable to that of the intraday reversal strategy.

To further evaluate the economic value that the intraday reversal strategy adds to the benchmarks, we regress the zero-cost intraday reversal strategy returns against that of the benchmarks:

$$r_{ZCIR,t} = \alpha_a + \beta_a r_{Always-long,t} + \epsilon_{a,t}; \tag{4.11}$$

$$r_{ZCIR,t} = \alpha_b + \beta_b r_{Buy-and-hold,t} + \epsilon_{b,t} \tag{4.12}$$

where $r_{ZCIR,t}$, $r_{Always-long,t}$, and $r_{Buy-and-hold,t}$ are the return of the zero-cost intraday reversal strategy, *Always-long*, and *Buy-and-hold* at time t respectively. A significantly positive alpha implies extra economic value added by the intraday reversal strategy. As shown in Panel A of Table 4.6, while the correlations are virtually 0, the intraday reversal strategy exhibits remarkably large alphas of 6.23% and 6.21%, which are both significant at 99% confidence level after Newey and West (1987) corrections.

We next compute the utility of the zero-cost intraday reversal strategy and the two zero-cost benchmarks for a mean-variance investor with a relative risk aversion γ of 5:

$$U = \mu - \frac{\gamma}{2}\sigma^2 \tag{4.13}$$

where μ is the average realised return of the strategy and σ is the standard deviation of realised returns. The utility gained by a mean-variance investor who employ the zero-cost intraday reversal strategy is 5.357% whereas the utility provided by both benchmarks is negative. Our analysis shows that the sign-based zero-cost intraday reversal strategy outperforms and adds economic value to the passive benchmarks.

4.5.2 Mean-variance strategy

Apart from the economic benefit gained from the sign-based strategy, we are also interested in how much economic value can be added by exploiting the predictive power of the predictive regression (4.3). We therefore, following Gao et al. (2018), compare the economic performance of using estimated first half-hour return and its simple historical average in the portfolio optimisation of a mean-variance investor who invests both SPY and the risk free asset. More specifically, we compute the optimal weights invested in SPY at day t as follows:

$$w_t = \frac{1}{\gamma} \frac{\hat{r}_{10:00,t}}{\hat{\sigma}^2_{10:00,t}} \tag{4.14}$$

where $\hat{r}_{10:00,t}$ and $\hat{\sigma}_{10:00,t}$ are estimated recursively using information up to day $t-1$, and again, γ is the risk aversion coefficient that is set to 5. Consistent with Gao et al. (2018), we constrain w_t to be within the range of [-0.5, 1.5], that is, the investor can only leverage up to 50% maximum on margin.[14] The first five-year period is used as the initial estimation period.

Panel B of Table 4.6 presents the mean-variance portfolios' performance. The portfolio constructed using the predictive regression (P_{IR}) yields an annualised average return of 5.326%, associated with a t-statistic of 3.22 computed using the Newey and West (1987) robust standard error. In contrast, the portfolio constructed using the historical average (P_{HA}) produce an annualised average return of only 1.492% which is significant at 5% confidence level. Despite that P_{IR} has a larger realised standard deviation, which is 6.070% per year, it dominates P_{HA} in terms of Sharpe ratio. The Sharpe ratio of P_{IR} is 0.877 whereas it is 0.555 for P_{HA}. Using the historical average as a benchmark, the certainty equivalent return (CER) of the intraday reversal is $U_{IR} - U_{HA} = 3.094\%$. This can be interpreted as the increase in utility of an investor who convert from historical mean to intraday reversal (Gao et al., 2018). The evidence shows clearly that the intraday reversal outperforms historical average in a mean-variance strategy.

4.6 Robustness check

4.6.1 Ohter ETFs

In this subsection, we study the robustness of the intraday time series reversal effect using alternative ETFs. Following Gao et al. (2018), we employ 10 ETFs with the highest daily trading volume. Table 4.7 reports the ETFs and the sample periods. As noted in Gao et al. (2018), these 10 ETFs cover a wide range of financial markets, such as the domestic stock market ((DIA, QQQ, and IWM), the international stock market (EEM, FXI, EFA, VWO), the Finance sector (XLF), the real estate sector (IYR), and the bond market (TLT). Table 4.8 presents the descriptive statistics for the alternative ETFs. Consistent with SPY, most ETFs (8 out of 10) have a larger overnight return compared to the first half-hour return and the last half-hour return.

In order to examine the robustness of the intraday time series reversal effect, we repeat our in-sample predictive regression and report the results in Panel A of Table 4.9. As

[14] As in Gao et al. (2018), we provide a robustness check with varying constraints on weights and different relative risk aversion coefficients in Appendix B Table B.2. The performance of the intraday reversal dominates that of the benchmark in all settings.

TABLE 4.7: Other ETFs

Symbol	Name	Sample period
QQQ	Powershare NASDAQ 100	1999/03/10 - 2019/10/15
XLF	Financial Select Sector SPDR	1998/12/22 - 2019/10/15
IWM	iShares Russell 2000 ETF	2000/05/26 - 2019/10/15
DIA	Dow Jones Industrial Average ETF	1998/02/10 - 2019/10/15
EEM	iShares MSCI Emerging Markets ETF	2003/04/11 - 2019/10/15
FXI	iShares China Large-Cap ETF	2004/10/08 - 2019/10/15
EFA	iShares MSCI EAFE ETF	2001/08/17 - 2019/10/15
VWO	Vanguard FTSE Emerging Markets ETF	2005/03/10 - 2019/10/15
IYR	iShares US Real Estate ETF	2001/04/27 - 2019/10/15
TLT	20+ Year Treasury Bond ETF	2004/02/27 - 2019/10/15

This table reports the symbols, names, and sample periods for the alternative ETFs used in the robustness check.

shown in the table, the slope coefficients of all ETFs are negative, ranging from -21.58 for XLF to -2.28 for VWO (scaled by 100). Nine out of ten slope coefficients are statistically significant, with seven at the 1% level, implying strong and prevalent intraday momentum effect across the ETFs. The adjusted R^2s are positive and remarkable, ranging from 0.30% (VWO) to 12.8% (XLF). Note that the weakest statistical evidence of the intraday reversal is observed in the ETFs that track the emerging markets. For example, the only ETF that does not show significant reversal effect is VWO, which tracks the FTSE Emerging Markets All Cap China A Inclusion Index. Similarly, EEM and FXI, that track the global emerging markets and China large-Cap stocks, respectively, are the only two ETFs (amongst the ETFs with a significant slope coefficient) on which the reversal effect is not significant at the 1% level.

In Panel B of Table 4.9, we repeat the portfolio construction in Panel B of Table 4.6 for each of the alternative ETFs. Specifically, we construct a mean-variance optimal portfolio for each ETF using the intraday reversal strategy and a risk free asset. Again, all the 10 ETFs show a positive annualised return, ranging from 17.57% (XLF) to 2.37% (DIA), amongst which 9 are statistically different from zero. Associated with the remarkable returns are the considerable Sharpe ratios, ranging from 1.54 (XLF) to 0.44 (DIA). In addition, all portfolios possess positive skewness, implying possible large returns. It is worth noting that while the emerging market based ETFs exhibit less solid statistical evidence of the intraday reversal effect, the economic evidence of the effect shown by these ETFs is strong. Especially, while the slope coefficient in the predictive regression for VWO is statistically insignificant, the mean-variance portfolio based on this ETF has an annualised return of 9.04% with a Newey and West (1987) t-statistic of 6.01 and a Sharpe ratio of 1.48.

Overall, the evidence from alternative ETFs suggests that the intraday reversal effect at the market open is significant and robust across a wide range of US-traded ETFs.

TABLE 4.8: Descriptive statistics for other ETFs

		No.Days	Avg ret (%)	Std dev (%)	Skewness	Kurtosis	AR(1)
QQQ	r^O	5092	14.19***	14.03	-0.03	3.04	-0.10
	$r^I_{10:00}$	5092	0.73	8.53	0.03	3.04	-0.03
	$r^I_{16:00}$	5092	-1.26	7.48	0.01	3.05	-0.09
XLF	r^O	4156	11.29***	16.85	0.17	3.27	-0.04
	$r^I_{10:00}$	4156	-5.80**	10.39	-0.03	3.08	-0.05
	$r^I_{16:00}$	4156	0.38	7.99	0.05	3.09	-0.21
IWM	r^O	4549	10.88***	11.50	0.00	3.06	-0.09
	$r^I_{10:00}$	4549	-4.97***	7.96	0.01	3.03	-0.03
	$r^I_{16:00}$	4549	0.93	6.62	0.03	3.09	-0.15
DIA	r^O	5230	9.07***	9.44	-0.05	3.06	-0.09
	$r^I_{10:00}$	5230	-0.99	5.16	0.03	3.06	-0.03
	$r^I_{16:00}$	5230	-0.88	5.26	-0.02	3.09	-0.14
EEM	r^O	3666	10.41***	18.70	0.01	3.05	-0.12
	$r^I_{10:00}$	3666	-8.53***	7.48	-0.01	3.06	0.04
	$r^I_{16:00}$	3666	0.52	6.65	0.02	3.15	-0.15
FXI	r^O	3510	7.51	24.84	0.00	3.03	-0.08
	$r^I_{10:00}$	3510	-4.88**	8.08	0.03	3.04	0.02
	$r^I_{16:00}$	3510	-0.61	7.69	0.01	3.14	-0.19
EFA	r^O	3997	1.06	15.30	-0.03	3.04	-0.10
	$r^I_{10:00}$	3997	-3.67***	4.47	0.02	3.05	-0.01
	$r^I_{16:00}$	3997	1.72*	4.53	0.05	3.16	-0.17
VWO	r^O	3226	17.22***	19.08	-0.01	3.04	-0.12
	$r^I_{10:00}$	3226	-14.30***	7.58	0.05	3.08	-0.05
	$r^I_{16:00}$	3226	0.17	6.19	0.03	3.12	-0.10
IYR	r^O	3565	-1.05	11.91	-0.03	3.10	-0.10
	$r^I_{10:00}$	3565	-14.90***	10.22	-0.03	3.07	-0.02
	$r^I_{16:00}$	3565	7.88***	9.06	0.08	3.10	-0.20
TLT	r^O	2893	2.96	9.46	0.01	3.01	0.00
	$r^I_{10:00}$	2893	1.99**	3.28	-0.01	3.01	-0.02
	$r^I_{16:00}$	2893	1.66***	2.34	-0.04	3.04	-0.12

This table reports the descriptive statistics for the alternative ETFs employed in the robustness. For each ETF, we eliminate a day if the return for one of the three intervals is not available. We report the number of days with available returns (No.Days), average return (Avg ret), standard deviation (Std dev), skewness, kutosis, and first order autocorrelation (AR(1)). Apart from NO.Day and AR(1), all figures are annualised and in percentage. Sample periods are reported in Table 4.7. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, after the Newey and West (1987) correction.

TABLE 4.9: Robustness check

	Panel A: Statistical significance			Panel B: Economic significance				
	Intercept	β	Adj.R^2 (%)	μ (%)	σ (%)	Skewness	Kurtosis	SRatio
QQQ	2.65	-12.53***	4.24	10.29***	7.42	0.20	3.18	1.39
	(1.54)	(-6.97)		(5.04)				
XLF	-3.18	-21.58***	12.18	17.57***	11.43	0.15	3.14	1.54
	(-1.38)	(-6.21)		(4.64)				
IWM	-3.22*	-14.82***	4.56	10.22***	8.25	0.16	3.12	1.24
	(-1.91)	(-5.56)		(4.35)				
DIA	0.08	-9.74***	3.16	2.37	5.44	0.25	3.27	0.44
	(0.07)	(-4.30)		(1.62)				
EEM	-8.36***	-3.19*	0.61	4.86**	6.27	0.16	3.25	0.77
	(-4.60)	(-1.80)		(2.83)				
FXI	-4.51**	-3.10**	0.88	3.37*	7.53	0.13	3.18	0.45
	(-2.18)	(-2.26)		(1.69)				
EFA	-3.55***	-4.51***	2.35	6.11***	4.79	0.14	3.16	1.27
	(-3.42)	(-4.49)		(4.80)				
VWO	-13.82***	-2.28	0.30	9.04***	6.09	0.11	3.42	1.48
	(-6.71)	(-1.55)		(6.01)				
IYR	-15.25***	-18.50***	4.64	9.47***	9.77	0.17	3.23	0.97
	(-5.33)	(-3.58)		(3.17)				
TLT	2.02**	-2.31***	0.41	2.75**	4.07	0.01	3.02	0.68
	(2.10)	(-2.91)		(2.27)				

This table reports the economic and statistical significance of the intraday reversal effect using 10 additional ETFs to SPY. Panel A presents the predictive regression results for each ETF. Panel B presents, the economic performance of a mean-variance portfolio that consists of the intraday reversal strategy and a risk free asset (we use the US one month T-bill rate) for each ETF. For each mean-variance portoflio, we report the mean return (μ), standard deviation (σ), skewness, kurtosis, and Sharpe ratio. Sample periods are reported in Table 4.7. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively, after the Newey and West (1987) correction.

4.6.2 Transaction costs

One potential concern about our strategy based on the intraday time series reversal is the transaction costs induced by the high turnover of trading. For example, the simplest strategy that trades in the first half hour based on overnight signals involves a buy transaction and a sell transaction everyday. Therefore, in this subsection we compute the strategy return using SPY quote data that contains bid and ask prices and compare it with the passive benchmark, always-long. Consistent with the timing strategy in Section 4.5.1, for a given day, the intraday reversal strategy takes a long (short) position in the first half hour if the overnight return is negative (positive) and compute the strategy return using the bid (ask) price at 09:30 am and the ask (bid) price at 10:00 am. By doing so, we take into account the bid-ask spread in the trading process. The passive benchmark strategy, always-long, simply takes a long-position in the first half hour and closes all position at 10:00 am everyday. Both strategies are self-financed, i.e. they take a long (short) position by borrowing (lending) at the risk-free rate.

TABLE 4.10: Intraday reversal after transaction costs

	μ (%)	σ (%)	Skewness	Kurtosis	SRatio	ρ	α (%)	Utility (%)
IR	2.006	6.733	-0.426	4.137	0.298	0.393	3.97**	0.872
	(1.24)						(2.55)	
AL	-5.607***	7.542	-0.983	5.714	-0.743	-	-	-7.029
	(-3.08)							

This table examines the economic significance of the intraday reversal effect after transaction costs. We compare the zero-cost market timing performance of intraday reversal strategy and a benchmark strategy that repeatedly takes a long position in the first half hour, namely, the always-long strategy. In the intraday reversal strategy, we buy (sell) SPY and borrow (lend) at the risk free rate simultaneously at 09:30 am if the overnight return is positive (negative) and clear all positions in SPY at 10:00 am. The strategy return is computed using the the bid (ask) price at 09:30 am and the ask (bid) price at 10:00 am for the long (short) position. We stay out of the market if the overnight return is 0. The table first reports the annualised average strategy return (μ), standard deviation (σ), skewness, kurtosis, and Sharpe ratio. We also reports the correlation coefficients (ρ) between the zero-cost intraday reversal and the zero-cost benchmark. The alpha (α) is obtained from the mean-variance spanning regressions: $r_{ZCIR,t} = \alpha + \beta r_{always-long,t} + \epsilon_t$, where $r_{ZCIR,t}$ is the market timing return of the zero-cost intraday reversal strategy at time t. We also report the utility of each strategy which is calculated as: $U = \mu - \frac{\gamma}{2}\sigma^2$, where μ is the realised strategy return, γ is the risk aversion coefficient and is set to 5, and σ is the standard deviation of realised returns. Newey and West (1987) t-statistics are reported in parentheses and all figures are annualised. The sample period spans from 03 Jan 2000 to 29 Dec 2017. *. **, and *** denote significant levels at 10%, 5% and 1% respectively.

Table 4.10 reports the performance for both strategies. The annualised return for the intraday reversal timing strategy drops from 6.386% to 2.006% after considering transaction costs. Similarly, we also observe a drop in the annualised return for the passive benchmark strategy, from -1.895% to -5.607%. However, when we regress the intraday reversal strategy against the benchmark, the spanning alpha remains significant at the 5% level, suggesting that the economic gains added by the intraday reversal survives transaction costs.

4.7 Conclusion

We study dynamic relationship between overnight and intraday returns, whereby we introduce a time series reversal effect at the market open, namely, the overnight return can significantly and negatively predict the first half hour on the following day.

We further show that this opening reversal is mainly significant on days with negative overnight returns, whereas the closing momentum of Gao et al. (2018) is mainly significant on days with positive overnight returns. The alternation of the opening reversal and closing momentum on days with positive and negative overnight return days implies investor heterogeneity on these two type of days.

The reversal is strongly significant both in- and out-of-sample. We find the effect is more pronounced during the financial crisis and recession periods. Further investigation suggests that stronger predictive power of the overnight return is observed on days with higher uncertainty, overnight volatility, and larger average overnight trade size. A closer examination of economic significance shows the intraday reversal effect can provide remarkable economic value in both market timing and a mean-variance portfolio. The intraday reversal at the open might be explained by the dynamic model proposed by Duffie (2010) and Bogousslavsky (2016), in which a sudden liquidity shock is predicted to be followed by a reversal.

Chapter 5

Conclusion

Employing high-frequency international data, this thesis studies intraday stock return predictability both in the time series and cross-section. Evidence of intraday stock return predictability is presented across major developed markets and the economic drivers behind are discussed. This thesis also looks into the dynamic overnight-intraday return relationship, wherein an intraday time series reversal effect at the market open is introduced.

In Chapter 2, we study the intraday time series momentum (ITSM), i.e. the return continuity between the first half-hour return and the last half-hour return on same day, in 16 developed markets around the world. We show that in 12 out of 16 markets a strong ITSM effect is observed. This intraday momentum is stronger over the financial crisis and economic recession periods in most of the markets, consistent with the empirical evidence of Gao et al. (2018). A thorough out-of-sample analysis confirms the in-sample evidence of intraday predictability.

Based on existing market microstructure and behavioural studies, four hypotheses that seek to understand the economic drivers of the phenomenon are developed. Particularly, we hypothesise that the ITSM is stronger when liquidity is low (based on the infrequent trading model of Bogousslavsky (2016)), new information arrives continuously (based on the 'frog-in-the-pan' hypothesis of Da et al. (2014)), volatility is high (based on the overconfidence model of Daniel and Titman (1999)), and the investor are from a high individualism culture (based on the explanatory power of cultural factors for the traditional momentum, as documented by Chui et al. (2010)). By testing the hypotheses both in the cross-section and time series, it is shown that the ITSM effect is indeed driven by those market microstructure and behavioural factors.

Chapter 3 further explores the predictability of information from the first half hour to the return of the last half hour. The cross-sectional intraday return predictability is first examined through cross-market portfolio sorting and Fama and MacBeth (1973) regressions. Our evidence shows that the first half-hour return and the first half-hour volatility possess significant cross-sectional predictability on the last half-hour return. A long-short portfolio that invests in the last half hour based on the first half-hour return generates a Sharpe ratio of 1.10, whereas the long-short portfolio based on the first half-hour volatility yields a Sharpe ratio of 0.84. Via a spanning analysis, we show that these two cross-sectional portfolios do not subsume each other, implying different sources of profitability. In fact, a strategy that invests simultaneously the two predictors produces significant and positive alphas against the portfolios that are based solely on either one of the predictors.

Chapter 3 also compares the cross-sectional portfolios with a global portfolio based on the intraday time series momentum of Gao et al. (2018). Goyal and Jegadeesh (2018) compares the time series momentum of Moskowitz et al. (2012) and the cross-sectional momentum of Jegadeesh and Titman (1993) and state that the time series momentum strategy implicitly incorporate a market timing component, whereby it outperforms the conventional cross-sectional momentum. Similarly, the last part of Chapter 3 shows that the profitability of the intraday time series momentum strategy is due largely to a market timing component. When controlling for this market timing component in the ITSM portfolio, it is shown that the ITSM portfolio can be subsumed by the intraday cross-sectional portfolios based on both the first half-hour return and the first half-hour volatility.

Restricting its attention on the US market, Chapter 4 examines the dynamic relationship between overnight and intraday returns. Employing a rolling window predictive regression analysis, Chapter 4 shows that while the overnight return possesses a positive predictive power on the last half-hour return, as documented in Gao et al. (2018), it also negatively predicts the first half-hour return immediately after the market open, i.e. a opening reversal effect is detected. A closer examination shows that this intraday reversal effect is stronger during the financial crisis, economic recessions and high uncertainty periods.

In addition, Chapter 4 further shows that this intraday reversal effect provides considerable economic benefit. A long-short portfolio that invests in a sign based intraday reversal and a risk free asset produces an annualised return of 6.386% and a Shape ratio of 1.115. In contrast, a benchmark portfolio that passively invests in the first half hour (whole day) merely generates an annualised return of -1.895% (3.753%) with a Sharpe ratio of -0.330 (0.198). Furthermore, a mean-variance portfolio that is based on the predicted last half-hour return from the intraday reversal model produces an annualised return of 5.326%, in contrast to 1.492% for a mean-variance portfolio based on the simple historical mean model.

More importantly, Chapter 4 also discovers that the observed intraday reversal at the market open mainly presents on days with negative overnight returns, whereas the momentum effect at market close presents mainly on days with positive overnight returns. We conjecture that this conditional return behaviour is due to the short selling restrictions of retail investors on days with negative overnight news.

Overall, this thesis sheds light on the international stock return predictability at the intraday level. It reveals pervasive intraday return patterns across major developed markets both economically and statistically. In addition, this thesis also examines the economic drivers that might explain the observed return predictability. The overall finding of this thesis highlights the importance of the micro-level trading process, particularly market microstructure and behavioural factors, in understanding short-term price and return dynamics.

Appendix A

Appendix to Chapter 2

This Appendix comprises three sections. In Sections A.1 and A.2 we explore potential explanations of the weak evidence of intraday time series momentum (ITSM) observed in the 4 out of the 16 countries (i.e. Austria, Canada, Ireland, and New Zealand) shown in the main analysis of the study. In particular, we examine whether this weak evidence can be explained by institutional trading behaviour or that these markets are led by other larger international markets in close proximity to them, such as Canada being led by the U.S. and Ireland being led by the U.K. Finally, Section A.3 presents additional tables to those in the main study.

A.1 Effect of Institutional Trading

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

Due to the lack of institutional ownership and trading data, we follow Gao et al. (2018) and split each month into month-end days and non-month-end days to study the effect of institutional trading on ITSM. Specifically, for each market we split our data into two sub-samples: (1) days from $T - n$ to $T + 3$ and (2) rest of the days, where T is the last trading day of each month and n is the number of days needed for settlement. The rationale is, due to the month-end cash demand and settlement rules, institutions tend to trade more intensively before day $T - n$ and less so over the month-end days,

$T - n$ to $T + 3$ (Etula et al., 2019; Gao et al., 2018). Note that the number of settlement days (n) varies across markets and sometimes within the same market due to change of regulations. We use the information of settlement rules from Etula et al. (2019) and present it in Panel A of Table A.1.

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

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

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

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

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

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

TABLE A.1: Institutional Trading & ITSM

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

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

A.2 Intraday Cross-country Predictability

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

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

$$r_{i,t}^L = \begin{cases} \alpha + \beta_{i,j} r_{j,t-1}^F + \beta_i r_{i,t}^F + \epsilon_t, & \text{if } i \text{ is an Asia-Pacific country and } j \text{ is not;} \\ \alpha + \beta_{i,j} r_{j,t}^F + \beta_i r_{i,t}^F + \epsilon_t, & \text{otherwise,} \end{cases} \tag{A.2}$$

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

Given the cross-country nature of the analysis, we use only the data from the common sample period, namely, from 4th October 2005 to 29th December 2017 (Sweden has the shortest sample period starting from 4th October 2005). Before the examination of cross-country predictability, we first repeat our main predictive regression of local ITSM using this shortened sample period. The results are shown in the first two columns of Table A.2 and confirm the evidence presented in the main analysis of the study; the ITSM effect is again observed in the same 12 countries, leaving Austria, Canada, Ireland, and New Zealand being the only four countries in which we do not observe significant ITSM.

TABLE A.2: Cross-country Predictability

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

This table reports the results of the ITSM predictive regression using the common sample period from 04 October 2005 to 29 December 2017, and the point estimate of $\beta_{i,j}$ in Equation (A.2), through which we study the predictability of the first half-hour return of the column country (country j) on the last half-hour return of the row country (country i). We control for the local ITSM effect by including the first half-hour return of the row country into the regression. When the row country is an Asia-Pacific country and the column country is not, we use the first half-hour return of the column country that is immediately available before the last half-hour return of the row country. The Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The sample period spans from 04 October 2005 to 29 December 2017.

The last 16 columns of Table A.2 report our estimates of the $\beta_{i,j}$s. We do not observe significant predictability of the US market on the Canadian market, despite they are in the same timezone. Similarly, the first half-hour return of UK does not appear to significantly predict the last half-hour return of Ireland.

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

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

$$\Delta Adj.R_i^2 = Adj.R_{i,c}^2 - Adj.R_{i,l}^2, \tag{A.3}$$

where $Adj.R_{i,c}^2$ is the adjusted R^2s of Equation (A.2) and $Adj.R_{i,l}^2$ is the adjusted R^2s of local ITSM regressions using common sample period (reported in the second column of Table A.2). Table A.3 reports the $\Delta Adj.R^2$s. Consistent with the evidence shown in Table A.2, adding the US first half-hour return into the model yields an increase in the adjusted R^2 for all but one international countries, implying its explanatory power on the variance of the last half-hour return of international markets.

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

$$r_{i,t}^L = \alpha + \beta_{i,j} r_{j,t}^F + \beta_i r_{i,t}^F + \beta_c r_{i,t}^C + \epsilon_t, \tag{A.4}$$

TABLE A.3: Cross-country Predictability – $\Delta Adj.R^2(\%)$

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

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

where $r^C_{i,t}$ is the contemporaneous half-hour return of country i. This model is applicable only to certain combinations of i and j, in which r^F_j realises after r^F_i but before r^L_i, Table A.4 provides detailed information. The regression results are presented in Table A.5. Again, we are mainly interested in the slope coefficient of the first half-hour return from country j, $\beta_{i,j}$. As shown in the table, the cross-market predictability of the US first half-hour return remains significant in most of the countries even after controlling for local contemporaneous half-hour return, suggesting that the in-sample evidence of the US dominance is robust at intraday level.

A.3 Additional Tables

In this section, we repeat several analyses in the main text with data based on local currency or pre-winsorized data. Specifically, in Table A.6 and Table A.7 we re-examine the statistical and economic significance of ITSM on each market using data based on local currency, whereas in Table A.8 and Table A.9 we repeat the cross-sectional and time series sorting analysis using pre-winsorized data.

TABLE A.4: Cross-country Predictability – r^C

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

This table provides detailed information of the local contemporaneous half-hour return included in Equation (A.4). The first column indicates adding which country (country j) into the model might result in the necessity of controlling for local contemporaneous half-hour return. Note that while there is one hour time difference between Canberra (Australia) and Tokyo (Japan), their stock markets open at the same time due to different arrangement on trading hours. The second column specifies the local contemporaneous half-hour interval, it is the same time period as the first half hour of country-j's trading hours. The rest four columns report annualised summary statistics. The sample period spans from 04 October 2005 to 29 December 2017.

TABLE A.5: Cross-country Predictability – $\beta_{i,j}$ (r^C included)

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

This table reports our estimate of $\beta_{i,j}$ in Equation (A.4). In addition to controlling for the local ITSM effect, we also control for the contemporaneous half-hour return of the local market. The row names denote the local market (country i) and the column names denote the foreign market (country j). The Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively. The sample period spans from 04 October 2005 to 29 December 2017.

TABLE A.6: Individual ITSM in Local Currency

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

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

TABLE A.7: Profitability of ITSM in Local Currency

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

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

TABLE A.8: Cross-market Sorting Using Pre-winsorized Estimates

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

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

TABLE A.9: Time series Sorting Using Pre-winsorized Estimates

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

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

Appendix B

Appendix to Chapter 4

B.1 Additional Tables

TABLE B.1: Non-zero-cost Market Timing

	AVE (%)	SD (%)	Skewness	Kurtosis	Raw Sharpe	*Correlation$_a$*	*Correlation$_b$*
Intraday reversal	6.281***	5.721	0.078	3.047	1.098	0.026	-0.029
	(4.34)						
Always-long	-0.469	5.747	0.018	3.048	-0.082	-	-
	(-0.38)						
Buy-and-hold	5.179	18.948	0.004	3.035	0.273	-	-
	(1.34)						

This table compares noun-zero-cost market timing performance of intraday reversal strategy and two zero-cost benchmarks, *Always-long* and *Buy-and-hold*. In the intraday reversal strategy, we buy (sell) SPY at 09:30 a.m. if the overnight return is positive (negative) and clear all positions at 10:00 a.m.. We stay out of the market if the overnight return is 0. In the *Always-long* strategy, we long SPY in the first half hour every day. In the *Buy-and-hold* strategy, we enter to the market with a long position at the beginning of our sample and hold the position to the end. The table reports average return, standard deviation, skewness, kurtosis, Sharpe ratio and correlations between the intraday reversal and the benchmarks. Newey and West (1987) *t*-statistics are reported in parentheses. All figures are annualised. Sample spans from 03 Jan 2000 to 29 Dec 2017. *. **, and *** denote significant levels at 10%, 5% and 1% respectively.

TABLE B.2: Robustness of MV Portfolio Performance

Constraint Interval		μ (%)	σ (%)	Skewness	Kurtosis	Sharpe	Utility (%)
		Panel A: $\gamma = 2$					
$[-0.5, 1.5]$	Predictive regression	5.579***	6.180	0.178	3.168	0.903	5.197
		(3.31)					
	Historical average	1.629**	2.811	-0.033	3.066	0.579	1.549
		(-2.31)					
$[0, 1.0]$	Predictive regression	3.104***	3.928	0.203	3.205	0.790	2.950
		(3.03)					
	Historical average	1.077***	0.115	0.086	3.001	9.363	1.076
		(10.53)					
$[-1.0, 1.0]$	Predictive regression	5.808***	5.551	0.107	3.068	1.046	5.499
		(3.68)					
	Historical average	1.953	5.484	-0.035	3.074	0.356	1.652
		(1.44)					
$[-1.0, 2.0]$	Predictive regression	7.940***	8.706	0.157	3.136	0.912	7.182
		(3.30)					
	Historical average	1.953	5.484	-0.035	3.074	0.356	1.652
		(1.44)					
		Panel B: $\gamma = 5$					
$[0, 1.0]$	Predictive regression	3.137***	3.873	0.212	3.217	0.810	2.762
		(3.11)					
	Historical average	1.077***	0.115	0.086	3.001	9.363	1.076
		(10.53)					
$[-1.0, 1.0]$	Predictive regression	5.713***	5.481	0.112	3.072	1.042	4.961
		(3.68)					
	Historical average	1.257	4.332	-0.104	3.141	0.290	0.788
		(1.21)					
$[-1.0, 2.0]$	Predictive regression	7.266***	8.521	0.166	3.148	0.853	5.451
		(3.08)					
	Historical average	1.257	4.332	-0.104	3.141	0.290	0.788
		(1.21)					
		Panel C: $\gamma = 10$					
$[-0.5, 1.5]$	Predictive regression	4.937***	5.914	0.201	3.201	0.835	3.188
		(3.06)					
	Historical average	1.167**	2.169	-0.105	3.141	0.538	0.931
		(2.20)					
$[0, 1.0]$	Predictive regression	2.883***	3.795	0.223	3.236	0.760	2.163
		(2.91)					
	Historical average	1.077***	0.115	0.086	3.001	9.363	1.076
		(10.53)					
$[-1.0, 1.0]$	Predictive regression	5.318***	5.357	0.120	3.079	0.993	3.883
		(3.51)					
	Historical average	1.090**	2.297	-0.188	3.247	0.475	0.827
		(1.98)					
$[-1.0, 2.0]$	Predictive regression	6.935***	8.240	0.184	3.170	0.842	3.541
		(3.03)					
	Historical average	1.090**	2.297	-0.188	3.247	0.475	0.827
		(1.98)					

This table compares the performance of (1) a mean-variance portfolio that invests in SPY and risk free asset using estimated value of $r_{10:00}$ and $\sigma_{10:00}$, which are estimated from the predictive regression, and that of (2) a mean-variance portfolio that invests in same assets but estimates $r_{10:00}$ and $\sigma_{10:00}$ using historical average. To test the robustness of our main results, we constrain the weights on SPY between -0.5 to 1.5, 0 to 1, -1 to 1, and -1 to 2, respectively. In Panel A, B, and C, the relative risk aversion γ is set to 2, 5, and 10, respectively. Newey and West (1987) t-statistics are reported in parentheses and all figures are annualised. Sample spans from 03 Jan 2000 to 29 Dec 2017. *. **, and *** denote significant levels at 10%, 5% and 1% respectively.

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