Overnight-Intraday Reversal Everywhere [1]

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Overnight-Intraday Reversal Everywhere

Abstract

A strategy that buys securities with low past overnight returns and sells securities with high past overnight returns generates sizeable out-of-sample intraday returns and Sharpe ratios in all major asset classes. This strategy – labeled as overnight-intraday reversal – delivers an average return that is about two to five times larger than those generated by the conventional reversal strategy. Investor heterogeneity, sentiment, market uncertainty and market-wide illiquidity fail to explain this overnight-intraday reversal return. Our findings are consistent with an asset class-specific market maker liquidity provision mechanism, and we find that cross-sectional return dispersion can predict the strategy returns in every asset class. A global two-factor model, consisting of the market and overnight-intraday reversal factor, well explains the intraday return variation of diversified portfolios across asset classes.

Keywords: Overnight return, Intraday return, Short-term reversal, Liquidity provision

JEL Classification: G11, G12, G15, G20

1 Introduction

One central task of financial economics is to understand what drives asset prices *universally*. However, most asset pricing tests are restrained on the US stock market. This may lead to two challenges: empirically, several studies reveal that the results in the US do not hold in other markets (e.g., Goyal and Wahal, 2015; Jacobs and Müller, 2020). Extensively repeated usage of the same data set further exacerbates the concern of data mining, sparking a heated debate about the replication crisis in finance currently (e.g., Hou et al., 2020; Jensen et al., 2023). Theoretically, since economic models are generally not built purposely specific to the US stock market,[1] evidence on a single market tends to provide spurious validity for the theory. While a higher hurdle for empirical results suggested by Harvey et al. (2016) is a natural statistical method to mitigate the above concerns, tests across various markets provide another intuitive solution. Analysis across multiple markets naturally improves validity by mitigating data-mining problems, and more importantly, it can provide more inspiring guides to understanding the fundamental force driving asset prices. To this end, fast-growing literature recently aims to uncover common return patterns across diverse markets (e.g., Bekaert et al., 2009; Brogaard et al., 2020; Cakici and Zaremba, 2022).

While a large number of studies extend the US stock analysis to international stock markets (e.g., Ang et al., 2009; Boehmer et al., 2022), few include other asset classes, such as equity indices, interest rates, commodities, and currencies, simultaneously in a unified framework.[2] Further, although existing literature extensively examines the conventional close-to-close return patterns, to the best of our knowledge, however, none investigates the intraday and overnight (i.e., open-to-close, close-to-open) components on an *across-asset-classes* basis. Hence, a gap remains in the literature regarding dissecting the intraday and overnight returns across multi-asset classes.

In this paper, we make four contributions. Firstly, we find ubiquitous evidence of an overnight-intraday reversal effect across multi-asset classes, including futures markets of equity indices, interest rates, commodities, and currencies, which are all novel to the literature. In sharp contrast to the insignificant and mixed results of the conventional short-term reversal effect (close-to-close price return) in these markets, the overnight-intraday reversal strategy, denoted as *CO-OC*, that buys

[1] Some models can be built purposely to capture the unique market feature. For example, Liu et al. (2024) propose an equilibrium model to capture the pricing implication of large individual trading in the Chinese stock market.

[2] Asness et al. (2013) find consistent value and momentum return premia across eight diverse markets and asset classes.

securities with low past overnight returns and sells those with high past overnight returns generates highly significant and consistent intraday return premia across the asset classes. In specific, the conventional reversal strategies generate relatively small returns or returns with inconsistent signs across the asset classes. It barely produces a vulnerable return of 1 bp daily with an insignificant t-statistic of 1.50 in interest rate futures. For commodity futures, there is a clear signal of daily momentum effect (e.g., Baltas and Kosowski, 2011), instead of short-term reversal. On the contrary, the overnight-intraday reversal strategy persistently yields positive and significant return premia in every asset class under examination, and its return and Sharpe ratio are about two to five times higher in magnitude than those of the conventional reversal strategy. The results hold at both the daily and weekly frequencies. Moreover, the *CO-OC* portfolios constantly earn significant alphas under multiple canonical factors, including the global value and momentum factors of Asness et al. (2013).

We confirm the robustness of our core findings regarding the overnight-intraday reversal effect. We first employ the intraday trade data to address the concern about price synchronization and investability. The results reveal that the *CO-OC* strategy based on the volume-weighted price remains both statistically and economically significant across all asset classes, and it continues to outperform the traditional short-term reversal strategy. We also examine the performance of the *CO-OC* strategy under various construction methods, including alternative windows to calculate the volume-weighted averaged price, alternative gaps between the formation and holding period, and alternative portfolio weight based on the rank of formation period returns. The results are robust and comparable. Moreover, we document that a similar short-term overnight-intraday reversal effect exists across international stock markets (the United States, the United Kingdom, continental Europe, and Japan).

Although Lou et al. (2019) examine the overnight-intraday reversal in the US stock markets, our study based on the across-asset-classes approach has unique features and important marginal contributions to the literature. First, the consistent and pervasive overnight-intraday reversal effect in the multi-asset classes mitigates the concern of data mining. Second, the broader set of portfolios across diverse asset classes generates a much larger cross-sectional dispersion in average returns than those from US stocks only, providing a richer set of asset returns that any asset pricing model should seek to explain. More importantly, as finance research and practice are becoming increasingly global, our across-asset-classes approach provides unique evidence on several key questions about the pervasive intraday-overnight reversal phenomena. Specifically, how well the existing theory can explain the *CO-OC* effect? Is there a unified economic driver of the *CO-OC* effect across the diverse asset classes?

To this end, our second contribution is to examine whether existing explanations accounting for conventional reversal effects can capture the overnight-intraday reversal effects across asset classes. In particular, Lou et al. (2019) link the investor heterogeneity to the intraday-overnight reversal effect in the US stock market, which they call the tug-of-war effect. Extending the analysis of Lou et al. (2019), Akbas et al. (2022) recently find a more intense daily tug-of-war effect, that the frequency of negative daily return reversals, which proxy the investor heterogeneity between opposing investor clientele, positively predicts future cross-section US stock returns in the next month. An interesting question is whether the investor heterogeneity can explain the *CO-OC* reversal effects in other asset classes. If so, one would expect the presence of the daytime reversal effect of Akbas et al. (2022) in the futures markets. Different from the US stock evidence, we find that the daytime reversal strategies fail to generate significant returns in futures markets. It only delivers a vulnerable monthly return of -0.001%, -0.068%, 0.137%, and 0.008% with t-statistics lower than 0.60 in the four futures asset classes, respectively. Interestingly, we find the daytime reversal effect also generates mixed results in the global stock markets. Specifically, although the daytime reversal results in Japan and continental Europe are aligned with the US evidence, it fails to hold in the UK stock market, yielding an ignorable monthly return premium of only 0.162% (t-statistic: 0.831). These results indicate that the existing investor heterogeneity mechanism proposed to explain the tug-of-war effect in the US stock market can not explain the *CO-OC* strategy across diverse asset classes.

We then turn to alternative explanations for the conventional short-term reversal, that is, investor sentiment and liquidity provision. We use the sentiment index from Baker and Wurgler (2006) and find that overnight-intraday reversal returns in every futures asset class are statistically similar across periods of high and low sentiment. Moreover, the sentiment index also exhibits limited explanatory power in capturing the *CO-OC* effect in the global stock markets. Specifically, although the sentiment positively predicts the *CO-OC* return with significant t-statistics in univariate regressions in the US, Japan, and France, the sentiment coefficients, however, become negative or insignificant once controlling for the proposed asset-specific liquidity provision mechanism discussed soon. These results challenge existing findings that short-term reversal return performance is stronger following high sentiment levels (e.g., Da et al., 2013; Stambaugh et al., 2012).

To analyze the liquidity provision channel, we first consider the market-wide illiquidity. Since financial intermediaries' activities are more constrained when market volatility is high, liquidity provision is more limited under a more volatile market state. Therefore, we use the VIX index to proxy the market-wide illiquidity. We find VIX has a significant positive effect on the *CO-OC* strategies in equity index futures, which is consistent with the results of Nagel (2012) that the conventional reversal return is highly predictable with the VIX index. However, our further analysis reveals that VIX only plays a marginal role with positive but insignificant coefficients in explaining the *CO-OC* performance in the other futures markets. In the global stock markets, although VIX positively predicts the *CO-OC* strategies return, as will be discussed soon, it is dominated by the proposed asset-specific liquidity provision mechanism. Since the financial crisis period is characterized by high market illiquidity, we also compare the reversal strategy performances during the financial crisis and non-crisis sample, and again find the results are mixed and inclusive across the asset classes. In addition, macro-news announcement is also documented to affect the conventional short-term return reversals via the liquidity provision mechanism, because uncertainty regarding information releases of the macro-news announcement increases the compensation demanded for providing liquidity (e.g., So and Wang, 2014). However, we find that *CO-OC* performance in the futures markets shows little difference between announcement days and non-announcement days, in terms of FOMC, nonfarm payrolls, PCE, and PMI announcements.

While the pervasive *CO-OC* effects present a challenge to existing asset pricing theories that largely focus on US equities, our third contribution is to provide a unified explanation based on the asset class-specific illiquidity, which is novel to the literature. Based on the model of market maker liquidity provision (e.g., Nagel, 2012), the cross-sectional dispersion of overnight return in each market could serve as a proxy for the uncertainty faced by the market maker. A higher return dispersion indicates more limited liquidity provision. Hence, we expect that the return on *CO-OC* should be positively related to the asset-specific return dispersion to reflect the compensation for the liquidity provision. Empirically, we find that the coefficients on the return dispersion, in regressions to predict *CO-OC* returns, indeed consistently exhibit positive values with highly significant t-statistics of around 4.0 across the four futures markets. By comparison, the coefficients on the VIX and sentiment are pretty weak with insignificant t-statistics below 0.7 in the four asset classes, except for the positive one for VIX in the equity indices futures. The evidence on the global stock markets echos the futures market results, jointly validating the power of the return dispersion in capturing the *CO-OC* performance. Specifically, the coefficients on the return dispersion are constantly highly significant and positive across every stock market examined. On the other hand, the positive and significant coefficients on the VIX and sentiment index become negative (i.e., the US and Japan) or insignificant (i.e., France) once we include the asset-specific return dispersion in the regression. In short, contrasted sharply with the mixed and inclusive results of the existing explanations, the asset class-specific illiquidity mechanism stands out for its pervasive role in explaining the *CO-OC* return across every asset class. The consistent results indicate that the liquidity provision mechanism is the fundamental economic driving force for the *CO-OC* effect across asset classes. This highlights the importance of illiquidity in driving asset prices universally and provides supportive evidence for the theory model of Nagel (2012).

Last, the pervasive *CO-OC* effect inspires us to construct a global factor model to explain the intraday return variation of diversified portfolios across multi-asset classes. Our model construction is motivated by finance research and practice becoming increasingly global and the desire for a signal model to capture return variation across asset classes. While Asness et al. (2013) finds a global three-factor model of market, value, and momentum factor does a good job capturing conventional close-to-close returns variation, there is no such global model, to the best of our knowledge, to explain the intraday returns across asset classes. To this end, we construct a global two-factor model consisting of $\{MKT^*, CO\text{-}OC^*\}$, where MKT^* is the average intraday return of the equal-weighted market portfolios and $CO\text{-}OC^*$ is the average *CO-OC* portfolio returns in the four futures markets, including equity indices, interest rates, commodities, and currencies. We then conduct the standard time-series asset pricing tests to examine how well our global two-factor model can describe the returns across asset classes. The test portfolio includes the usual long-short portfolios of *CO-OC*, value, and momentum strategies across the four futures asset classes. In particular, we also follow Asness et al. (2013) to construct their global three-factor model in our sample as the benchmark model.[3]

[3]Since we are interested in explaining the intraday return, all the test portfolios and the pricing factors use the intraday return as the holding period return.

Interestingly, our proposed global two-factor model $\{MKT^*, CO\text{-}OC^*\}$, though parsimonious, does a better job than the global three-factor model of Asness et al. (2013) of capturing the intraday returns on diversified portfolios across asset classes. Specifically, the average absolute alpha under the global three-factor model is up to 1.27% per month. In comparison, its counterpart under our global two-factor model shrinks dramatically to only 0.29%. The associated average t-statistic under our model (0.55) is also much lower than that under the three-factor one (3.25). Moreover, the p-value from the Gibbons et al. (1989) (GRS) test is less than 10^{-10} for the global three-factor model of Asness et al. (2013), indicating a rejection of the joint hypothesis that the factor model can fully explain the test assets returns. On the contrary, the GRS p-value for our global two-factor model is 0.17, suggesting that our global two-factor model does a much better job than the three-factor one in explaining the $CO\text{-}OC$, value, and momentum portfolio returns across asset classes. We also use the long and short legs of the $CO\text{-}OC$, value, and momentum zero-investment portfolios as the test assets. The aggregate pricing error of our global two-factor model is again much lower than the three-factor model.

Literature

Our paper is related to three streams of the literature. First, it is related to research that explores short-term reversals in stocks. Jegadeesh and Titman (1995) show that the pattern of short-term negative serial autocorrelation for stock returns is consistent with the predictions of inventory-based microstructure models. Empirically, Conrad et al. (1994) provide supportive evidence that market-adjusted return reversals are stronger for stocks that experience a large increase in volume in a sample of NASDAQ stocks. Conrad et al. (1997) suggest that much of the reversal profitability is within the bid-ask bounce. More recently, Hameed and Mian (2015) document pervasive evidence of a monthly intra-industry reversal effect that is persistent over time and larger in magnitude compared to that of a conventional reversal strategy. Da et al. (2013) show that stock returns unexplained by "fundamentals", such as cash flow news, are more likely to reverse in the short-term than those linked to fundamental information.

The second stream of the literature that our paper is related to is on intraday versus overnight returns. Our work contributes to the fast-growing literature on intraday and overnight returns. Oldfield and Rogalski (1980) is one of the earliest studies that develop a general stochastic process for stock returns over trading and non-trading periods. Lockwood and Linn (1990) find that the stock market return volatility displays a U-shape during the trading period, and is significantly greater for intraday than overnight periods. Hong and Wang (2000) solve an equilibrium model with periodic market closures and show greater trading activity around the open and close. Recent work by Kelly and Clark (2011) suggests that aggregate stock returns on average are higher overnight than intraday.

By decomposing the daily return into overnight and intraday returns, Lou et al. (2019) show that all of the abnormal returns of a momentum strategy occur during the non-trading period, while other anomalies' returns are accumulated during the trading period. In monthly frequency, they show that there are overnight-intraday and intraday-overnight reversals with monthly returns. Our approach is different from theirs in several aspects. Firstly, using daily and weekly frequency enhances our understanding of the short-term reversal effect. Secondly, we provide similar short-term reversal patterns comprehensively across several different asset classes and international stock markets. For the cross-section return predictability, extending the analysis in Lou et al. (2019), Akbas et al. (2022) further show that the frequency of daily return reversals positively predicts future cross-section stock returns. Hendershott et al. (2020) find that stock returns are positively related to beta overnight, but negatively related to beta during the day. Bogousslavsky (2021) documents that the stock anomalies display positive returns throughout the day but perform poorly at the end of the day, due to the greater margin requirements and lending fees associated with the position held overnight.

The third stream of the literature that our research is related to is on multi-asset class return predictability in derivatives and ETFs. Koijen et al. (2018) document global "carry" returns, which predict returns both in the cross-section and the time series for various asset classes, including global equities, global bonds, commodities, US Treasuries, credit, and options. Moskowitz et al. (2012) provide global evidence of time series momentum related to an asset's own past returns. Time series momentum strategies significantly differ from cross-sectional momentum strategies. Asness et al. (2013) find consistent value and momentum return premia across eight diverse markets and asset classes, and present a common factor structure among their returns.

Sheikh and Ronn (1994) study the intraday return behavior of option returns, and find that it is consistent with a model of strategic trading by informed and discretionary liquidity traders. More recently, Jones and Shemesh (2018) report that option returns are significantly lower over nontrading periods, due to highly persistent option mispricing driven by the incorrect treatment of stock return variance during periods of market closure. Muravyev and Ni (2020) find that option returns in equity and index options earn positive returns intraday but negative returns overnight, which is consistent with the fact that stock volatility is substantially greater intraday than overnight. For ETFs, Gao et al. (2018) document an intraday momentum effect that the first half-hour return on the market near open positively predicts the last half-hour return before the close. Baltussen et al. (2021) find a stronger momentum effect in the futures market that the last half-hour return before the market close is positively predicted by the return during the rest of the day. Based on a clientele perspective, Lou et al. (2022) decompose the equity market return into overnight and intraday components and show that the overnight returns negatively predict subsequent close-to-close returns, while intraday market returns positively forecast following overnight returns.

The remainder of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 reports the empirical results. Section 4 discusses the economic mechanisms that can explain the empirical findings. In Section 5, we complement our core findings with a range of robustness tests. Section 6 proposes a global two-factor model. We provide our concluding remarks in Section 7. A separate Online Appendix contains additional empirical results.

2 Data and methodology

This section describes the data on futures contracts in different asset classes employed in our empirical analysis. We also summarize the data on international stock markets used as robustness checks. Then, we define a short-term reversal strategy that uses overnight (that is close-to-open) returns as formation period returns and the following intraday (that is open-to-close) returns as trading period returns, and compare it to a variety of alternative short-term reversal strategies based on different combinations of open and close prices. We provide a statistical and economic evaluation of these strategies in the next section.

2.1 Data

Futures Contracts. From TickData, we obtain daily open and close prices on 32 futures contracts traded on the Chicago Mercantile Exchange. The sample ranges from January 2004 to December 2018 and consists of futures written on 5 equity indices (DJIA, NASDAQ, NIKKEI

225, S&P400 and S&P500), 9 interest rates (30-day Federal Funds, Eurodollar CME, 1-month Municipal Bonds, 5-year Interest Rate Swap, US 2-year T-Note, US 5-year T-Note, US 10-year T-Note, US 30-year T-Bond, and Ultra T-Bond), 10 commodities (Corn, Corn E-Mini, Ethanol CBOT, Live Cattle, Oats, Pork Bellies, Rough Rice, Soybean Meal, Soybeans, Wheat CBOT) and 8 currencies (Australian Dollar, British Pound, Canadian Dollar, Euro, Japanese Yen, Mexican Peso, New Zealand Dollar, and Swiss Franc vis-a-vis the US dollar). For each contract, we always select the most liquid contract, as in De Roon. (2000) and Moskowitz et al. (2012). The most liquid contract is generally the nearest-to-delivery (front) contract. When the second-to-delivery (first-back) contract becomes the most liquid one, a rollover takes place.

International Stocks. We collect daily open and close prices ranging from January 1993 to December 2018 for the following stock markets: the US, the UK, Japan, and France. The universe of US stock consists of all common equities in CRSP with share codes 10 and 11. We only select firms for which the open price is available. To mitigate microstructure issues, we exclude stocks with a share price below \$5 as well as stocks whose market capitalization falls within the bottom 5%. For the remaining markets, we source daily open and close prices from Datastream and employ the same filtering rules applied to US stocks.[4]

2.2 Methodology

We construct the short-term reversal strategies as in Lehmann (1990), Jegadeesh and Titman (1995) and Nagel (2012). Consider a zero-investment trading strategy with portfolio weight for asset i at time $t-1$ given by

$$w_{i,t-1} = -\frac{1}{N}(r_{i,t-1} - \overline{r}_{t-1}), \tag{1}$$

where $r_{i,t-1}$ is the discrete return on the asset i at time $t-1$ and $\overline{r}_{t-1} = N^{-1}\sum_{i=1}^{N} r_{i,t-1}$ is the equally-weighted average return on all N assets available at time $t-1$. This strategy is by construction a contrarian strategy as it sells past winners and buys past losers and is a zero-investment strategy as $\sum_{i=1}^{N} w_{i,t-1} = 0$. With a 50% margin on long and short positions as in Lehmann (1990) and Nagel (2012), this strategy requires \$1 dollar of capital and its payoff is given

[4]In the Online Appendix, we also report the results of excluding stocks within the smallest 50% market capitalization. The results are shown to be robust to this exclusion.

by

$$r_{p,t} = \frac{\sum_{i=1}^{N} w_{i,t-1} r_{i,t}}{d_{t-1}/2}, \tag{2}$$

where $\sum_{i=1}^{N} w_{i,t-1} r_{i,t}$ denotes the accounting profits at time t and $d_{t-1} = \sum_{i=1}^{N} |w_{i,t-1}|$ is the total amount of dollars invested in both long and short positions at time $t-1$.

The traditional short-term reversal strategy uses the underlying assets' close-to-close daily returns on day $t-1$ as long/short signals. The portfolio return is then realized on the subsequent business day using the underlying assets' close-to-close daily returns on day t. The short-term reversal strategy studied in this paper differs from the traditional reversal strategy in that it uses overnight returns as signals and then takes a long or short position in the following intraday returns. To clarify our notation, let $P^{o}_{i,t}$ and $P^{c}_{i,t}$ denote the open and close prices for asset i on day t, respectively. The close-to-close daily return on day t is defined as

$$r^{cc}_{i,t} = \frac{P^{c}_{i,t}}{P^{c}_{i,t-1}} - 1. \tag{3}$$

The close-to-close daily return is decomposed into close-to-open (or overnight) daily return

$$r^{co}_{i,t-1} = \frac{P^{o}_{i,t}}{P^{c}_{i,t-1}} - 1, \tag{4}$$

and open-to-close (or intraday) daily return

$$r^{oc}_{i,t} = \frac{P^{c}_{i,t}}{P^{o}_{i,t}} - 1, \tag{5}$$

such that $r^{cc}_{i,t} \approx r^{co}_{i,t-1} + r^{oc}_{i,t}$. The traditional short-term reversal strategy uses $r^{cc}_{i,t-1}$ for the portfolio weights in Equation (1) and $r^{cc}_{i,t}$ for the portfolio return in Equation (2). Our short-term reversal strategy, instead, uses $r^{co}_{i,t-1}$ for the portfolio weights in Equation (1) and $r^{oc}_{i,t}$ for the portfolio return in Equation (2). We refer to the former as *CC-CC* strategy and the latter as *CO-OC* strategy (i.e., the first two letters define the formation period return, whereas the last two letters indicate the trading period return). We also consider two alternative specifications for robustness: a strategy labeled as *OC-OC* that uses $r^{oc}_{i,t-1}$ for the portfolio weights and $r^{oc}_{i,t}$ for the portfolio return, and a strategy identified as *OO-OO* that employs $r^{oo}_{i,t-1}$ for the portfolio weights and $r^{oo}_{i,t}$ for the portfolio return with $r^{oo}_{i,t} = (P^{o}_{i,t}/P^{o}_{i,t-1}) - 1$ indicating the open-to-open daily return on day t. In sum, the empirical analysis will make use of four different short-term reversal strategies characterized by different formation and trading period returns.[5] We summarize these strategies in Table 1.

[5]We do not discuss the following two strategies in the main results: (i) a purely overnight reversal strategy (*CO-*

3 Empirical results

This section presents the empirical evidence on four different short-term reversal strategies implemented in four different asset classes, including equity indices, interest rates, commodities, and currencies.

3.1 Baseline results

Table 2 reports the summary statistics of the short-term reversal strategies.[6] Panel A shows the empirical evidence for equity index futures. Recall that a short-term reversal strategy takes advantage of the tendency of assets with strong losses and assets with strong gains to reverse in a short interval, typically up to one day or one week. An investor would typically buy past losers and sell past winners using close-to-close returns on day $t-1$ as signals and then realize the profit (loss) on the following day using close-to-close returns on day t. This traditional strategy which we refer to as *CC-CC* produces a statistically significant average return of 0.056% per day (with a t-statistic of 3.862). A related version of this strategy – labeled as *OO-OO* – employs open-to-open returns instead of close-to-close returns and displays a similar but more pronounced pattern. The average return on *OO-OO* is 0.164% per day (with a t-statistic of 7.685) and the annualized Sharpe ratio is 2.568, more than doubling the Sharpe ratio of 1.041 granted by the *CC-CC* strategy.

Both variants of the short-term reversal strategy discussed above implicitly aggregate overnight and intraday information. Therefore, we decompose the total (or close-to-close) daily return into an overnight (or close-to-open) and intraday (or open-to-close) return and study whether short-term reversal strategies are different when using these return components. To this end, we first examine a purely intraday reversal strategy that uses intraday (or open-to-close) returns on day $t-1$ as trading signals and the following intraday returns (i.e., open-to-close returns on day t) for the realization of the trading gain. This strategy, defined as *OC-OC*, displays a weak positive return of 0.020% per day (with a t-statistic of 1.465).

CO) that uses close-to-open returns on day $t-1$ as trading signals and close-to-open returns on day t as trading period returns, and (ii) an intraday-overnight reversal strategy (*OC-CO*) that uses open-to-close returns on day $t-1$ as trading signals and close-to-open returns on day t as trading period returns. These strategies would require trading overnight when liquidity is low and transaction costs are fairly prohibitive. Table A.6 in the Online Appendix reports the results for the above strategies.

[6]The strategies' returns are winsorized at 1% and 99% level. The results are robust and very similar without winsorization.

Last, we examine a simple overnight-intraday reversal strategy that uses information accumulated overnight as trading signals (i.e., buying overnight losers and selling overnight winners) and the following intraday returns for the accounting profit. The former set of returns is measured at the beginning of day t using close-to-open returns whereas the latter set of returns is observed at the end of day t using open-to-close returns. This strategy, identified as *CO-OC*, earns the greatest average return of 0.238% per day (with a t-statistic of 15.735). Among these strategies, *CO-OC* produces the lowest volatility of 0.685%. This translates into the largest annualized Sharpe ratio up to 5.516, more than doubling the second highest Sharpe ratio of 2.568 generated by the *OO-OO* strategy.[7]

It is worth noting that all short-term reversal strategies display positive skewness thus implying that downside or crash risk is not a plausible explanation for the strategy's high Sharpe ratio. In addition, the *CO-OC* reversal strategy is fairly uncorrelated with the traditional short-term reversal strategies as its sample correlation remains below 10%.

Turning to the results for other asset classes, the empirical evidence reveals that the traditional *CC-CC* reversal strategy displays negative returns in commodities and insignificant returns in interest rates. The related *OO-OO* strategy generates negative returns in commodities and weak returns in currencies. The purely intraday return strategy *OC-OC* produces negligible positive returns in interest rate futures (0.006% per day with a Sharpe ratio of 0.165) and currency futures (0.005% per day with a Sharpe ratio of 0.116). On the contrary, it generates significant negative returns in commodity futures (-0.182% per day with a Sharpe ratio of -2.039), suggesting the presence of a fairly strong intraday momentum effect.

While results for traditional short-term reversal strategies and intraday momentum patterns are mixed, the overnight-intraday strategy continues to deliver economically and statistically significant returns across all these asset classes. For instance, the return on this *CO-OC* strategy is 0.049% per day with a Sharpe ratio of 1.896 in interest rates, 0.284% per day with a Sharpe ratio of 3.541 in commodities, and 0.052% per day with a Sharpe ratio of 1.624 in currencies, which generally more than doubles the performance compared to other conventional reversal strategies in each asset class.

Figure 1 further shows the average daily return on the long- and short-leg of the *CO-OC*

[7] Table A.1 in the Online Appendix examines the reversal strategies under alternative constructions, where the portfolio weight is based on the rank of formation period returns. The results are similar and robust.

strategy. The long-leg persistently earns positive returns of 0.147%, 0.040%, 0.127%, and 0.032% per day, while the short-leg constantly produces negative returns of -0.093%, -0.010%, -0.158%, and -0.020% per day in the equity index, interest rate, commodity, and currency futures, respectively. On average across the four asset classes, the return on the long- and short-leg is 0.087% and -0.070% per day, indicating both legs contribute to the *CO-OC* strategy performance.

Figure 2 reports the average daily return of the *CO-OC* strategy in different calendar years, months, and days of the week. Panel A shows the results for the equity index futures. *CO-OC* constantly earns positive average returns every year in our sample, which is consistent with the positive skewness reported previously in Table 2. At the monthly level, the average return also shows a positive and flat pattern, indicating that the profitability is evenly distributed over the months. Regarding the day of the week, the average return on *CO-OC* stays positive and exhibits a slight "U" shape pattern from Monday to Friday. The results are similar and robust in other asset classes. In short, *CO-OC* earns pervasively positive returns during our sample, and its performance is not driven by outliers or seasonality.

3.2 Weekly strategy

We now examine the performance of the weekly strategies. At weekly frequency, the intraday period is now from Monday open to Friday close, and the overnight period is from Friday close to next Monday market open.

Table 3 reports the summary statistics of weekly strategies. Interestingly, the conventional reversal strategies at weekly frequency either generate insignificant returns or returns with inconsistent signs compared with the daily strategies. For example, the *CC-CC* strategy in equity indices, commodities, and currencies, the *OO-OO* strategy in commodities, and the *OC-OC* strategy in equity indices, commodities, and currencies only produce marginal positive returns with t-statistics below 2. Besides, while the daily strategy of *CC-CC* and *OC-OC* in commodity futures produces significantly negative returns in Table 2, the return on their weekly counterparts moves into the positive territory with an insignificant return of 0.178% and 0.066% per week with a fragile t-statistic of 1.198 and 0.447, respectively. These findings suggest improving market liquidity conditions over time.

In contrast to the mixed results for conventional reversal strategies, the profitability of the overnight-intraday reversal strategy *CO-OC* at weekly frequency remains economically and statistically significant across all asset classes examined in this paper. Although the Sharpe ratio shrinks by more than half compared with its daily counterpart, the weekly *CO-OC* strategy continues to substantially outperform traditional reversal strategies by constantly earning positive and significant returns. Specifically, it yields a sizable return of 0.293%, 0.121%, 0.421%, and 0.117% per week with a t-statistic of 4.116, 3.388, 3.710, and 2.633 in equity index, interest rate, commodity and currency futures, respectively.

3.3 Risk-adjusted performance

We examine the risk-adjusted performance of the overnight-intraday reversal *CO-OC* strategy. To this end, we collect a number of asset class-specific risk factors from AQR's website and canonical risk factors for the US stock market from Kenneth French's website. Table 4 presents time-series regression estimates for the factor regressions.

The first specification employs the asset class-specific value and momentum factors of Asness et al. (2013):

$$R_t^P = \alpha^P + \beta_1^P VAL_t + \beta_2^P MOM_t + \varepsilon_t^P, \tag{6}$$

where the dependent variable is the monthly return on the overnight-intraday reversal strategy (*CO-OC*), which is the cumulative return compounded from the daily strategy. VAL_t and MOM_t are the Asness et al. (2013) asset class-specific value and momentum factor, respectively. The results show that intercepts are both statistically and economically significant. For example, the average excess return unexplained by the risk factors is about 5.15%, 1.00%, 5.97%, and 1.10% per month with a large t-statistic of 7.63, 6.29, 10.28, and 6.16 for the futures written on equity indices, interest rates, commodities, and currencies, respectively. Meanwhile, the goodness of fit is rather poor as the adjusted R^2 turns out to be 4.25% and 3.65% for equity index and interest rate futures and below 1% for commodity and currency futures.

In the second specification, we add the Fama and French (2015) 5-factors plus the conventional momentum factor and short-term reversal factor:

$$\begin{aligned} R_t^P = \alpha^P &+ \beta_1^P VAL_t + \beta_2^P MOM_t + \beta_3^P MKT_{FF,t} + \beta_4^P SMB_{FF,t} + \beta_5^P HML_{FF,t} \\ &+ \beta_6^P RMW_{FF,t} + \beta_7^P CMA_{FF,t} + \beta_8^P MOM_{FF,t} + \beta_9 STR_{FF,t} + \varepsilon_t^P, \end{aligned} \tag{7}$$

where $MKT_{FF,t}$, $SMB_{FF,t}$, $HML_{FF,t}$, $RMW_{FF,t}$, and $CMA_{FF,t}$ is the market, size, value, profitability, and investment factor in Fama and French (2015) 5-factor model, respectively, and $MOM_{FF,t}$ is the conventional momentum factor of Carhart (1997) which goes long diversified portfolios of past winner stocks and short diversified portfolios of past loser stocks, and $STR_{FF,t}$ is the traditional short-term reversal factor based on daily close-to-close returns.

Adding additional factors as explanatory variables improves the adjusted R^2s. However, the αs remain both statistically and economically significant. For instance, the average excess return unexplained by the risk factors is 5.33%, 0.99%, 5.84%, and 1.18% per month with highly significant t-statistics in the four asset classes. In short, the largely unexplained abnormal returns suggest that our overnight-intraday reversal returns cannot be rationalized by a risk-based explanation related to canonical factors.

4 Explanation

The evidence reported earlier suggests that the overnight-intraday reversal strategy displays excess returns that are both economically and statistically significant, and it is markedly different from the conventional short-term reversal strategy studied in the literature. In this section, we inspect possible mechanisms that could drive our results. While the mechanisms that account for the recently documented daily tug-of-war reversal effect (i.e., investor heterogeneity) and the conventional reversal effect (i.e., investor sentiment, macro-news announcement, and market-wide illiquidity) fail to explain our results, we provide a unified explanation based on the asset class-specific liquidity provision for the *CO-OC* performance on all the asset classes.

4.1 Investor heterogeneity

Lou et al. (2019) link the investor heterogeneity to the offsetting cross-period reversal effect for the overnight and intraday returns in the stock market, which they called the tug-of-war effect. Extending the analysis of Lou et al. (2019), Akbas et al. (2022) find a more intense daily tug-of-war effect between opposing investor clienteles. In specific, they find that the frequency of negative daily return reversals positively predicts future cross-section US stock returns in the next month. An interesting question is that does the investor heterogeneity mechanism in the stock market also helps to explain the *CO-OC* reversal effects in futures. If so, one would expect to see the negative daytime reversal effect of Akbas et al. (2022) in futures.

To this end, we examine the daytime reversal effects in futures markets. Specifically, we first calculate the frequency of negative daytime reversal ($NR_{i,t}$), defined as the frequency of a positive overnight return followed by a negative trading day within a month, for each futures monthly. The abnormal frequency of negative daytime reversal ($AB\_NR_{i,t}$) is $NR_{i,t}$ scaled by the average $NR_{i,t}$ over the prior 12 months. We then build a negative daytime reversal strategy based on $AB\_NR_{i,t}$ according to Eq (1) within each futures class, where the formation period return in Eq (1) is placed by $AB\_NR_{i,t}$ to determine the portfolio weight and the holding period return is the return in the next month. The abnormal frequency of positive daytime reversal ($AB\_PR_{i,t}$) and the resultant positive daytime reversal strategy are constructed similarly.

Table 5 reports the results. Different from the stock market evidence that the frequency of negative daytime reversals positively predicts future cross-section returns, the negative daytime reversal strategies fail to generate significant returns in futures, delivering a vulnerable monthly return of only -0.001%, -0.068%, 0.137%, and 0.008% with annualized Sharpe ratio below 0.20 in the four asset classes, respectively. The positive daytime reversal strategies in Panel B also fail to produce significant returns in futures markets, and this is similar to its limited predictability in the stock markets shown in Akbas et al. (2022).

In short, we find that different from the US stock market evidence, the daytime reversal effect, or the more intense daily tug-of-war effect, does not exist in futures markets. It is interesting to note that, as will be shown soon, the daytime reversal effect also fails to hold in the global stock market (i.e., the UK),[8] while the *CO-OC* strategy and the asset class-specific illiquidity mechanism proposed later in Section 4.3.3 persistently hold in all the eight asset classes in futures and major stock markets. The results indicate that investor heterogeneity can not explain the *CO-OC* strategy across asset classes.

4.2 Investor sentiment

Investor sentiment plays a non-trivial role in driving short-term reversals. Da et al. (2013), for example, find that the short-term reversal return is attributable to investor sentiment on the short side. We use the investor sentiment measure from Baker and Wurgler (2006).

Table 6 reports the strategy performances under various levels of investor sentiment. Day t

[8] The results are shown in Table A.12 in the Online Appendix.

is defined as a high (low) sentiment period if the sentiment level on day $t-1$ is above (below) the sample median. Overall, the effect of investor sentiment on the reversal strategies is mixed and insignificant across strategies and markets. Specifically, all return differences between the high- and low-sentiment period are insignificant with t-statistics below 2.00, except for *CC-CC* in commodity futures, whose return difference is -0.106% per day with a t-statistic of -2.16. Hence, investor sentiment fails to explain the reversal strategies' performance in different asset classes.

It is interesting to note the above result in futures contrasts the finding of Stambaugh et al. (2012) in the stock market that return anomalies' performance is stronger following high sentiment levels. In Table A.11 in the Online Appendix, we examine the effects of the sentiment index on *CO-OC* strategies in international stock markets. The resultant results are consistent with Stambaugh et al. (2012) in the sense that the sentiment index indeed positively predicts the return of the *CO-OC* strategy, but the sentiment mechanism is dominated by the asset-specific liquidity provision mechanism discussed soon in the Section 4.3.3. and Section 5.2.2

4.3 Liquidity provision

The last possible explanation for the overnight-intraday reversal strategy that we consider is liquidity provision, which is shown to affect the conventional reversal strategies (e.g., Nagel, 2012; So and Wang, 2014). We explore this mechanism at three levels by examining the effects of the market-wide illiquidity, macro-news announcement, and asset class-specific illiquidity, respectively.

4.3.1 Market-wide illiquidity

Consider the market-wide illiquidity first. Though commonly used as a market-wide uncertainty metric, the VIX index can also be regarded as a market-wide illiquidity proxy. Specifically, it is well known that VIX can predict the risk-taking behaviors of financial intermediaries (e.g., Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010). Since the financial intermediaries' activities are more constrained when market volatility is high, liquidity provision is also more limited under a more volatile market state. Hence, the VIX index can be regarded as a market-wide illiquidity proxy, and the higher the VIX level, the greater the liquidity level. Nagel (2012) finds that the VIX index highly positively predicts the conventional (close-to-close) reversal return, suggesting that market-wide illiquidity explains the conventional reversal strategy. Here, we examine whether it can also account for the *CO-OC* return.

Panel A of Table 7 reports the strategy performances in different market-wide illiquidity states measured by VIX index. Day t is defined as a high (low) VIX period if the VIX on day $t-1$ is above (below) the sample median. The results show that VIX has a significant effect on all four reversal strategies in equity index futures, but it plays a limited role in other three asset classes. For example, the *CO-OC* strategy in equity index futures earns a daily average return of 0.354% following high VIX, while it produces a much smaller daily return of 0.121% following low VIX. The resultant return difference is economically and statistically significant at 0.232% per day with a sizable t-statistic of 9.80. This is consistent with the finding of Nagel (2012) that the return of the reversal strategy is highly predictable with the VIX index. The results are similar for other three reversal strategies in equity index futures. The associated return differences between high- and low-VIX states remain significant at 0.116%, 0.240%, and 0.074% per day. In contrast, although the return differences in other three asset classes generally remain positive, except for the negative one of -0.016% for *OO-OO* in interest rates, they are all insignificant with small t-statistics below 1.50, indicating that VIX has a limited role in affecting the strategy performances in interest rate, commodity, and currency futures.

It is well known that the financial crisis period is characterized by pretty high market illiquidity. Hence, Panel B further compares the strategy performances during the financial crisis and non-crisis sample. Echoing Panel A, Panel B shows that all types of reversal strategies in the equity index futures earn substantially greater returns during the crisis, while the results are weak and mixed in other three asset classes. Specifically, the return difference in equity index futures between the crisis and non-crisis period is significant at 0.186%, 0.547%, 0.174%, and 0.471% per day with a t-statistic of 3.59, 5.61, 2.74, and 10.11 for the four reversal strategies. On the other hand, the return differences in the other three markets are insignificant with weak t-statistics below 1.40, except for *CO-OC* in currency futures, which earns a higher return that is 0.063% per day greater (with a t-statistic of 1.91) in the crisis period than in the non-crisis period.

In short, the reversal strategies in equity index futures earns substantially greater return during the high VIX and financial crisis period, but the results are generally mixed and inconclusive for interest rate, commodity, and currency futures. The result is to some extent expected as the two proxies mainly reflect the equity market state, and it concludes that the market-wide illiquidity in general fails to explain the *CO-OC* performance across various asset classes.

4.3.2 Macro-news announcement

Macro-news announcement is also documented to affect the conventional short-term return reversals via the liquidity provision mechanism. This is because uncertainty regarding information releases of the macro-news announcement increases the compensation demanded for providing liquidity. So and Wang (2014), for instance, find a six-fold increase in short-term return reversals during earnings announcements relative to non-announcement periods for individual stocks.

In our analysis of different asset classes, we examine information releases such as the FOMC, nonfarm payrolls, PCE, and PMI announcements. Table 8 reports the strategies' performances under various macro-news announcements. The results show that the strategies' performance shows little difference between announcement days and non-announcement days. For example, the return difference for the four reversal strategies between the announcement and non-announcement days in the currency futures is weak at -0.015%, -0.050%, -0.016%, and -0.012% per day with insignificant t-statistics below 2.00. The results are similar in other markets. Table A.9 in the Online Appendix reports the detailed results for FOMC and other announcements separately, and the results are similar. In short, macro-news announcements fail to affect the reversal strategy performances.

4.3.3 Asset class-specific illiquidity

Last, we examine the asset class-specific liquidity provision mechanism. Based on the simple model in Nagel (2012), the profit of a market maker's liquidity provision converges to a linear function of the volatility of the net demand absorbed by the market maker. Therefore, order imbalance volatility is positively related to the reversal strategy returns. However, the order imbalance during the overnight period is unobservable and hard to measure precisely for these markets. Alternatively, we use the cross-sectional dispersion of the overnight return as a proxy for order imbalance volatility. We expect that the return on *CO-OC* should be related to the asset class-specific liquidity provision during the overnight period, which is measured by overnight return dispersion.

Figure 3 reports the performance of *CO-OC* under high and low overnight return dispersion periods. Day t is defined as the high (low) dispersion period if the return dispersion measure on day $t-1$, which is the cross-sectional volatility of the overnight return $r^{co}_{i,t-1}$, is higher (lower) than the sample median. Consistent with our hypothesis, in all asset classes we considered, the

CO-OC reversal return is remarkably higher return following the high return dispersion period. For example, *CO-OC* in equity index futures earns 0.377% per day following high return dispersion, versus a much lower return of 0.097% following low return dispersion. As reported in Table A.7 in the Online Appendix, this return difference is highly significant at 0.279% per day with a t-statistic of 11.97. The results are similar and significant for other asset classes, as the return difference is positive at 0.072%, 0.260%, and 0.050% per day with a t-statistic of 5.32, 6.12, and 3.08 for interest rate, commodity, and currency futures markets, respectively.

We further examine the relationship between the *CO-OC* strategy and return dispersion using regressions. The dependent variable is the overnight-intraday reversal strategy return on day t ($CO\text{-}OC_t$). The independent variables include the lagged return dispersion measure, $Dispersion_{t-1}$, defined as the cross-sectional volatility of the overnight return $r^{co}_{i,t-1}$, the lagged VIX, and the lagged overnight-intraday strategy return. We also include the lagged Baker and Wurgler (2006) sentiment index in the previous month ($Sentiment_{m-1}$), where m is the month that day t belongs.

Table 9 reports the results of the regressions. Firstly, we separately examine the role of the return dispersion, VIX index, and sentiment in affecting the reversal returns using univariate regressions. The coefficients on the return dispersion are positive and statistically significant across the four futures markets, which confirms the findings in Figure 3 that *CO-OC* earns substantially greater return following high return dispersion. By comparison, the coefficients on the VIX index and sentiment are much weaker. Specifically, although the VIX coefficients in univariate regressions are positive across the four markets, they are all statistically insignificant except for that in equity index futures. The investor sentiment index coefficients, on the other hand, are generally negative and insignificant across the four markets. The above results on the coefficients on VIX index and sentiment are consistent with the inconclusive findings shown earlier in Table 7 and Table 6. Secondly, controlling for all variables simultaneously, we find that the coefficients on return dispersion remain highly positively significant across the four asset classes, while the coefficients on VIX and sentiment are basically weak and insignificant. In terms of goodness of fit, the resultant adjusted R^2 is very close to that of using return dispersion alone, indicating that the VIX and investor sentiment provide little explanatory power beyond overnight return dispersion in capturing the *CO-OC* return.

In sum, while the market-wide illiquidity shows limited ability in explaining the *CO-OC* returns, the asset class-specific overnight return dispersion positively and consistently predicts the *CO-OC* strategy performance across the four asset classes of futures.[9] Further, as will be discussed soon, in stark contrast to the inconclusive results of other mechanisms, the overnight return dispersion again persistently drives the strategy performance in four major international stock markets.[10] Thus, the overnight return dispersion provides a unified explanation for the *CO-OC* effect across eight diverse markets and asset classes, which is in favour of the asset class-specific liquidity provision mechanism.

5 Robustness check

Next, we complement our core analysis with a range of robustness exercises. We first use alternative open and close prices. Secondly, we extend the main findings to international stock markets and confirm the same pattern in those markets. Lastly, we show our results are robust in different sample periods.

5.1 Alternative open and close prices: Volume-weighted average price

We first consider concerns related to price synchronization and investability. In some days, the open and close prices in the TickData daily data are not synchronized across different futures contracts. This happens as TickData uses the first traded price as the open price and the last traded price as the close price. As a result, one might argue that the overnight-intraday reversal strategy is difficult to implement in practice and the profitability recorded above is mechanically driven by a lead-lag effect in prices. In addition to the lack of trading synchronization, it is natural to ask whether there is sufficient trading volume around the market open and close. This is critical to understanding whether our strategy can be implemented at scale in the real world.

To address these two concerns, we employ intraday trades data from TickData and construct volume-weighted open and close prices using a given trading synchronization rule. Specifically, we define a time window of 30 minutes for the open and the close price and select only those futures contracts with prices falling within these narrow windows. Then, we weigh all traded prices by

[9] A potential concern is that the greater return dispersion may mechanically imply stronger *CO-OC* performances since they are both based on overnight returns. To address this concern, Table A.8 in the Online Appendix reports the regressions for the *CO-OC* strategy under alternative constructions, where the portfolio weight is based on the rank of overnight returns. The results are similar and robust.

[10] The detailed results are shown in Table A.11 in the Online Appendix.

volume within the fixed interval and examine the reversal strategies based on the resultant volume-weighted averaged prices (VWAP). Table A.2 in the Appendix reports the specific windows for each assets to calculate the VWAP.

Table 10 reports the performances for the strategies based on volume-weighted prices. Compared with the baseline results, the average excess return for the *CO-OC* strategy remains statistically and economically significant across all asset classes. Moreover, our *CO-OC* reversal strategy continues to outperform the traditional close-to-close short-term reversal strategy. For example, *CO-OC* earns a daily average return of 0.079%, 0.017%, 0.092%, and 0.027% with a significant t-statistic of 4.376, 2.033, 3.780 and 2.697 across the four asset classes. On the other hand, the conventional *CC-CC* strategy produces weak returns with insignificant t-statistics lower than 2 in equity index and currency futures. Besides, *OO-OO* and *OC-OC* generally yield insignificant or negative returns across the four markets.

In Table A.3, we construct the volume-weighted price using alternative windows of 15, 45, and 60 minutes. The resultant strategy performances are similar: our *CO-OC* strategy remains statistically and economically significant across all markets under alternative windows, while the results for conventional reversal strategies are weaker and mixed.

We also skip a gap window between the formation and holding period.[11] Table A.5 in the Online Appendix reports the resultant strategy performances for the gap window of 3, 5, and 15 minutes. *CO-OC* again generates positive returns across various gap windows.

5.2 International stock markets

In this subsection, we first examine the strategy performance in the international stock markets and then verify the asset class-specific illiquidity as a unified force driving the *CO-OC* returns across all the eight asset classes examined in the paper.

5.2.1 Strategy performances

Table 11 reports the strategies' performance in international stock markets. The empirical evidence reveals that the traditional *CC-CC* reversal strategy displays a sizeable return for the US (0.485% per day with a Sharpe ratio of 9.562), Japan (0.202% per day with a Sharpe ratio of

[11]Table A.4 in the Online Appendix reports the detailed time window to construct the VWAP for the formation and holding period return where there is a gap window.

4.367), and France (0.213% per day with a Sharpe ratio of 5.271), but generates an insignificant return in the UK (0.021% per day with a Sharpe ratio of 0.382). The related *OO-OO* reversal strategy yields a strong return of about 0.550% per day in the four asset classes.

In contrast, *OC-OC* produces negative returns, suggesting the presence of a fairly strong intraday momentum effect across stock markets. These results, together with the findings shown earlier in Table 2 in futures markets, reveal mixed evidence for both traditional short-term reversal strategies and intraday momentum patterns across various asset classes. The overnight-intraday reversal strategy, instead, is characterized by much stronger and universally positive profitability in all markets: the return is about 1.595% per day with a Sharpe ratio of 27.293 in the US, 1.377% per day with a Sharpe ratio of 21.972 in the UK, 0.840% per day with a Sharpe ratio of 21.514 in Japan, and 1.078% per day with a Sharpe ratio of 25.231 in France stock markets.

Table A.10 in the Online Appendix reports the results of excluding the bottom 50% stocks based on market capitalization. Switching to this more liquid universe, the performance of all strategies generally shrinks on average by about 40%, which is expected given the results on the liquidity provision mechanism in Table 9. However, it is worth noting that the *CO-OC* strategy still generates economically and statistically significant returns. It substantially dominates conventional reversal strategies across the markets by doubling their mean return and Sharpe ratio. Specifically, *CO-OC* produces the largest return of 0.963%, 1.311%, 0.626%, and 1.159% per day with the greatest annualized Sharpe ratio of 16.390, 21.342, 16.651, and 22.813 in the four stock markets, respectively. The results suggest that the performance of the *CO-OC* strategy is not entirely driven by illiquidity stocks.

5.2.2 Mechanisms

Table A.11 in the Online Appendix examines the asset class-specific illiquidity provision mechanism in four major global stock markets, and it highlights the importance of return dispersion in capturing the *CO-OC* returns. Firstly, consistent with the futures markets results in Table 9, return dispersion positively and highly significantly forecasts the *CO-OC* return across international stock markets. Interestingly, unlike the relatively weak VIX coefficients in futures, VIX positively and significantly predicts the *CO-OC* return in univariate regressions across the stock markets. However, once controlling for return dispersion, the VIX coefficients again turn weaker and mixed.

For example, the VIX coefficient becomes negative in the US stock market in the multivariate regression, while the return dispersion coefficient remains significantly positive with a t-statistic of 31.92. As for the sentiment index, in contrast to the negative coefficients in futures markets shown in Table 9, the sentiment coefficients in univariate regressions are positive and highly significant in the US, Japan, and France stock markets. This is consistent with the sentiment explanation for the stock anomalies in Stambaugh et al. (2012). However, the sentiment coefficients become negative or insignificant once controlling for return dispersion. These results indicate that return dispersion essentially dominates other alternative explanations in capturing the *CO-OC* return.

In contrast to the pervasive validity of asset class-specific illiquidity, the investor heterogeneity mechanism tends to produce inclusive results in the international stock market. Table A.12 examines the daytime reversal effects in the global stock markets, based on the same method previously used in Table 5. The negative return of -0.273% (t-statistic: -2.963) in the US stock market suggests positive predictability of the frequency of the negative daytime reversal, which confirms the findings of Akbas et al. (2022). Similar patterns are also found in Japan and France. However, the negligible return of 0.100% per month (t-statistic: 0.427) in the UK indicates there is no daytime reversal effect. Similarly, Cheema et al. (2022) also find no daytime reversal effect in the Chinese stock market. Coupled with the insignificant daytime reversal effects in the futures previously shown in Table 5, these weak and inconsistent results of tug-of-war effect indicate that the investor heterogeneity mechanism can not explain the *CO-OC* return across the asset classes.

Overall, our results indicate that alternative mechanisms, including investor heterogeneity, market-wide illiquidity, and sentiment, show limited explanatory power in capturing the *CO-OC* return. On the other hand, the return dispersion strongly and positively predicts the *CO-OC* return in all asset classes, including the futures and international stock markets. These universally consistent results indicate that the liquidity provision mechanism is the fundamental economic driving force for the *CO-OC* performance.

5.3 Subperiods performance

In Table 12, we split the entire sample into two subperiods and examine the statistical properties of the short-term reversal strategies before and after the sample median of 2010. Our findings are easy to summarize as the *CO-OC* strategy consistently outperforms all other strategies in both subperiods for all four asset classes. This suggests that the overnight-intraday reversal pattern is not purely driven by large price adjustments and has not disappeared in the most recent period. Across the four asset classes, the annualized Sharpe ratio of the *CO-OC* strategy ranges between 2.106 and 7.988 in the first period and between 1.067 and 4.858 in the more recent sample. The evidence in favour of the traditional *CC-CC* and *OO-OO* strategy is weak as the associated returns are positive and statistically significant in both subperiods only for equity indices. The *OC-OC* strategy also displays weak and inconclusive results by producing either insignificant returns across the subperiods (i.e., in interest rate and currency futures) or returns with inconsistent signs across the asset classes (i.e., in equity index versus commodity futures).

6 A global two-factor model

Here, we propose a simple global two-factor model to explain the intraday return variation on various portfolios across asset classes.

The proposed global two-factor model consists of $\{MKT^*, CO\text{-}OC^*\}$, where MKT^* is the average intraday return of the equal-weighted market portfolios in the four asset classes, and $CO\text{-}OC^*$ is the average *CO-OC* portfolio returns in the four asset classes, including equity indices, interest rates, commodities, and currencies. Specifically, we estimate the following monthly time-series asset pricing regression of diversified test portfolios across asset classes:

$$R_t^P = \alpha^P + \beta_1^P MKT_t^* + \beta_2^P CO\text{-}OC_t^* + \varepsilon_t^P, \tag{8}$$

where all returns are the cumulative monthly intraday returns.

Asness et al. (2013) find that a global three-factor model $\{MKT^*, VAL^*, MOM^*\}$, consisting of market, value, and momentum factors, does a good job of capturing the return variation of the portfolios across asset classes. Hence, we also examine the following regressions for comparison:

$$R_t^P = \alpha^P + \beta_1^P MKT_t^* + \beta_2^P VAL_t^* + \beta_2^P MOM_t^* + \varepsilon_t^P, \tag{9}$$

where MKT^*, VAL^*, and MOM^* are the average intraday return of the market, value, and momentum factors in the four asset classes, including equity indices, interest rates, commodities, and currencies. It is worth noting that since we are interested in the intraday return variation, all the test portfolios and pricing factors in regression (8) and (9) use the intraday return as the holding period return.

We examine two sets of test portfolios R_t^P. The first includes the zeros-investment portfolios of *CO-OC*, value, and momentum strategies across the four asset classes, and hence 12 (3×4) portfolios. The second consists of the long and short legs of these 12 zeros-investment strategies, and hence 24 (2×12) portfolios. Following Asness et al. (2013), the formation period signal for the value strategy is the cumulative return over the past 5 years, and that for the momentum strategy is the cumulative return over the past 12 months skipping the previous 1 month. Similar to the *CO-OC* construction, we then calculate the value and momentum zero-investment portfolio return based on Equation (2).

Table 13 compares the pricing performance of the two global factor models in explaining the portfolios' intraday returns across asset classes. For each model, we report the average absolute monthly alphas (%), the average absolute t-statistics, and the Gibbons et al. (1989) GRS test results. Interestingly, our proposed global two-factor model $\{MKT^*$, $CO\text{-}OC^*\}$, though parsimonious, does a better job than the global three-factor model of Asness et al. (2013) of capturing the intraday returns across asset classes. Specifically, Panel A shows that the average absolute alpha for the 12 zero-investment portfolios under the global three-factor model is up to 1.27% per month. In comparison, its counterpart under our global two-factor model shrinks dramatically to only 0.29%. The associated average t-statistics (3.25 vs 0.55) tell a similar story. Moreover, the p-value from the GRS test is less than 10^{-10} for the global three-factor model, indicating a rejection of the joint hypothesis that the factor model can fully explain the test assets returns. On the contrary, the GRS p-value for our global two-factor model is 0.17, suggesting that our global two-factor model does a much better job than the three-factor one in explaining the *CO-OC*, value, and momentum portfolio returns across asset classes. Panel B reports the results for the 24 long and short legs of the *CO-OC*, value, and momentum zero-investment portfolios. Again, the aggregate pricing error of our global two-factor model is much lower than the three-factor model.

In short, our global two-factor model $\{MKT^*$, $CO\text{-}OC^*\}$ outperforms the global three-factor model $\{MKT^*, VAL^*, MOM^*\}$ in capturing the portfolios' intraday returns across asset classes.

7 Conclusion

In this paper, we study the overnight-intraday short-term reversal strategy (*CO-OC*) in multiple asset classes. We find that a simple overnight-intraday reversal strategy delivers an average excess return and a Sharpe ratio that is about two to five times larger than those generated by the conventional close-to-close short-term reversal strategy in the equity index, interest rate, commodity, and currency futures. This pattern is consistent over time and robust across major international stock markets. The *CO-OC* strategy return cannot be explained by canonical asset class-specific factors and stock return factors.

We test several possible economic channels, including investor sentiment, macro-news announcements, market liquidity condition, and asset class-specific liquidity provision. First, investor sentiment fails to explain the strategy return, as the *CO-OC* strategy performs similarly in high and low sentiment periods or during news announcement windows. Second, the market liquidity conditions, proxied by the VIX index, also do not predict the *CO-OC* strategy return well. Last, we construct an empirical liquidity provision measure for each asset class. We use the cross-sectional dispersion of overnight return as a proxy for the uncertainty faced by market makers at the open. This dispersion measure predicts the profitability of the *CO-OC* strategy return well across all asset classes.

Overall, our results suggest that market structure imposes non-trivial frictions on asset prices, even in very liquid markets such as futures markets.

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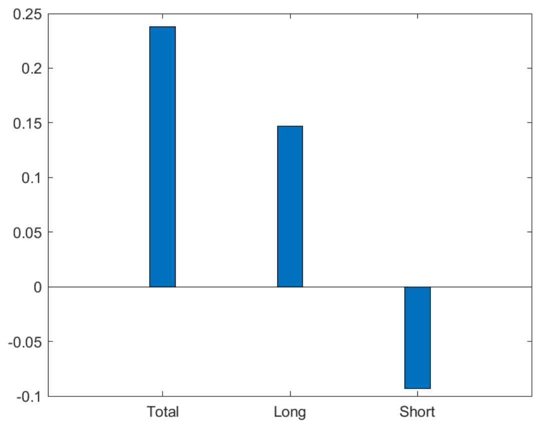
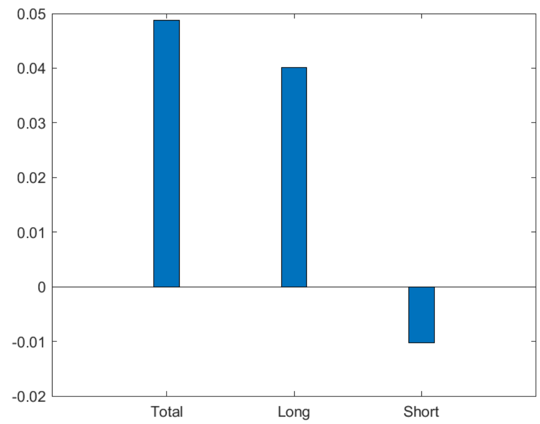
Figure 1: *CO-OC*: **Long leg versus short leg**

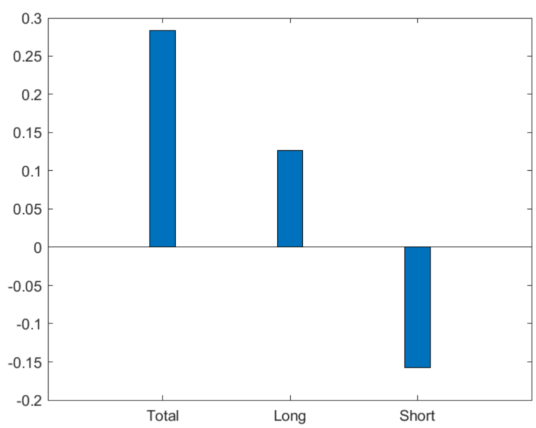
The figure reports the average daily return (in %) of the long and short leg of the overnight-intraday reversal strategies (*CO-OC*) in futures written on four asset classes, including equity indices, interest rates, commodities, and currencies. The sample period is from 2004/01 to 2018/12.



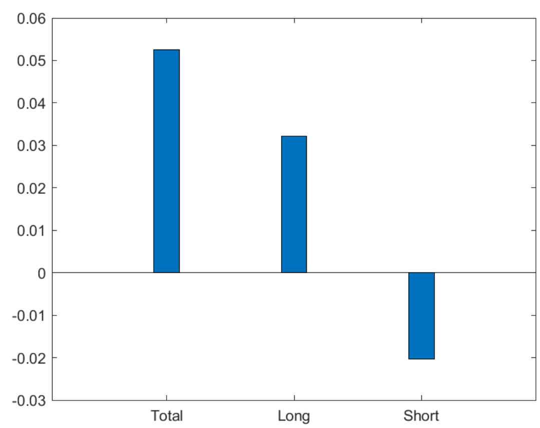
(A) Equity indices



(B) Interest rates



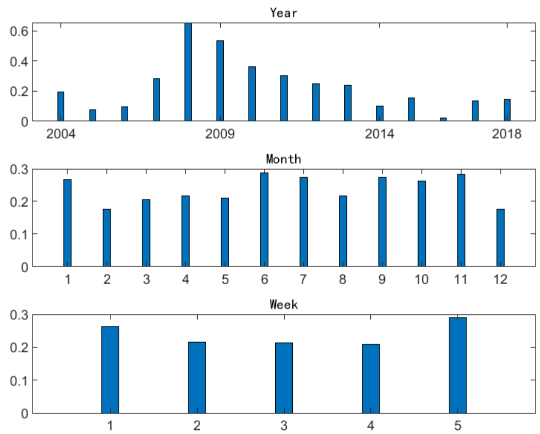
(C) Commodities



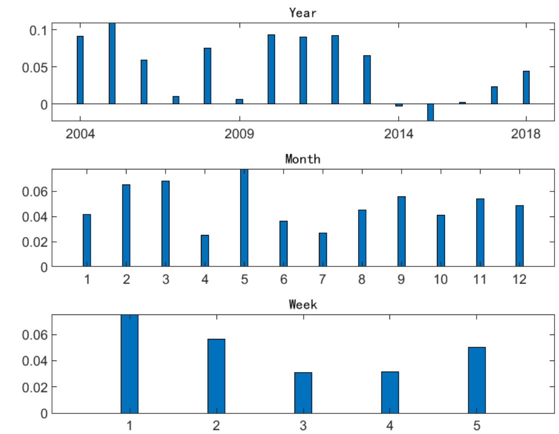
(D) Currencies

Figure 2: *CO-OC*: **Calendar effects**

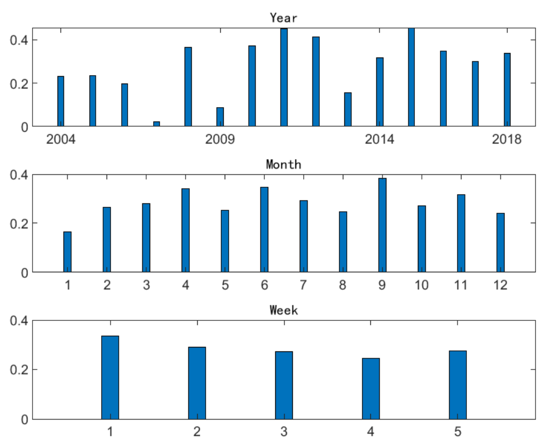
This figures displays the average daily return (in %) of the overnight-intraday reversal strategy (*CO-OC*) averaged across different years, months and days of the week.



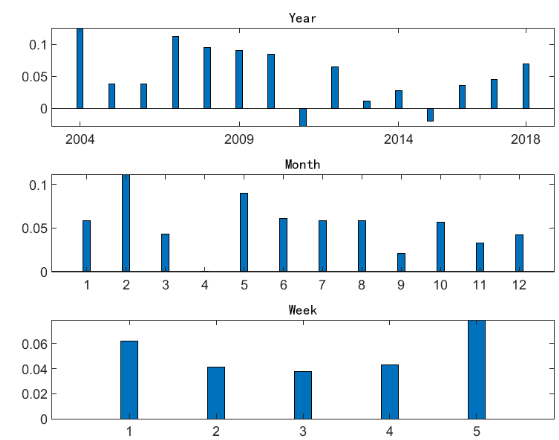
(A) Equity indices



(B) Interest rates



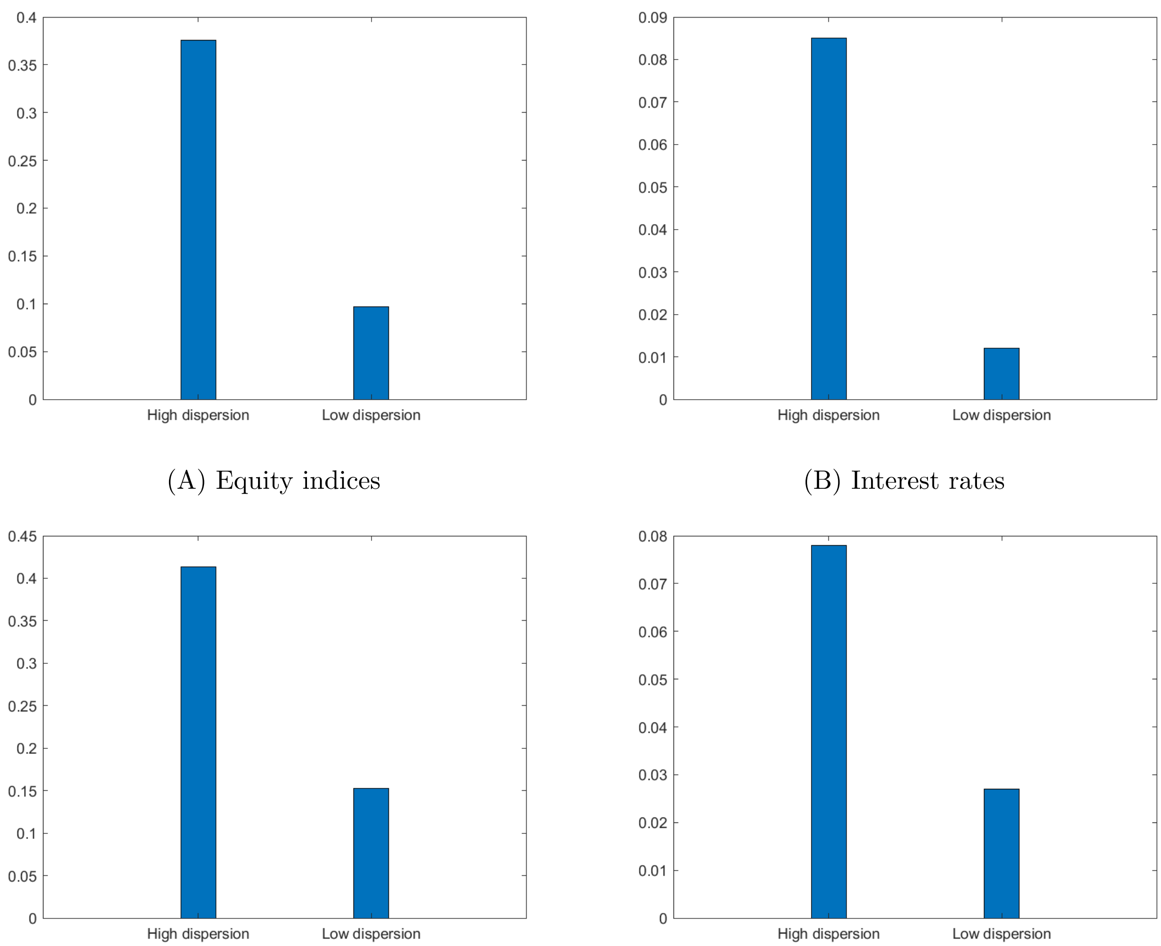
(C) Commodities



(D) Currencies

Figure 3: *CO-OC* **and return dispersion**

The figure reports the average daily return (in %) of *CO-OC* in the high- and low- return dispersion subperiods. The strategies are rebalanced daily. Day t is defined as the high (low) dispersion period if the return dispersion measure on day $t-1$, which is the cross-sectional volatility of the overnight return $r^{co}_{i,t-1}$, is higher (lower) than the sample median.



(A) Equity indices

(B) Interest rates

(C) Commodities

(D) Currencies

Table 1: Description of short-term reversal strategies

This table describes the short-term reversal strategies examined in the paper. (i) *CC-CC* uses close-to-close daily returns $r^{cc}_{i,t-1}$ on day $t-1$ as formation period returns (i.e., to compute portfolio weights) and close-to-close daily returns $r^{cc}_{i,t}$ on day t as holding period returns (i.e., to construct the portfolio realized return); (ii) *OO-OO* uses open-to-open daily returns $r^{oo}_{i,t-1}$ on day $t-1$ as formation period returns and open-to-open daily returns $r^{oo}_{i,t}$ on day t as holding period returns; (iii) *OC-OC* uses open-to-close daily returns $r^{oc}_{i,t-1}$ on day $t-1$ as formation period returns and open-to-close daily returns $r^{oc}_{i,t}$ on day t as holding period returns; and (iv) *CO-OC* uses close-to-open daily returns $r^{co}_{i,t-1}$ on day $t-1$ as formation period returns and open-to-close daily returns $r^{oc}_{i,t}$ on day t as holding period returns. $P^o_{i,t}$ and $P^c_{i,t}$ denote the open and close price, respectively, on day t for asset i.

Strategy	Formation period returns	Holding period returns
CC-CC	close-to-close: $r^{cc}_{i,t-1} = \frac{P^c_{i,t-1}}{P^c_{i,t-2}} - 1$	close-to-close: $r^{cc}_{i,t} = \frac{P^c_{i,t}}{P^c_{i,t-1}} - 1$
OO-OO	open-to-open: $r^{oo}_{i,t-1} = \frac{P^o_{i,t-1}}{P^o_{i,t-2}} - 1$	open-to-open: $r^{oo}_{i,t} = \frac{P^o_{i,t}}{P^o_{i,t-1}} - 1$
OC-OC	open-to-close: $r^{oc}_{i,t-1} = \frac{P^c_{i,t-1}}{P^o_{i,t-1}} - 1$	open-to-close: $r^{oc}_{i,t} = \frac{P^c_{i,t}}{P^o_{i,t}} - 1$
CO-OC	close-to-open: $r^{co}_{i,t-1} = \frac{P^o_{i,t}}{P^c_{i,t-1}} - 1$	open-to-close: $r^{oc}_{i,t} = \frac{P^c_{i,t}}{P^o_{i,t}} - 1$

Table 2: Summary statistics for baseline reversal strategies

This table reports the summary statistics of reversal strategies in futures written on four asset classes, including equity indices, interest rates, commodities, and currencies. The strategies are rebalanced daily, and returns are expressed in percent per day. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (in %), the skewness, the kurtosis, the annualized Sharpe ratio (SR), and the sample correlation between the *CO-OC* strategy and other strategies. The sample period is from 2004/01 to 2018/12.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: Equity indices				Panel B: Interest rates			
mean	0.056	0.164	0.020	0.238	0.013	0.023	0.006	0.049
t-stat	3.862	7.685	1.465	15.735	1.508	2.593	0.695	7.243
sdev	0.852	1.013	0.810	0.685	0.578	0.569	0.567	0.408
skew	0.364	0.992	0.485	0.398	-0.210	-0.251	-0.132	-0.011
kurt	8.426	11.718	9.905	4.094	6.261	7.482	6.259	4.298
SR	1.041	2.568	0.393	5.516	0.366	0.632	0.165	1.896
corr	-0.031	0.093	0.018	1.000	-0.126	0.026	-0.159	1.000
	Panel C: Commodities				Panel D: Currencies			
mean	-0.098	-0.030	-0.182	0.284	0.020	0.016	0.005	0.052
t-stat	-4.035	-1.150	-8.014	13.062	2.054	1.624	0.487	6.742
sdev	1.547	1.626	1.418	1.271	0.653	0.657	0.633	0.513
skew	0.142	-0.021	-0.106	0.048	0.596	0.308	0.193	0.118
kurt	8.323	7.083	5.304	3.418	15.701	14.137	12.992	3.931
SR	-1.010	-0.298	-2.039	3.541	0.482	0.385	0.116	1.624
corr	0.029	-0.010	-0.014	1.000	-0.007	0.011	-0.006	1.000

Table 3: Reversal strategies at the weekly frequency

This table reports the summary statistics of weekly reversal strategies in futures written on four asset classes, including equity indices, interest rates, commodities, and currencies. The strategies are rebalanced weekly, and returns are expressed in percent per week. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (in %), the skewness, the kurtosis, the annualized Sharpe ratio (SR), and the sample correlation between the *CO-OC* and the other strategies.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: Equity indices				Panel B: Interest rates			
mean	0.121	0.224	0.112	0.293	0.134	0.133	0.098	0.121
t-stat	1.990	3.408	1.881	4.116	2.814	2.865	2.092	3.388
sdev	1.845	1.916	1.813	1.654	1.249	1.250	1.234	1.002
skew	0.615	0.989	0.735	0.252	0.339	0.356	0.330	0.168
kurt	6.038	8.558	7.349	4.023	4.427	4.659	4.651	3.918
SR	0.468	0.832	0.438	1.258	0.762	0.755	0.565	0.858
corr	-0.076	0.059	-0.067	1.000	-0.037	-0.027	-0.015	1.000
	Panel C: Commodities				Panel D: Currencies			
mean	0.178	0.268	0.066	0.421	0.081	0.092	0.073	0.117
t-stat	1.198	1.631	0.447	3.710	1.840	2.045	1.690	2.633
sdev	3.656	3.730	3.445	3.136	1.417	1.376	1.378	1.184
skew	0.163	0.364	0.427	0.255	-0.771	0.316	-0.512	0.267
kurt	4.176	5.746	5.090	3.310	21.436	12.214	18.956	3.731
SR	0.346	0.510	0.136	0.954	0.406	0.473	0.375	0.703
corr	0.078	-0.012	0.049	1.000	0.030	0.070	0.038	1.000

Table 4: Risk-adjusted performance of the overnight-intraday reversal strategy

This table presents the risk-adjusted performances and the associated Newey-West t-statistics (in parentheses) of the overnight-intraday reversal strategies (CO-OC) in futures written on four asset classes, including equity indices, interest rates, commodities, and currencies. The dependent variable is the monthly return on the overnight-intraday reversal strategy, which is the cumulative return compounded from the daily strategy. The alphas are expressed in percent per month. The set of risk factors includes the Asness et al. (2013) asset class-specific value and momentum factors (first specification) and the five Fama and French (2015) factors as well as a momentum factor and a short-term reversal factor (second specification). The risk factors are from the AQR website and Kenneth French's website.

	Panel A: Equity indices		Panel B: Interest rates		Panel C: Commodities		Panel D: Currencies	
alpha	5.15***	5.33***	1.00***	0.99***	5.97***	5.84***	1.10***	1.18***
	(7.63)	(8.86)	(6.29)	(6.09)	(10.28)	(9.85)	(6.16)	(7.17)
VAL	-0.56	-0.58**	-0.39	-0.04	-0.05	-0.04	0.02	-0.07*
	(-1.51)	(-2.49)	(-1.44)	(-1.03)	(-0.45)	(-0.37)	(0.28)	(-1.94)
MOM	-0.21	0.31**	0.26	0.21***	-0.14	0.46**	0.02	0.06
	(-1.06)	(1.97)	(1.54)	(3.10)	(-1.25)	(2.07)	(0.22)	(0.80)
MKT_{FF}		-0.33		-0.03		-0.11		-0.02
		(-1.38)		(-0.56)		(-0.39)		(-0.30)
SMB_{FF}		0.35		-0.01		0.34		-0.07
		(1.33)		(-0.13)		(1.10)		(-0.76)
HML_{FF}		0.36		0.05		-0.13		-0.08
		(0.92)		(0.50)		(-0.35)		(-0.81)
RMW_{FF}		-0.35		-0.01		0.19		0.01
		(-1.37)		(-0.46)		(1.62)		(0.38)
CMA_{FF}		0.24		0.05		0.07		-0.02
		(1.43)		(1.00)		(0.53)		(-0.43)
MOM_{FF}		-0.13		-0.35		-0.08		-0.00
		(-0.70)		(-1.62)		(-0.72)		(-0.03)
STR_{FF}		0.10		0.29*		-0.20*		-0.00
		(0.50)		(1.85)		(-1.87)		(-0.00)
R^2	4.25%	21.27%	3.65%	10.31%	0.97%	5.76%	0.08%	2.63%

Table 5: Daytime reversal effects in futures

This table examines the daytime reversal effects of Akbas et al. (2022) in futures at the monthly frequency. A negative (positive) daytime reversal is defined as a positive (negative) overnight return followed by a negative (positive) intraday return. The frequency of negative daytime reversal ($NR_{i,t}$) is defined as the ratio of the number of days with negative daytime reversals to the number of trading days in that month. The abnormal frequency of negative daytime reversal ($AB\_NR_{i,t}$) is $NR_{i,t}$ scaled by the average $NR_{i,t}$ over the prior 12 months. The abnormal frequency of positive daytime reversal ($AB\_PR_{i,t}$) is defined similarly. We then form a strategy based on the abnormal frequency, where the formation period return in Eq (1) is placed by the abnormal frequency of daytime reversal to determine the portfolio weight, and the holding period return is the return in the next month. Panel A and Panel B reports the summary statistics for the negative and positive daytime reversal strategies, respectively. The strategies are rebalanced monthly, and the returns are expressed in percent per month. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (in %), the skewness, the kurtosis, and the annualized Sharpe ratio (SR).

	Equity indices	Interest rates	Commodities	Currencies
Panel A: Negative daytime reversal				
mean	-0.001	-0.068	0.137	0.008
t-stat	-0.006	-0.591	0.217	0.056
sdev	3.296	1.559	6.341	1.868
skew	-0.393	-0.076	0.552	0.158
kurt	3.163	4.875	3.060	4.072
SR	-0.002	-0.150	0.075	0.016
Panel B: Positive daytime reversal				
mean	0.141	-0.222	-1.396	-0.012
t-stat	0.487	-1.756	-1.876	-0.072
sdev	3.551	1.590	6.270	2.162
skew	-0.435	-1.355	0.206	-0.195
kurt	4.589	7.788	2.700	4.398
SR	0.138	-0.484	-0.771	-0.019

Table 6: Strategy performance and investor sentiment

This table reports the mean returns and the associated Newey-West t-statistics (in parentheses) for the strategies under various sentiment levels of Baker and Wurgler (2006). The strategies are rebalanced daily, and returns are expressed in percent per day. Day t is defined as a high (low) sentiment period if the sentiment level on day $t-1$ is above (below) the sample median. The strategies are rebalanced daily, and returns are expressed in percent per day.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: Equity indices				Panel B: Interest rates			
High sentiment	0.038	0.131	0.004	0.217	0.008	0.019	0.004	0.055
	(1.75)	(5.34)	(0.26)	(12.95)	(0.64)	(1.48)	(0.38)	(5.91)
Low sentiment	0.070	0.198	0.032	0.256	0.019	0.026	0.008	0.042
	(3.49)	(5.95)	(1.58)	(10.84)	(1.57)	(2.21)	(0.70)	(4.39)
Difference	-0.032	-0.067	-0.027	-0.040	-0.010	-0.007	-0.003	0.013
	(-1.13)	(-1.85)	(-1.00)	(-1.59)	(-0.57)	(-0.39)	(-0.19)	(0.97)
	Panel C: Commodities				Panel D: Currencies			
High sentiment	-0.151	-0.078	-0.214	0.241	0.017	0.016	0.012	0.040
	(-4.39)	(-2.05)	(-6.68)	(7.84)	(1.36)	(1.24)	(0.94)	(3.74)
Low sentiment	-0.046	0.012	-0.150	0.324	0.022	0.015	-0.001	0.064
	(-1.32)	(0.34)	(-4.62)	(10.63)	(1.52)	(1.02)	(-0.08)	(5.56)
Difference	-0.106	-0.090	-0.066	-0.083	-0.004	0.000	0.013	-0.024
	(-2.16)	(-1.71)	(-1.43)	(-1.98)	(-0.24)	(0.04)	(0.68)	(-1.54)

Table 7: Strategy performance and market-wide illiquidity

This table reports the mean returns and the associated Newey-West t-statistics (in parentheses) for reversal strategies under various market-wide illiquidity states. The strategies are rebalanced daily, and returns are expressed in percent per day. Panel A and Panel B reports the results for VIX market states and financial crisis, respectively. Day t is defined as a high (low) VIX period if the VIX on day $t-1$ is above (below) the sample median. The financial crisis period is from 2007/12 to 2009/06.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
Panel A: VIX								
	Equity indices				Interest rates			
High VIX	0.113	0.286	0.056	0.354	0.014	0.014	0.008	0.052
	(4.90)	(8.08)	(2.44)	(15.53)	(1.01)	(1.07)	(0.58)	(5.20)
Low VIX	-0.003	0.046	-0.018	0.121	0.013	0.031	0.005	0.044
	(-0.20)	(2.42)	(-1.15)	(8.34)	(1.24)	(2.69)	(0.51)	(5.10)
Difference	0.116	0.240	0.074	0.232	0.001	-0.016	0.003	0.007
	(4.11)	(6.74)	(2.75)	(9.80)	(0.09)	(-0.91)	(0.18)	(0.57)
	Commodities				Currencies			
High VIX	-0.067	-0.014	-0.173	0.306	0.034	0.015	0.012	0.060
	(-1.82)	(-0.34)	(-5.03)	(9.95)	(2.02)	(0.90)	(0.71)	(5.04)
Low VIX	-0.127	-0.049	-0.189	0.260	0.005	0.015	-0.001	0.045
	(-3.94)	(-1.42)	(-6.30)	(8.33)	(0.57)	(1.60)	(-0.16)	(4.36)
Difference	0.059	0.035	0.014	0.044	0.028	-0.000	0.013	0.014
	(1.19)	(0.66)	(0.31)	(1.05)	(1.41)	(-0.00)	(0.69)	(0.91)
Panel B: Financial crisis								
	Equity indices				Interest rates			
Crisis	0.222	0.653	0.176	0.659	-0.008	-0.013	-0.022	0.038
	(4.23)	(5.98)	(2.60)	(12.86)	(-0.26)	(-0.41)	(-0.76)	(1.65)
Non-crisis	0.036	0.106	0.001	0.188	0.015	0.026	0.009	0.049
	(2.50)	(6.71)	(0.13)	(14.89)	(1.71)	(2.97)	(1.05)	(7.14)
Difference	0.186	0.547	0.174	0.471	-0.023	-0.040	-0.032	-0.011
	(3.59)	(5.61)	(2.74)	(10.11)	(-0.69)	(-1.12)	(-0.95)	(-0.45)
	Commodities				Currencies			
Crisis	-0.131	-0.021	-0.174	0.285	0.082	0.035	0.036	0.108
	(-1.34)	(-0.19)	(-1.81)	(3.98)	(1.66)	(0.73)	(0.74)	(3.44)
Non-crisis	-0.094	-0.031	-0.183	0.283	0.012	0.013	0.000	0.045
	(-3.86)	(-1.19)	(-8.13)	(12.29)	(1.36)	(1.44)	(0.09)	(5.79)
Difference	-0.037	0.009	0.008	0.002	0.070	0.022	0.035	0.063
	(-0.38)	(0.08)	(0.08)	(0.02)	(1.33)	(0.43)	(0.70)	(1.91)

Table 8: Strategy performance and macro-news

This table reports the mean returns and the associated Newey-West t-statistics (in parentheses) for the strategies under various news announcements. The strategies are rebalanced daily, and returns are expressed in percent per day. We consider the announcements of FOMC, nonfarm payrolls, PCE and PMI. The strategies are rebalanced daily, and returns are expressed in percent per day.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: Equity indices				Panel B: Interest rates			
Announcement	0.023	0.155	-0.017	0.270	0.035	0.025	0.034	0.077
	(0.59)	(2.91)	(-0.56)	(7.11)	(1.25)	(0.91)	(1.30)	(3.72)
Non-announcement	0.060	0.168	0.026	0.231	0.010	0.022	0.001	0.043
	(3.86)	(7.43)	(1.73)	(14.41)	(1.13)	(2.31)	(0.20)	(6.13)
Difference	-0.036	-0.012	-0.043	0.039	0.025	0.002	0.032	0.034
	(-0.93)	(-0.27)	(-1.20)	(1.18)	(0.86)	(0.10)	(1.09)	(1.60)
	Panel C: Commodities				Panel D: Currencies			
Announcement	-0.126	-0.087	-0.215	0.234	0.007	-0.026	-0.008	0.042
	(-1.76)	(-1.09)	(-3.38)	(4.27)	(0.27)	(-1.11)	(-0.32)	(1.97)
Non-announcement	-0.093	-0.021	-0.176	0.292	0.022	0.023	0.007	0.054
	(-3.42)	(-0.71)	(-7.00)	(12.21)	(2.09)	(2.16)	(0.74)	(6.38)
Difference	-0.033	-0.066	-0.039	-0.058	-0.015	-0.050	-0.016	-0.012
	(-0.43)	(-0.82)	(-0.60)	(-0.98)	(-0.51)	(-1.70)	(-0.57)	(-0.53)

Table 9: *CO-OC* and asset class-specific liquidity provision

In the regressions, the dependent variable is the overnight-intraday reversal strategy return on day t ($CO\text{-}OC_t$). The predictor variables include the lagged return dispersion measure, $Dispersion_{t-1}$, defined as the cross-sectional volatility of the overnight return $r^{co}_{i,t-1}$ on day $t-1$, the lagged VIX on day $t-1$ (VIX_{t-1}), and the lagged overnight-intraday strategy return on day $t-1$ ($CO\text{-}OC_{t-1}$). We also include the lagged Baker and Wurgler (2006) sentiment index in the previous month ($Sentiment_{m-1}$), where m is the month that day t belongs. We report the regression coefficients and the associated Newey-West t-statistics (in parentheses).

	Panel A: Equity indices				Panel B: Interest rates			
$Dispersion_{t-1}$	0.882***			0.757***	0.674***			0.668***
	(16.35)			(13.12)	(4.64)			(4.57)
VIX_{t-1}		1.954***		0.784***		0.023		-0.006
		(10.36)		(4.00)		(0.21)		(-0.05)
$Sentiment_{m-1}$			-0.813**	0.016			-0.250	-0.131
			(-2.15)	(0.04)			(-1.10)	(-0.54)
$CO\text{-}OC_{t-1}$	0.044**	0.039**	0.097***	0.028	-0.002	0.001	0.001	-0.002
	(2.38)	(2.01)	(4.56)	(1.50)	(-0.12)	(0.08)	(0.07)	(-0.13)
constant	0.025*	-0.130***	0.198***	-0.085***	0.023***	0.044**	0.043***	0.022
	(1.75)	(-4.03)	(15.33)	(-2.87)	(2.86)	(2.37)	(5.66)	(1.15)
R^2	11.27%	6.16%	1.02%	11.86%	0.70%	-0.05%	-0.03%	0.66%

	Panel C: Commodities				Panel D: Currencies			
$Dispersion_{t-1}$	0.272***			0.271***	0.319**			0.312**
	(4.01)			(3.99)	(2.30)			(2.23)
VIX_{t-1}		0.108		0.027		0.081		0.014
		(0.38)		(0.09)		(0.62)		(0.10)
$Sentiment_{m-1}$			-0.642	-0.544			-0.245	-0.103
			(-0.75)	(-0.62)			(-0.75)	(-0.30)
$CO\text{-}OC_{t-1}$	0.012	0.013	0.013	0.012	-0.031*	-0.029	-0.029	-0.031*
	(0.70)	(0.75)	(0.74)	(0.69)	(-1.70)	(-1.60)	(-1.60)	(-1.71)
constant	0.165***	0.259***	0.267***	0.150**	0.028**	0.039*	0.049***	0.024
	(5.05)	(4.77)	(9.85)	(2.55)	(2.30)	(1.72)	(5.29)	(1.03)
R^2	0.75%	-0.03%	-0.02%	0.71%	0.30%	0.05%	0.05%	0.25%

Table 10: Strategy performance based on volume-weighted price

This table reports the summary statistics of the strategies in the four asset classes based on volume-weighted price data. We define a open and close time window of 30 minutes for each of the four asset classes, respectively. The open and close price used to construct the strategies are defined as the volume-weighted price in the associated window. The strategies are rebalanced daily, and returns are expressed in percent per day. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (in %), the skewness, the kurtosis, the annualized Sharpe ratio (SR), and the sample correlation between the *CO-OC* strategy and the other strategies.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: Equity indices				Panel B: Interest rates			
mean	0.030	-0.005	0.010	0.079	0.021	0.021	0.017	0.017
t-stat	1.474	-0.244	0.501	4.376	2.241	2.284	1.937	2.033
sdev	0.841	0.837	0.836	0.749	0.537	0.503	0.504	0.481
skew	-0.054	-0.255	-0.044	0.194	-0.035	-0.085	-0.049	-0.160
kurt	3.850	4.432	4.315	4.217	3.463	3.358	3.321	3.628
SR	0.571	-0.088	0.181	1.673	0.615	0.663	0.542	0.570
corr	0.104	0.025	0.072	1.000	-0.103	0.022	-0.123	1.000
	Panel C: Commodities				Panel D: Currencies			
mean	-0.178	-0.072	-0.124	0.092	0.003	0.004	0.001	0.027
t-stat	-7.037	-2.570	-5.167	3.780	0.304	0.381	0.132	2.697
sdev	1.492	1.559	1.345	1.338	0.603	0.616	0.583	0.589
skew	-0.027	-0.021	-0.112	0.132	0.077	0.014	0.010	0.140
kurt	3.625	3.518	3.248	3.418	5.047	4.841	4.830	4.584
SR	-1.890	-0.731	-1.458	1.094	0.082	0.099	0.034	0.717
corr	0.078	-0.011	0.075	1.000	0.003	0.026	0.032	1.000

Table 11: Strategy performance in international stock markets

This table reports summary statistics of the strategies in international stock markets. The strategies are rebalanced daily, and returns are expressed in percent per day. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (in %), the skewness, the kurtosis, the annualized Sharpe ratio (SR), and the sample correlation between the *CO-OC* and other strategies. The sample period starts from 1993/01 to 2018/12.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: US				Panel B: UK			
mean	0.485	0.622	-0.156	1.595	0.021	0.299	-0.691	1.377
t-stat	22.560	31.566	-16.862	48.818	1.355	17.322	-25.932	43.633
sdev	0.805	0.777	0.574	0.928	0.855	0.892	0.922	0.995
skew	0.408	0.373	-0.025	0.425	-0.085	0.166	-1.307	0.946
kurt	3.857	4.151	5.347	2.519	4.480	4.103	5.765	4.149
SR	9.562	12.707	-4.305	27.293	0.382	5.324	-11.900	21.972
corr	0.402	0.407	-0.153	1.000	0.020	0.153	-0.327	1.000
	Panel C: Japan				Panel D: France			
mean	0.202	0.480	-0.015	0.840	0.213	0.537	-0.304	1.078
t-stat	14.807	29.589	-2.238	45.835	17.600	32.922	-32.975	55.933
sdev	0.736	0.816	0.502	0.620	0.642	0.756	0.516	0.678
skew	-0.031	0.877	0.174	1.340	-0.060	0.697	-0.013	1.115
kurt	5.077	5.903	5.361	5.629	3.752	4.716	4.384	4.982
SR	4.367	9.331	-0.461	21.514	5.271	11.273	-9.349	25.231
corr	0.295	0.276	0.155	1.000	0.154	0.264	-0.057	1.000

Table 12: Strategy performance in the subperiods

This table reports the subperiod performances of the reversal strategies in futures written on four asset classes, including equity indices, interest rates, commodities, and currencies. The strategies are rebalanced daily, and returns are expressed in percent per day. The table reports the mean return (in %), Newey-West t-statistic, the annualized Sharpe ratio (SR), and the sample correlation between the *CO-OC* and the alternative ones. The sample period in Panel A is from 2004/01 to 2010/12. The sample period in Panel B is from 2011/01 to 2018/12.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
Panel A: Pre-2010								
	Equity indices				Interest rates			
mean	0.068	0.271	0.034	0.308	0.007	0.019	-0.003	0.058
t-stat	3.101	6.849	1.575	12.345	0.618	1.558	-0.266	6.547
SR	1.336	3.860	0.777	7.988	0.223	0.603	-0.095	2.828
corr	-0.003	0.159	0.085	1.000	-0.091	0.109	-0.114	1.000
	Commodities				Currencies			
mean	-0.151	-0.072	-0.239	0.190	0.036	0.032	0.019	0.083
t-stat	-3.661	-1.615	-6.080	5.269	2.056	1.854	1.138	6.273
SR	-1.349	-0.620	-2.357	2.106	0.749	0.675	0.418	2.354
corr	0.032	-0.008	0.004	1.000	-0.012	0.030	-0.006	1.000
Panel B: Post-2010								
	Equity indices				Interest rates			
mean	0.048	0.092	0.011	0.191	0.017	0.025	0.011	0.043
t-stat	2.519	4.551	0.620	11.323	1.383	2.089	0.951	4.570
SR	0.862	1.573	0.194	4.185	0.440	0.651	0.294	1.506
corr	-0.047	0.040	-0.013	1.000	-0.138	-0.004	-0.175	1.000
	Commodities				Currencies			
mean	-0.062	-0.002	-0.142	0.350	0.009	0.005	-0.005	0.032
t-stat	-2.080	-0.048	-5.274	13.457	0.797	0.431	-0.473	3.429
SR	-0.718	-0.017	-1.785	4.858	0.250	0.138	-0.152	1.067
corr	0.022	-0.014	-0.040	1.000	-0.004	-0.009	-0.008	1.000

Table 13: Asset pricing tests of global factor models

This table reports results from the monthly time-series asset pricing tests of various test portfolios across asset classes on two global asset pricing models. All the test portfolios and pricing factors use the intraday return as the holding period return, and all returns are monthly. The first model is the global three-factor model $\{MKT^*, VAL^*, MOM^*\}$ of Asness et al. (2013), where MKT^*, VAL^* and MOM^* is the average intraday return of the market, value, and momentum factors in the four asset classes, including equity indices, interest rates, commodities, and currencies. The second model is our global two-factor model $\{MKT^*, CO\text{-}OC^*\}$, where $CO\text{-}OC^*$ is the average *CO-OC* portfolio returns in the four asset classes. Panel A uses the *CO-OC*, value and momentum portfolios across the four asset classes, and hence 12 portfolios as the test assets. Panel B uses the long and short legs of the *CO-OC*, value and momentum portfolios across the four asset classes, and hence 24 portfolios as the test assets. For each model, the table shows the average absolute monthly alphas (%), the average absolute t-statistics, and the Gibbons et al. (1989) (GRS) F-statistics with associated p-values in the brackets.

	$\{MKT^*, VAL^*, MOM^*\}$	$\{MKT^*, CO\text{-}OC^*\}$
Panel A: 12 zero-investment portfolios of *CO-OC*, value and momentum across asset classes		
Average $\|\alpha\|$ (%)	1.27	0.29
Average $\|t\|$	3.25	0.55
GRS: F-stat	26.07***	1.41
GRS: p-value	[$<10^{-10}$]	[0.17]
Panel B: 24 long and short legs of *CO-OC*, value and momentum portfolios across asset classes		
Average $\|\alpha\|$ (%)	0.76	0.51
Average $\|t\|$	2.67	1.03
GRS: F-stat	12.97***	1.89**
GRS: p-value	[$<10^{-10}$]	[0.01]

Online Appendix

A.1 Alternative strategy construction

Table A.1 reports the summary statistics for reversal strategies, where the portfolio weight is based on the rank of formation period returns.

Table A.2 reports the window to construct the volume-weighted open and close prices.

Table A.3 reports the strategy performances under alternative windows to construct volume-weighted prices.

Table A.4 reports the detailed time window to construct volume-weighted price when there is a gap between the formation and holding period.

Table A.5 reports the strategy performance when there is a gap window between the formation and holding period.

Table A.6 reports the summary statistics of CO-CO, and OC-CO strategies.

A.2 Additional results on the explanation

Table A.7 reports strategy performances in the subsamples divided by the return dispersion.

Table A.8 reports the predictive regression of *CO-OC* and return dispersion in futures markets, where the portfolio weight is based on the rank of formation period returns.

Table A.9 reports the additional results about the strategy performances and macro-news announcements.

A.3 Additional results on the global stock markets

Table A.10 reports the summary statistics of strategies in international stock markets for the stocks whose market capitalization falls within the largest 50%.

Table A.11 reports the predictive regression of *CO-OC* and return dispersion in international stock markets.

Table A.12 examines the daytime reversal effects of Akbas et al. (2022) in the global stock markets.

**Table A.1: Summary statistics for reversal strategies:
rank-based strategy construction**

This table reports the summary statistics of reversal strategies under alternative constructions, where the portfolio weight is based on the rank of formation period returns. Take *CO-OC* for example, the portfolio weight $w_{i,t-1} = -(Rank_{i,t-1} - \overline{Rank}_{t-1})/N$, where $Rank_{i,t-1}$ is the rank of $r^{co}_{i,t-1}$ among the N assets available at time t-1, and $\overline{Rank}_{t-1}$ is the mean of $Rank_{i,t-1}$. The rank for the asset with the lowest (highest) overnight return is 1 (N). The strategies are rebalanced daily, and returns are expressed in percent per day. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (in %), the skewness, the kurtosis, the annualized Sharpe ratio (SR), and the sample correlation between the *CO-OC* strategy and other strategies. The sample period is from 2004/01 to 2018/12.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: Equity indices				Panel B: Interest rates			
mean	0.051	0.149	0.015	0.218	0.013	0.021	0.008	0.034
t-stat	3.783	7.249	1.276	15.847	1.681	2.741	1.014	6.076
sdev	0.763	0.930	0.736	0.643	0.528	0.523	0.519	0.352
skew	0.422	1.085	0.446	0.281	-0.086	-0.206	-0.080	-0.019
kurt	7.529	11.160	8.244	4.073	5.835	7.582	6.173	4.357
SR	1.054	2.546	0.325	5.382	0.403	0.652	0.237	1.532
corr	-0.023	0.088	0.009	1.000	-0.134	0.024	-0.156	1.000
	Panel C: Commodities				Panel D: Currencies			
mean	-0.081	-0.027	-0.155	0.186	0.019	0.012	0.003	0.039
t-stat	-3.731	-1.149	-7.872	9.869	2.183	1.365	0.379	5.773
sdev	1.353	1.395	1.239	1.077	0.577	0.586	0.563	0.447
skew	-0.023	0.065	-0.158	0.023	0.341	0.348	0.177	0.025
kurt	5.628	6.511	4.450	3.338	13.348	14.824	12.487	3.966
SR	-0.950	-0.303	-1.985	2.735	0.520	0.331	0.091	1.374
corr	-0.018	-0.002	-0.045	1.000	-0.025	-0.002	-0.023	1.000

Table A.2: The window to calculate volume-weighted price

This table reports the window of 15 and 30 minutes to construct the volume-weighted open and close prices.

	Open window (in the previous day)		Close window	
Year	15 minutes	30 minutes	15 minutes	30 minutes
Panel A: Equity indices				
2004-2018	17:00-17:15	17:00-17:30	15:00-15:15	14:45-15:15
Panel B: Interest rates				
2004-2004	19:00-19:15	19:00-19:30	15:45-15:60	15:30-15:60
2005-2007	18:00-18:15	18:00-18:30	15:45-15:60	15:30-15:60
2008-2010	17:30-17:45	17:30-17:60	15:45-15:60	15:30-15:60
2011-2018	17:00-17:15	17:00-17:30	15:45-15:60	15:30-15:60
Panel C: Commodities				
2004-2004	19:30-19:45	19:30-19:60	13:00-13:15	12:45-13:15
2005-2007	18:30-18:45	18:30-18:60	13:00-13:15	12:45-13:15
2008-2011	18:00-18:15	18:00-18:60	13:00-13:15	12:45-13:15
2012-2013	17:00-17:15	17:00-17:60	13:45-13:60	13:30-13:60
2014-2018	19:00-19:15	19:00-19:60	13:00-13:15	12:45-13:15
Panel D: Currencies				
2004-2018	17:00-17:15	17:00-17:60	15:45-15:60	15:30-15:60

Table A.3: Strategy performance under alternative windows for volume-weighted price

This table reports the mean return and the associated t-statistic (in parentheses) for the reversal strategies in futures written on four asset classes based on the volume-weighted averaged price (VWAP) data with alternative windows. Panel A, B, and C reports the results with a open and close time window of 15, 45, and 60 minutes, respectively. The strategies are rebalanced daily, and returns are expressed in percent per day.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
Panel A: 15 minutes window to construct VWAP								
	Equity indices				Interest rates			
Mean	0.038	-0.021	0.004	0.046	0.022	0.019	0.016	0.015
	(1.52)	(-0.85)	(0.17)	(1.95)	(2.38)	(2.23)	(1.88)	(1.82)
	Commodities				Currencies			
Mean	-0.154	-0.083	-0.118	0.091	0.005	0.006	0.005	0.025
	(-5.95)	(-2.87)	(-4.73)	(3.75)	(0.50)	(0.66)	(0.60)	(2.67)
Panel B: 45 minutes window to construct VWAP								
	Equity indices				Interest rates			
Mean	0.031	0.004	0.027	0.048	0.016	0.019	0.013	0.019
	(1.69)	(0.25)	(1.64)	(2.72)	(1.72)	(2.16)	(1.53)	(2.25)
	Commodities				Currencies			
	-0.205	-0.073	-0.130	0.092	0.002	0.001	-0.001	0.024
	(-8.20)	(-2.65)	(-5.57)	(3.80)	(0.23)	(0.19)	(-0.13)	(2.45)
Panel C: 60 minutes window to construct VWAP								
	Equity indices				Interest rates			
Mean	0.023	0.001	0.007	0.044	0.016	0.018	0.013	0.019
	(1.32)	(0.08)	(0.50)	(2.64)	(1.71)	(2.07)	(1.56)	(2.11)
	Commodities				Currencies			
Mean	-0.230	-0.066	-0.125	0.101	0.002	0.000	-0.000	0.025
	(-9.10)	(-2.39)	(-5.43)	(4.08)	(0.22)	(0.05)	(-0.07)	(2.57)

Table A.4: The window to calculate volume-weighted price for equity indices: with a gap between the formation and holding period

We use a 30-minute window to construct the volume-weighted average price, and skip a 3-, 5-, or 15-minute gap between the formation and holding period for the *CO-OC* strategy. For illustration, take 5 minute gap in the equity indices as an example: to construct the formation period return ($r^{co}_{i,t-1} = P^{o}_{i,t}/P^{c}_{i,t-1} - 1$), we use the volume-weighted price in 14:45-15:15 in day t-1 for P^{c}_{t-1} and use the volume-weighted price in 17:00-17:30 in day t-1 for P^{o}_{t}, which is consistent with Panel A in Table A.2. Here, we skip 5 minutes between the formation and holding period, and hence we use the volume-weighted price in 17:35-18:05 (rather than 17:30-17:60) in day t-1 for P^{o}_{t} and use the volume-weighted price in 14:45-15:15 in day t for P^{c}_{t} to construct the holding period return ($r^{oc}_{i,t} = P^{c}_{i,t}/P^{o}_{i,t} - 1$).

	Start window	End window
Panel A: 3 minute gap		
Formation period	14:45-15:15 in day t-1 for P^{c}_{t-1}	17:00-17:30 in day t-1 for P^{o}_{t}
Holding period	17:33-18:03 in day t-1 for P^{o}_{t}	14:45-15:15 in day t for P^{c}_{t}
Panel B: 5 minute gap		
Formation period	14:45-15:15 in day t-1 for P^{c}_{t-1}	17:00-17:30 in day t-1 for P^{o}_{t}
Holding period	17:35-18:05 in day t-1 for P^{o}_{t}	14:45-15:15 in day t for P^{c}_{t}
Panel C: 15 minute gap		
Formation period	14:45-15:15 in day t-1 for P^{c}_{t-1}	17:00-17:30 in day t-1 for P^{o}_{t}
Holding period	17:45-18:15 in day t-1 for P^{o}_{t}	14:45-15:15 in day t for P^{c}_{t}

Table A.5: Strategy performance with a gap window between the formation and holding period

This table reports the mean return and the associated t-statistic (in parentheses) for the *CO-OC* strategies in futures written on four asset classes based on the 30-minutes volume-weighted averaged price (VWAP) data with various gap windows between the formation and holding period. Panel A, B, and C reports the results with a gap window of 3, 5, and 15 minutes, respectively. Table A.4 reports the detailed time window to construct the VWAP. The strategies are rebalanced daily, and returns are expressed in percent per day.

	Equity indices	Interest rates	Commodities	Currencies
Panel A: 3 minutes gap window				
Mean	0.063	0.017	0.056	0.035
	(2.28)	(1.83)	(2.29)	(3.08)
Panel B: 5 minutes gap window				
Mean	0.067	0.016	0.057	0.033
	(2.43)	(1.75)	(2.35)	(2.92)
Panel C: 15 minutes gap window				
Mean	0.050	0.016	0.060	0.028
	(1.83)	(1.80)	(2.39)	(2.49)

Table A.6: *CO-CO* and *OC-CO* Strategy Returns

This table compares the summary statistics of *CO-CO* and *OC-CO* strategies in futures written on four asset classes, including equity indices, interest rates, commodities, and currencies. The strategies are rebalanced daily, and returns are expressed in percent per day. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (in %), the skewness, the kurtosis, and the annualized Sharpe ratio (SR).

	Equity indices	Interest rates	Commodities	Currencies
Panel A: CO-CO				
mean	0.013	-0.001	-0.026	-0.004
t-stat	1.516	-0.745	-2.318	-2.252
sdev	0.596	0.097	0.635	0.123
skew	0.006	0.213	0.295	-0.291
kurt	6.680	8.907	6.518	7.289
SR	0.356	-0.194	-0.638	-0.565
Panel B: OC-CO				
mean	0.034	0.007	0.053	0.010
t-stat	4.610	5.743	5.400	4.951
sdev	0.432	0.078	0.564	0.120
skew	0.741	0.235	0.048	0.076
kurt	7.888	10.363	8.168	7.653
SR	1.253	1.483	1.478	1.340

Table A.7: Strategy performance in subsamples divided by return dispersion

This table reports the mean return and the associated t-statistic (in parentheses) for the strategies under various return dispersion conditions. The strategies are rebalanced daily, and returns are expressed in percent per day. Day t is defined as the high (low) dispersion period if the return dispersion measure on day $t-1$, which is the cross-sectional volatility of the overnight return $r^{co}_{i,t-1}$, is higher (lower) than the sample median.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: Equity indices				Panel B: Interest rates			
High dispersion	0.100	0.266	0.034	0.377	0.013	0.015	0.002	0.085
	(4.28)	(7.41)	(1.57)	(16.64)	(0.99)	(1.11)	(0.20)	(8.54)
Low dispersion	0.009	0.065	0.003	0.097	0.014	0.030	0.011	0.012
	(0.50)	(3.42)	(0.22)	(6.80)	(1.33)	(2.85)	(0.99)	(1.35)
Difference	0.091	0.201	0.030	0.279	-0.001	-0.015	-0.008	0.072
	(3.20)	(5.63)	(1.11)	(11.97)	(-0.06)	(-0.82)	(-0.44)	(5.32)
	Panel C: Commodities				Panel D: Currencies			
High dispersion	-0.078	-0.016	-0.189	0.413	0.036	0.016	0.012	0.078
	(-2.00)	(-0.38)	(-5.39)	(12.35)	(2.40)	(1.02)	(0.84)	(6.01)
Low dispersion	-0.118	-0.046	-0.175	0.153	0.004	0.015	-0.001	0.027
	(-4.07)	(-1.56)	(-6.03)	(5.62)	(0.31)	(1.12)	(-0.13)	(2.57)
Difference	0.040	0.030	-0.013	0.260	0.032	0.001	0.013	0.050
	(0.80)	(0.56)	(-0.28)	(6.12)	(1.61)	(0.07)	(0.70)	(3.08)

Table A.8: *CO-OC* Strategy returns and asset class-specific liquidity provision: rank-based strategy construction

In the regressions, the dependent variable is the overnight-intraday reversal strategy return on day t ($CO\text{-}OC_t$). The portfolio weight for $CO\text{-}OC_t$ is based on the rank of the overnight return. That is, $w_{i,t-1} = -(Rank_{i,t-1} - \overline{Rank}_{t-1})/N$, where $Rank_{i,t-1}$ is the rank of $r^{co}_{i,t-1}$ among the N assets available at time t-1, and $\overline{Rank}_{t-1}$ is the mean of $Rank_{i,t-1}$. The rank for the asset with the lowest (highest) overnight return is 1 (N). The predictor variables include the lagged return dispersion measure, $Dispersion_{t-1}$, defined as the cross-sectional volatility of the overnight return $r^{co}_{i,t-1}$ on day $t-1$, the lagged VIX on day $t-1$ (VIX_{t-1}), and the lagged overnight-intraday strategy return on day $t-1$ ($CO\text{-}OC_{t-1}$). We also include the lagged Baker and Wurgler (2006) sentiment index in the previous month ($Sentiment_{m-1}$), where m is the month that day t belongs. We report the regression coefficients and the associated Newey-West t-statistics (in parentheses).

	Panel A: Equity indices				Panel B: Interest rates			
$Dispersion_{t-1}$	0.797***			0.693***	0.457***			0.457***
	(16.55)			(13.26)	(3.62)			(3.60)
$VIXt-1$		1.719***		0.647***		0.054		0.048
		(10.12)		(3.64)		(0.62)		(0.53)
$Sentiment_{m-1}$			-0.656*	0.056			-0.054	0.073
			(-1.85)	(0.17)			(-0.27)	(0.35)
$CO\text{-}OC_{t-1}$	0.026	0.023	0.074***	0.013	-0.023	-0.020	-0.020	-0.023
	(1.44)	(1.22)	(3.58)	(0.74)	(-1.16)	(-1.03)	(-1.02)	(-1.17)
constant	0.029**	-0.102***	0.188***	-0.061**	0.017**	0.024	0.033***	0.010
	(2.10)	(-3.48)	(15.46)	(-2.24)	(2.48)	(1.59)	(4.99)	(0.63)
R^2	10.15%	5.16%	0.58%	10.59%	0.46%	0.01%	-0.01%	0.41%

	Panel C: Commodities				Panel D: Currencies			
$Dispersion_{t-1}$	0.197***			0.197***	0.212*			0.205*
	(3.80)			(3.78)	(1.85)			(1.80)
$VIXt-1$		0.061		0.004		0.060		0.012
		(0.23)		(0.01)		(0.51)		(0.10)
$Sentiment_{m-1}$			-0.441	-0.383			-0.206	-0.110
			(-0.57)	(-0.49)			(-0.72)	(-0.37)
$CO\text{-}OC_{t-1}$	0.039**	0.039**	0.039**	0.038**	-0.041**	-0.040**	-0.040**	-0.041**
	(2.12)	(2.14)	(2.14)	(2.11)	(-2.14)	(-2.11)	(-2.10)	(-2.15)
constant	0.094***	0.166***	0.169***	0.087*	0.023**	0.029	0.036***	0.019
	(3.57)	(3.36)	(7.33)	(1.67)	(2.25)	(1.46)	(4.48)	(0.92)
R^2	0.68%	0.10%	0.11%	0.63%	0.26%	0.12%	0.12%	0.21%

Table A.9: Strategy performance and news announcements: additional results

This table reports the mean return and the associated t-statistic (in parentheses) for the reversal strategies under various news announcements. Panel A reports the results for FOMC announcements. Panel B reports the results for the announcements of nonfarm payrolls, PCE and PMI. The strategies are rebalanced daily, and returns are expressed in percent per day.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
Panel A: FOMC announcements								
	Equity indices				Interest rates			
Announcement	0.231	0.288	0.054	0.146	0.083	0.054	0.128	0.003
	(1.88)	(2.56)	(0.77)	(1.88)	(1.26)	(1.35)	(2.14)	(0.07)
Non-announcement	0.048	0.161	0.018	0.240	0.011	0.022	0.002	0.050
	(3.41)	(7.56)	(1.31)	(15.74)	(1.35)	(2.45)	(0.33)	(7.40)
Difference	0.182	0.126	0.036	-0.094	0.071	0.032	0.125	-0.046
	(1.71)	(1.51)	(0.42)	(-1.22)	(0.97)	(0.62)	(1.86)	(-1.01)
	Commodities				Currencies			
Announcement	-0.086	0.050	-0.255	0.352	0.118	-0.005	0.136	0.092
	(-0.93)	(0.52)	(-2.49)	(2.95)	(1.59)	(-0.10)	(1.81)	(1.71)
Non-announcement	-0.098	-0.034	-0.179	0.280	0.017	0.016	0.000	0.051
	(-3.90)	(-1.28)	(-7.70)	(12.62)	(1.70)	(1.60)	(0.08)	(6.47)
Difference	0.012	0.085	-0.075	0.071	0.101	-0.022	0.135	0.040
	(0.10)	(0.61)	(-0.61)	(0.59)	(1.69)	(-0.31)	(2.25)	(0.81)
Panel B: Other announcements								
	Equity indices				Interest rates			
Announcement	-0.033	0.119	-0.038	0.289	0.028	0.018	0.014	0.095
	(-0.92)	(2.15)	(-1.15)	(7.02)	(1.01)	(0.58)	(0.50)	(4.30)
Non-announcement	0.067	0.172	0.027	0.229	0.012	0.023	0.005	0.042
	(4.15)	(7.61)	(1.80)	(14.63)	(1.32)	(2.49)	(0.66)	(5.96)
Difference	-0.101	-0.053	-0.066	0.059	0.015	-0.005	0.008	0.053
	(-2.58)	(-1.04)	(-1.70)	(1.69)	(0.50)	(-0.18)	(0.25)	(2.27)
	Commodities				Currencies			
Announcement	-0.138	-0.125	-0.206	0.217	-0.021	-0.034	-0.046	0.029
	(-1.64)	(-1.37)	(-2.72)	(3.70)	(-0.72)	(-1.25)	(-1.54)	(1.18)
Non-announcement	-0.092	-0.018	-0.178	0.293	0.026	0.023	0.012	0.056
	(-3.51)	(-0.62)	(-7.31)	(12.52)	(2.47)	(2.14)	(1.21)	(6.58)
Difference	-0.046	-0.107	-0.027	-0.075	-0.047	-0.057	-0.059	-0.026
	(-0.53)	(-1.17)	(-0.37)	(-1.18)	(-1.50)	(-1.84)	(-1.84)	(-1.00)

Table A.10: Strategy performance in international stock markets: only the largest 50% stocks

This table reports the summary statistics of strategies in international stock markets for the stocks whose market capitalization falls within the largest 50%. The strategies are rebalanced daily, and returns are expressed in percent per day. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (%), the skewness, the kurtosis, the annualized Sharpe ratio (SR), and the sample correlation between the *CO-OC* and other strategies.

	CC-CC	*OO-OO*	*OC-OC*	*CO-OC*	*CC-CC*	*OO-OO*	*OC-OC*	*CO-OC*
	Panel A: US				Panel B: UK			
mean	0.115	0.308	-0.120	0.963	0.033	0.296	-0.656	1.311
t-stat	9.222	21.422	-12.176	31.776	2.156	17.035	-24.922	42.672
sdev	0.725	0.750	0.608	0.933	0.857	0.892	0.919	0.975
skew	-0.097	0.364	-0.170	0.461	-0.074	0.149	-1.343	0.968
kurt	5.218	5.208	5.383	3.115	4.539	4.151	6.074	4.209
SR	2.528	6.516	-3.136	16.390	0.609	5.269	-11.333	21.342
corr	0.164	0.226	-0.110	1.000	0.008	0.160	-0.307	1.000
	Panel C: Japan				Panel D: France			
mean	0.108	0.332	-0.012	0.626	0.175	0.504	-0.290	1.159
t-stat	8.500	24.050	-1.828	41.182	15.374	32.403	-31.229	52.654
sdev	0.752	0.810	0.518	0.597	0.697	0.820	0.561	0.806
skew	-0.263	0.615	0.190	1.181	-0.084	0.772	-0.093	1.092
kurt	5.264	5.575	4.895	5.448	3.860	5.151	4.314	4.980
SR	2.271	6.509	-0.374	16.651	3.985	9.756	-8.220	22.813
corr	0.238	0.174	0.201	1.000	0.116	0.207	-0.060	1.000

Table A.11: *CO-OC* and return dispersion: international stock markets

In the regressions, the dependent variable is the overnight-intraday reversal strategy return on day t ($CO\text{-}OC_t$). The predictor variables include the lagged return dispersion measure, $Dispersion_{t-1}$, defined as the cross-sectional volatility of the overnight return $r^{co}_{i,t-1}$ on day $t-1$, the lagged VIX on day $t-1$ (VIX_{t-1}), and the lagged overnight-intraday strategy return on day $t-1$ ($CO\text{-}OC_{t-1}$). We also include the lagged Baker and Wurgler (2006) sentiment index in the previous month ($Sentiment_{m-1}$), where m is the month that day t belongs. We report the regression coefficients and the associated Newey-West t-statistics (in parentheses).

	Panel A: US				Panel B: UK			
$Dispersion_{t-1}$	0.880***			0.950***	0.226***			0.146***
	(30.42)			(31.92)	(8.86)			(3.74)
VIX_{t-1}		0.524***		-0.964***		1.600***		0.940***
		(4.13)		(-7.40)		(9.33)		(3.61)
$Sentiment_{m-1}$			1.941***	-0.347**			-0.271	-0.592***
			(11.03)	(-2.02)			(-1.39)	(-2.95)
lagged return	0.254***	0.651***	0.612***	0.241***	0.512***	0.505***	0.535***	0.501***
	(13.30)	(45.16)	(41.74)	(12.51)	(30.28)	(28.37)	(30.60)	(28.45)
constant	-0.103***	0.454***	0.597***	0.002	0.398***	0.372***	0.642***	0.335***
	(-5.15)	(17.07)	(25.93)	(0.09)	(11.94)	(11.08)	(26.36)	(9.58)
R^2	57.59%	43.42%	44.76%	58.09%	29.95%	30.06%	28.71%	30.23%

	Panel C: Japan				Panel D: France			
$Dispersion_{t-1}$	0.582***			0.506***	0.547***			0.453***
	(26.53)			(19.57)	(23.33)			(16.78)
VIX_{t-1}		2.944***		1.162***		2.974***		1.727***
		(20.51)		(7.94)		(20.51)		(12.07)
$Sentiment_{m-1}$			0.392***	-0.312***			1.069***	-0.202
			(3.64)	(-2.69)			(6.72)	(-1.20)
lagged return	0.205***	0.297***	0.475***	0.172***	0.219***	0.258***	0.391***	0.168***
	(11.50)	(15.75)	(27.64)	(9.68)	(12.87)	(14.26)	(22.02)	(9.67)
constant	-0.213***	0.023	0.435***	-0.289***	-0.039	0.225***	0.643***	-0.163***
	(-9.43)	(1.17)	(29.30)	(-12.51)	(-1.29)	(9.42)	(35.53)	(-4.83)
R^2	41.46%	32.67%	23.02%	42.66%	30.01%	25.38%	17.56%	32.61%

Table A.12: Daytime reversal effects in global stock markets

This table examines the daytime reversal effects of Akbas et al. (2022) in four major global stock markets at the monthly frequency. A negative (positive) daytime reversal is defined as a positive (negative) overnight return followed by a negative (positive) intraday return. The frequency of negative daytime reversal ($NR_{i,t}$) is defined as the ratio of the number of days with negative daytime reversals to the number of trading days in that month. The abnormal frequency of negative daytime reversal ($AB\_NR_{i,t}$) is $NR_{i,t}$ scaled by the average $NR_{i,t}$ over the prior 12 months. The abnormal frequency of positive daytime reversal ($AB\_PR_{i,t}$) is defined similarly. We then form a strategy based on the abnormal frequency, where the formation period return in Eq (1) is placed by the abnormal frequency of daytime reversal to determine the portfolio weight, and the holding period return is the return in the next month. Panel A and Panel B reports the summary statistics for the negative and positive daytime reversal strategies, respectively. The strategies are rebalanced monthly, and the returns are expressed in percent per month. The table reports the mean return (in %), Newey-West t-statistic, the standard deviation (in %), the skewness, the kurtosis, and the annualized Sharpe ratio (SR).

	US	UK	Japan	France
Panel A: Negative daytime reversal				
mean	-0.532	0.162	-0.265	-0.298
t-stat	-5.975	0.831	-4.187	-3.220
sdev	1.258	3.169	1.228	1.669
skew	-0.525	0.031	-0.518	-0.682
kurt	9.689	6.746	6.200	6.364
SR	-1.465	0.177	-0.749	-0.619
Panel B: Positive daytime reversal				
mean	0.326	0.184	0.296	-0.107
t-stat	4.232	1.031	4.384	-0.996
sdev	1.251	3.151	1.196	1.664
skew	1.049	-0.380	0.315	-0.077
kurt	8.469	6.741	5.300	4.156
SR	0.902	0.202	0.856	-0.222