Market Closure and Short-Term Reversal*

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Abstract

A strategy that holds daily long and short positions, respectively, in assets with low and high past overnight returns – overnight-intraday reversal strategy - generates for the US stock market an average excess return that is five times larger when compared to a conventional short-term reversal strategy. Our results remain robust to using international stocks as well as equity index, interest rate, commodity, and currency futures. We find that overnight-intraday reversals are consistent with the simulated patterns generated by the continuous-time model with periodic market closures of Hong and Wang (2000). Finally, we demonstrate that only intraday returns matter for the reversal-based liquidity measure of Pastor and Stambaugh (2003).

Keywords: Short-term reversal, Liquidity, Market closure

JEL Classification: G11, G12, G15, G20

1 Introduction

Financial markets are typically closed overnight and during a weekend. These periodic closures affect trading conditions as non-trading hours are characterized by low trading activity and low liquidity (Barclay and Hendershott, 2003, 2004). Among the several anomalies, a short-term reversal strategy that buys past loser and sells past winner stocks (Jegadeesh, 1990; Lehmann, 1990), is theoretically and empirically linked to liquidity (Grossman and Miller, 1988; Campbell, Grossman, and Wang, 1993; Avramov, Chordia, and Goyal, 2006), and the return of this strategy is used as a proxy for profit from liquidity provision (Nagel, 2012). The different liquidity conditions in these two periods highlight the necessity of investigating the effects of market closures on short-term reversal.

The short-term reversal strategy has been explored at various frequencies: daily, weekly and monthly.[1] The failure of the monthly short-term reversal strategy to deliver positive return in stock market in recent decade coincides with market technology advancement and market microstructure development, and it also indicates improved liquidity provision activity. Hendershott and Menkveld (2014) measure the price pressures induced by risk-averse market makers supplying liquidity to asynchronously arriving investors. They show that based on New York Stock Exchange data, the price pressure is 0.49% on average with a half life of 0.92 days. In addition, the liquidity measure of Pastor and Stambaugh (2003) relies on the daily reversals. Therefore, analysing short-term reversal in daily, even in intra-daily frequency allows to better capture the liquidity effect.

In addition, the reversal strategy has been widely examined in United States, but there is little or no research on international stock, equity index, interest rate, commodity and currency markets. The extension of the analysis to international stock markets and other asset classes is of interest for several reasons. On one hand, it provides robustness test to the empirical findings and theoretical models in United States, especially in more recent and liquid stock samples. On the other hand, the analysis of short-term reversal on very liquid markets (equity index, interest rate, commodity and currency futures markets) provides useful insights for the research on liquidity.

The theoretical motivation of short-term reversal is from Grossman and Miller (1988) in which

[1] There is a broad literature that documents short-term reversal effects using monthly (e.g., Jegadeesh, 1990; Da, Liu, and Schaumburg, 2013; Hameed and Mian, 2015), weekly (e.g., Jegadeesh, 1990; Avramov, Chordia, and Goyal, 2006), and daily (e.g., Nagel, 2012; So and Wang, 2014; Collin-Dufresne and Daniel, 2013) returns.

risk-averse market makers demand compensation for providing liquidity. They also discuss different market structures of futures market and stock market, and the high demand for immediacy of futures market causes the market to be designed to supply maximal immediacy of order execution, especially at the open. Therefore, the illiquidity effect, measured by short-term reversal, is absent or trivial in futures market. Based on the model of Kyle (1985) and Grossman and Miller (1988), Nagel (2012) shows that the short-term reversal strategy is highly predictable by the VIX index, which is commonly used to measure the market-wide uncertainty level. Financial intermediaries' activities are limited and constrained when the market volatility is high (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010), so the liquidity provision is limited.

The market opens and closes are the most specific points in the intra-daily periods. Amihud and Mendelson (1987) document that open-to-open returns have higher variance and more negative serial autocorrelation than close-to-close returns, which result from different trading mechanisms at the open and close. Consistent with the literature, we denote the trading hours as the intraday period and the non-trading hours as the overnight period[2]. Stoll and Whaley (1990) find a high negative overnight-intraday serial autocorrelation and argues that it indicates a high profit of liquidity provision at the open. We extend the work by Stoll and Whaley (1990) to check the economic value of the negative serial autocorrelation, and show it measures more than the implied bid-ask spread. Furthermore, the issue of errors in open prices in Stoll and Whaley (1990) is mitigated in our paper, since we use samples in more recent period and also analyze subsample of large and liquid stocks (for instance, S&P100 stocks) or futures data.

The market open[3] is the time of interest, since liquidity provision is more likely to happen during trading hours, while the time after close typically with little (stock markets) or no (futures markets) trading volume. The market open has the highest uncertainty level measured by the realized volatility as in Barclay and Hendershott (2003), and also by the VIX index level shown in this paper, which a forward-looking measure. The high volatility at the open potentially results from information asymmetry or high informationless trading shocks. The high asymmetric

[2]In weekly frequency, the intraday period is the weekday, and the overnight period is the weekend.

[3]A lot of papers have examined the microstructure issues at market open and the preopening time. However, the microstructure of the stock and other asset markets are quite different, for instance, as discussed by Grossman and Miller (1988) for futures and stock. We only focus on the most common features: the open and close of the markets, and the high uncertainty at the open.

information in pre-open period may also exaggerates the price impact induced by adverse selection problem. However, the price impact of private information is permanent and does not induce short-term reversal (Glosten and Milgrom, 1985), which instead captures the transitory component. Due to the high uncertainty level, the downward-sloping demand curves become steep for the increasing inventory risks faced by the market makers at the open, thus the liquidity provisions ask for high compensation. Focusing on the open time at the expiration days of index futures contracts, when there are large order imbalances in the underlying stocks caused by largely informationless liquidity shocks, Barclay, Hendershott, and Jones (2008) show that there are large excess volatility and overnight-intraday reversal.

The market opens and closes are perfectly anticipated and repeated events, which will affect short-term reversals. So and Wang (2014) study short-term reversal during earning announcements and find that market makers demand high compensation prior to announcements because of the increasing inventory risks that induced by the uncertainty of anticipated information event. Lou, Yan, and Zhang (2013) show that Treasury security prices in the secondary markets significantly decrease before Treasury auctions and recover thereafter, even though these events are perfectly anticipated. They confirm that the dealers' limited risk-bearing capacity and the imperfect capital mobility explain the reversal in this very liquid market. In this paper, instead of focusing only on the earning/auction announcement window, we show that it is a story that repeated in daily frequency. The general market makers anticipate high uncertainty level during the open, which implies high inventory risks of holding stocks.

Our findings can be summarized as follows. Firstly, in US stock market, both the return and Sharpe ratio of the reversal strategy that takes into account the different conditions in trading and non-trading hours (overnight-intraday reversal, denoted as *CO-OC* strategy thereafter) are on average five times in magnitude of the conventional reversal strategy, and the pattern is consistently present over time. In addition, the short-term reversal strategy achieves better performance based on open-to-open returns than close-to-close returns, which is consistent with the serial autocorrelation tests in Amihud and Mendelson (1987). Using the autocorrelation regression, we find that the 39% (25%) of the overnight return will reverse in the later (first) intraday periods, while the number for intraday return is only 2%.

Secondly, we document that a similar short-term reversal effect exists across international stock, equity index, interest rate, commodity and currency markets. This result is novel to the best of our knowledge. On one hand, international stock markets have the same pattern of short-term reversal as in US stock market. On the other hand, we find no evidence of short-term reversal of the conventional strategy from the interest rate, commodity and currency markets, consistent with the arguments in Grossman and Miller (1988). Specifically, in commodity market, there is a clear signal of daily momentum (Baltas and Kosowski, 2011), instead of short-term reversal. In contrast, the *CO-OC* strategy delivers positive and significant returns across all of these asset classes, and outperforms the other three short-term reversal strategies, both in daily and weekly frequency.

Thirdly, extending the analysis in Nagel (2012), we find that the increment of the uncertainty during the non-trading hours (change of VIX from the last close to open) adds explanatory power for the returns of *CO-OC* strategies in different equity markets and other asset classes, aside from the uncertainty at the market close. Besides, we empirically confirm that the VIX level at the open is significantly higher than any other time, the average VIX level is 20.37 around the market open window, while the average level is 20.21 in other time, and the difference is significant with a Newey-West adjusted t-statistic of 5.42, based on the sample from January 1993 to December 2013.

Fourthly, based on the continuous-time model with periodic market closures in Hong and Wang (2000), we show that overnight-intraday reversal pattern is consistent with an equilibrium in a market periodically closed. In the model, the investors have periodic trading behaviors due to the exogenous market closures. The two investors use stock to hedge their private investment opportunities[4], which have correlated payoffs with stock. In equilibrium, the investors' optimal hedging demands are time-varying, due to the anticipated market open and close. The stock price has higher exposure to the liquidity shocks at the open than at the close, since the investors could trade stock to hedge the private investment after the open, when the accumulated trading demand during the closure period is released. The higher exposure to the private investment at the open induces higher return variance. Based on the simulated results, we confirm that the empirical results are consistent with the model's implication. In addition, changing the parameters related to liquidity shocks supports the predication that the hedging demands induce overnight-intraday

[4]This specification of the model allows for generating the hedging demand of the investors.

reversals.

Lastly, the diverse patterns of overnight and intraday returns have implications for the reversal-based market liquidity measure in Pastor and Stambaugh (2003). Following the steps in their paper, we form the tradable long-short portfolios based on the stocks' exposure to the historical liquidity measures. The tradable factor based on intraday return liquidity measure captures the return of the original Pastor and Stambaugh (2003) liquidity factor, while the overnight part shows insignificant return. For the market liquidity measure, the intraday return element is the important component. The overnight-intraday reversal is more likely induced by firm specific liquidity characteristics.

Literature

In addition to the literature mentioned above, our paper is related to the broad researches that explore short-term reversal in stock market. Jegadeesh and Titman (1995) show that the pattern of short-term negative serial autocorrelation for stock returns is consistent with the implications of inventory-based microstructure models. Empirically, Conrad, Hameed, and Niden (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, Gultekin, and Kaul (1997) suggest that much of the reversal profitability is within the bid-ask bounce.

More recently, Hameed and Mian (2015) document pervasive evidence of intra-industry reversal in monthly returns, and intra-industry reversal is larger in magnitude than conventional reversal strategy and persistent over time. Da, Liu, and Schaumburg (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.

Through decomposing the daily return into overnight and intraday returns, Lou, Polk, and Skouras (2015) show that all of the abnormal returns on momentum strategy occur during the non-trading period, while other anomalies' returns are accumulated during the trading period. In monthly frequency, they also show a long-short portfolio in the past one month overnight returns has a three-factor overnight alpha of 3.47% per month and a three-factor intraday alpha of -3.02% per month. We differ from them in several aspects. Firstly, using daily and weekly frequency allows better understanding of the short term reversal effects. Secondly, we provide similarly short-term reversal patterns comprehensively across international stock markets and other asset classes. Based on 48,000 stocks from 35 countries including US, Aretz and Bartram (2015) extend the work of Lou, Polk, and Skouras (2015), and show that most well-known anomalies, including momentum, have positive returns over the trading period.

Our work also relates to the recent studies on global asset pricing. Fama and French (2012) study the returns to size, value, and momentum in individual stocks across global equity markets and find consistent risk premia across different markets. Koijen, Moskowitz, Pedersen, and Vrugt (2013) document global "carry" returns, which predict returns both in the cross section and time series for a variety of different asset classes including global equities, global bonds, commodities, US Treasuries, credit, and options. Moskowitz, Ooi, and Pedersen (2012) demonstrate global evidence of time series momentum strategy that using each asset's own past returns. Time series momentum is significantly different from the cross-sectional momentum strategies. Asness, Moskowitz, and Pedersen (2013) find consistent value and momentum return premia across eight diverse markets and asset classes, and present a common factor structure among their returns.

2 Data and Methodology

This section describes the data on international stock markets as well as futures contracts on different asset classes employed in our empirical analysis. We also summarize the data on exchange traded funds and volatility indices used as robustness checks. Finally, we define a short-term reversal strategy that uses overnight (or close-to-open) returns as formation period returns and the next following intraday (or 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 will provide a statistical and an economic evaluation of these strategies in the next section.

International Stocks. We collect daily open and close prices ranging from January 1993 to December 2014 for the following stock markets: the US, continental Europe (France and Germany), Japan and the UK. 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. In order 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 countries, we source daily open and close prices from Datastream and employ the same filtering rules applied to US stocks.

As a robustness check, we also collect the best bid and offer quotes at the open and minute level trade prices from Trade and Quote (TAQ) database from January 2011 to December 2014 for a subsample of US stocks.

Futures Contracts. We obtain from TickData daily open and close prices on 35 futures contracts traded on Chicago Mercantile Exchange. The sample ranges from July 1982 to December 2014[5] and consists of futures written on 5 equity indices (DJIA, NASDAQ, NIKKEI 225, S&P400 and S&P500), 11 interest rates (30-day Federal Funds, Eurodollar CME, LIBOR 1-month, Municipal Bonds, T-Bills, 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), 11 commodities (Corn, Ethanol CBOT, Lumber, Live Cattle, Lean Hogs, Oats, Pork Bellies, Rough Rice, Soybean Meal, Soybeans, Wheat CBOT) and 9 currencies (Australian dollar, British pound, Canadian dollar, Deutsche mark, 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, Nijman, and Veld (2000) and Moskowitz, Ooi, and Pedersen (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 and a rollover takes place.[6]

Exchange Traded Funds. We collect daily open and close prices on equity index, government bond, commodity and currency exchange traded funds (ETF) from March 1999 to December 2014. ETFs on equity indices (identified by the following tickers: IVV, IJH, IWB, IWM, IWV, OEF, and QQQ), government bonds (AGZ, GOVT, IEF, IEI, SHV, SHY, STIP, TFLO, TLH, TLT, TIP), commodities (CMDT, COMT, FILL, GSG, IAU, PICK, RING, SLV, SLVP, VEGI) and currencies (DBV, EUO, FXA, FXC, FXE, FXF, FXY, USDU, UUP, YCS) from CRSP. For the first three asset classes, we use ETFs issued by iShares except QQQ. For the currency ETFs, we select funds with assets under management higher than $100 millions from various providers.

[5]Not all futures contracts start from July 1982.

[6]Our findings are robust to using front contracts and futures contracts in other international exchanges. Results are available upon request.

Volatility Index and Futures. We obtain data on volatility indices from Chicago Board Options Exchange. The sample consists of the S&P500 volatility index (VIX), S&P100 volatility index (VXO), NASDAQ volatility index (VXN) and the DJIA volatility index (VXD). From the same source, we also collect open and close prices for VIX futures contracts. The EURO STOXX 50 volatility (VSTOXX), Nikkei stock average volatility index (VNKY) and FTSE 100 implied volatility index (IVI) are from Bloomberg.

Short-term reversal strategy. We construct our short-term reversal strategy as in Lehmann (1990), Jegadeesh and Titman (1995) and Nagel (2012). We consider a zero-investment portfolio strategy where the portfolio weight on asset i at time $t-1$ is given by

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

where $r_{i,t-1}$ denotes the discrete return on the asset i at time $t-1$, $\overline{r}_{t-1} = N^{-1}\sum_{i=1}^{N} r_{i,t-1}$ is the equally-weighted average return on all assets N available at time $t-1$. This strategy is by construction a contrarian strategy as it sells past winners and buys past losers, and is zero-investment strategy as $\sum_{i=1}^{N} w_{i,t-1} = 0$. The portfolio returns are then computed assuming a 50% margin position as in Lehmann (1990) and Nagel (2012)

$$r_{p,t} = \frac{\pi_t}{d_{t-1}/2}. \tag{2}$$

where $\pi_t = \sum_{i=1}^{N} w_{i,t-1} r_{i,t}$ 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 differently uses overnight returns as signals and then realizes 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

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

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

$$r_{i,t}^{co} = \frac{P_{i,t}^{o}}{P_{i,t-1}^{c}} - 1 \quad (4)$$

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

$$r_{i,t}^{oc} = \frac{P_{i,t}^{c}}{P_{i,t}^{o}} - 1. \quad (5)$$

such that $r_{i,t}^{cc} \approx r_{i,t}^{co} + r_{i,t}^{oc}$. The traditional short-term reversal strategy uses $r_{i,t-1}^{cc}$ for the portfolio weights in Equation (1) and $r_{i,t}^{cc}$ for the portfolio return in Equation (2). Our short-term reversal strategy, instead, uses $r_{i,t}^{co}$ for the portfolio weights in Equation (1) and $r_{i,t}^{oc}$ 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 as robustness: a strategy labeled as *OC-OC* that uses $r_{i,t-1}^{oc}$ for the portfolio weights and $r_{i,t}^{oc}$ for the portfolio return, and a strategy identified as *OO-OO* that employs $r_{i,t-1}^{oo}$ for the portfolio weights and $r_{i,t}^{oo}$ for the portfolio return with $r_{i,t}^{oo} = (P_{i,t}^{o}/P_{i,t-1}^{o}) - 1$ 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.[7] We summarize these strategies in Table 1.

3 Empirical Evidence on Short-term Reversal Strategies

This section presents the empirical evidence on four different short-term reversal strategies implemented using international stock returns as well as returns on equity index, interest rate, commodity and currency futures. We complement our core analysis with a battery of robustness exercises.

[7] We do not present results for (i) a purely overnight reversal strategy 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 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 to trade overnight when liquidity is tiny and transaction costs are fairly prohibitive.

International Equities. We form the short-term reversal strategies described in Table 1 using international stock market returns and present them in Table 2. The top right panel of this table shows the empirical evidence for the United States. 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 next 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 0.33% per day (with a t-statistic of 16.57) for the United States, in line with the 0.3% per day reported in Nagel (2012). A related version of this strategy – labeled as *OO-OO* – employs open-to-open returns as opposed to close-to-close returns and generates a similar but more pronounced pattern since the average return is 0.63% per day (with a t-statistic of 28.09) and the annualized Sharpe ratio is 9.96, close to double the Sharpe ratio of 5.52 granted by the *CC-CC* strategy.

Both variants of the short-term reversal strategy discussed above implicitly aggregate overnight and intraday information. Furthermore, we decompose the overall (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 with these returns. 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 next 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 negative returns of -0.17% per day (with a t-statistic of -14.65) and suggests the presence of a fairly strong intraday momentum effect. We then examine a naive overnight-intraday reversal strategy that uses information accumulated overnight as trading signals (i.e., buying overnight losers and selling overnight winners) and the next following intraday returns for the accounting profit. The former set of returns are measured at the beginning of day t using close-to-open returns whereas the latter set of returns are observed at the end of day t using open-to-close returns. This strategy, identified as *CO-OC*, earns a large average return that is about 1.68% per day (with a t-statistic of 46.52). As a comparison, recall that the CRSP value-weighted index for the same sample period generates a mean return of 0.04% per day with a standard deviation of 1.16%. Overall, the overnight-intraday reversal strategy exhibits roughly the same volatility as the traditional short-term *CC-CC* strategy but a way larger return; this translates into a Sharpe ratio of 24.16 that almost five times larger.

It is worth to notice that all short-term reversal strategies display positive skewness thus implying that downside or crash risk is not a plausible explanation. In particular, the overnight-intraday *CO-OC* strategy presents positive returns within the $5th$-$95th$ percentile range. We also find that returns exhibit strong and persistent serial correlation, especially for the *CO-OC* strategy, which implies that there are potential high fixed costs (for instance, bid-ask spread) embedded in the returns. Finally, the overnight-intraday reversal strategy is fairly uncorrelated with the traditional short-term reversal strategies as its sample correlation evolves around 25%.

Turning to other stock markets, the empirical evidence reveals that the traditional *CC-CC* reversal strategy displays sizeable returns for both Continental Europe (0.23% per day with a Sharpe ratio of 4.02) and Japan (0.26% per day with a Sharpe ratio of 4.55) but generates negative returns for stocks traded in London (−0.24% per day with a Sharpe ratio of −3.30). The purely intraday return short-term reversal strategy *OC-OC* produces negative returns for stocks traded in Continental Europe (−0.21% per day with a Sharpe ratio of −4.63) and the United Kingdom (−0.66% per day with a Sharpe ratio of −9.67) but positive returns for stocks traded in Tokyo (0.04% per day with a Sharpe ratio of 0.70). These results, taken together, reveal mixed evidence for both traditional short-term reversal strategies and intraday momentum patterns. The overnight-intraday reversal strategy, instead, is characterized by a large and positive profitability in all stock markets: the return is about 1.02% per day with a Sharpe ratio of 16.79 in Continental Europe, 0.74% per day with a Sharpe ratio of 16.25 in Japan, and 1.94% per day with a Sharpe ratio of 17.41 in the United Kingdom.

Exchange traded futures. In addition to using international stock markets, we also examine the profitability of short-term reversal strategies for exchange traded futures on equity indices, interest rates, commodities and currencies. These results are reported in Table 3. The summary statistics for short-term reversal strategies implemented using equity index futures are reported in top right panel and remain fairly comparable with the previous table. The result for traditional *CC-CC* strategy as expected is both economically and statistically significant since it earns an average return of 0.08% per day (with a t-statistic of 5.20) and an annualized Sharpe ratio of 1.15. The *OO-OO* strategy tends to perform better as it yields an average return of 0.20%

per day (with a t-statistic of 9.36) and an annualized Sharpe ratio of 2.43. The profitability of these conventional strategies, however, is largely outperformed by the overnight-intraday reversal strategy which delivers an average return of 0.25% per day (with a t-statistic of 13.18) and an annualized Sharpe ratio of 4.08. Yet, its sample correlation with the other three strategies remain extremely low, ranging from 1% to 4%.

For futures contracts written on other asset classes, the traditional short-term reversal strategy *CC-CC* produces either negative returns (interest rate and commodity futures) or low and insignificant returns (currency futures). The performance of the related *OO-OO* strategy is positive for interest rate and currency futures but insignificant for commodity futures. While results for conventional short-term reversal strategies are mixed, the overnight-intraday strategy continues to deliver economically and statistically significant returns across all futures contracts considered in this paper. We find an average return of 0.06% per day (with a t-statistic of 11.85) and an annualized Sharpe ratio of 2.20 for interest rate futures, an average return of 0.17% per day (with a t-statistic of 10.84) and an annualized Sharpe ratio of 1.93, and an average return of 0.04% per day (with a t-statistic of 6.76) and an annualized Sharpe ratio of 1.26. Skewness, moreover, is positive for interest rate and commodity futures but slightly negative for currency futures. Finally, the sample correlations confirm that *CO-OC* is fairly uncorrelated with the other strategies.

Robustness check I: subperiods. In Table 4, we split the entire sample in two subperiods and examine the statistical properties of the short-term reversal strategies before and after (includes) the recent financial crisis. The first subperiod ranges from January 1993 (July 1982) to December 2006 for international stocks (exchange traded futures) whereas the second subperiod ranges from January 2007 to December 2014 for both international stocks and exchange traded futures.

Our findings are easy to summarize as the *CO-OC* strategy consistently outperforms all other strategies in both subperiods for all international stock markets and exchange traded futures. This suggests that the overnight-intraday reversal pattern is not purely driven by large price adjustments and has not disappeared in the second period. For international stock markets, the annualized Sharpe ratio of the *CO-OC* strategy ranges between 26.20 and 33.34 for the first period, and between 11.46 and 21.71 for the more recent sample. For exchange traded futures, the annualized Sharpe ratio ranges between 1.26 and 2.51 for the early period, and between 1.30 and 6.68 for the later sample. The evidence in favor of the traditional *CC-CC* strategy is weak as returns are statistically significant for both subperiods only for equity markets in US and Europe. The related *OO-OO* strategy performs marginally better as it works for all equity markets but it fails to maintain the same pattern for exchange traded futures.

Robustness check II: subsamples. Avramov, Chordia, and Goyal (2006) find that illiquid stocks account for most of the profitability of the short-term reversal strategy. We check the robustness of our findings by performing the following exercises. Firstly, we split the sample of US stocks in two groups using the median value of their market capitalizations, and refer to them as small stocks (i.e., the bottom 50% of the stocks based on market capitalization) and large stocks (i.e., the top 50% of the stocks based on market capitalization). In the second exercise, we only consider the stocks underlying two representative stock market indices – the S&P500 and S&P100 index – as they are widely recognized as the most liquid stocks for the US equity market.

We report these robustness checks in Table 5, and find in line with Avramov, Chordia, and Goyal (2006) that the profits of the traditional *CC-CC* strategy are mainly concentrated in low liquidity stocks: the risk-adjusted profitability as measured by the annualized Sharpe ratio is high for small stocks (9.34), it falls dramatically for large stocks and S&P500 stocks (slightly above 1.00), and becomes economically small for S&P100 stocks (0.47). The *OO-OO* strategy displays a similar pattern as it earns an annualized Sharpe ratio o 14.72 for small stocks which then decline to 2.18 for the most liquid S&P100 stocks. The overnight-reversal strategy, in contrast, remains both statistically and economically the best performing short-term reversal strategy even after controlling for low liquidity stocks, with an annualized Sharpe ratio ranging between 29.91 for small stocks and 4.07 for the S&P100 stocks. Interestingly, the correlation between the *CO-OC* strategy and the conventional *CC-CC* strategy is about 37% for the low liquidity stocks and 5% for the high liquidity stocks in the S&P100. Overall, our findings seem to suggest that the performance of the *CO-OC* strategy is not entirely driven by illiquid stocks.

Robustness III: bid-ask bounce. Conrad, Gultekin, and Kaul (1997) demonstrate that the profits from short-term price reversals are predominantly driven by the negative serial covariance induced by bid-ask bounce in prices. The profits disappear when the strategy is replicated using solely bid prices. We account for the bid-ask bounce by collecting bid and ask quotes for large and liquid stocks (i.e., the S&P500 constituents) from the TAQ database from January 2011 to December 2014. Armed with this data, we rerun our short-term reversal strategies using in turn bid, ask and mid quotes, and present them in Table 6. Consistent with the findings of Conrad, Gultekin, and Kaul (1997), the profitability of the traditional short-term reversal strategy *CC-CC* becomes insignificant when using bid prices: the average return in Panel A is 0.03% per day (with an associated t-statistic of 1.54) and the annualized Sharpe ratio is 0.51. The profits from the overnight-intraday reversal strategy, conversely, are robust to bid-ask bounce in prices. The *CO-OC* strategy based on bid prices generates an average return of 1.26% per day (with an associated t-statistic of 20.55) and an annualized Sharpe ratio of 19.09. Results remain largely comparable when we use ask (in Panel B) and mid (in Panel C) quotes. Overall, *CO-OC* remains the best performing strategy even after controlling for the bid-ask bounce.

Robustness IV: formation/trading period returns. When we construct the *CO-OC* strategy, the open price on day t enters both the formation period return for the construction of the portfolio weights and the trading period returns for the calculation of the portfolio return. In other words, the strategy may not be implementable in real-time as an investor should observe the open prices, form the signals, and instantaneously sell winners and buy losers at the same prices. To address this concern, we collect from the TAQ database transaction prices at regular intervals around the opening time for the S&P500 stocks, and report the results in Table 7.

In Panel A, our investors observe the prices when the stock market opens at 9.30 am, form the signals and then buy losers and sell winners using the transaction prices available one second after the opening (9.30 am), one minute after the opening (9.31 am), and up to 15 minutes after the opening (9.45 am). The portfolio's return is then measured at the end of the day using the close prices. We find that the average return is about 0.36% per day (with a t-statistic of 10.98) when the trading period starts immediately after 9.30 am, it declines sharply to 0.11% per day (with a t-statistic of 3.81) when the trading period starts at 9.31 am, and then decreases monotonically to 0.04% per day (with a t-statistic of 1.99) when starting at 9.45 am.

In Panel B and Panel C, we repeat the experiment that our investors observe the pre-opening prices available at 9.29 am and 9.25 am, respectively. The trading, however, will take place using the same time-stamps employed in Panel A. The profitability of the *CO-OC* exhibits the same pattern observed in Panel A: the mean return is large when the trading period starts immediately after 9.30 am (0.34% per day with a t-statistic of 10.89 in Panel B and 0.32% per day with a t-statistic of 8.09 in Panel C) but then declines rapidly when the trading period starts at 9.45 (0.04% per day with a t-statistic of 2.03 in Panel B and 0.03% per day with a t-statistic of 1.27 in Panel C). This evidence suggest that i) the strategy can implemented in real-time, and ii) most of its profitability occurs at the opening.

Robustness V: weekly returns. We also consider weekly reversal strategies based on Mondays and Fridays' open and close prices. Specifically, the *CC-CC* (*OO-OO*) strategy uses the close-to-close (open-to-open) returns between two consecutive Mondays to compute the portfolio weights in Equation (1), and the subsequent close-to-close (open-to-open) weekly returns to construct the portfolio excess return in Equation (2). The *OC-OC* (*CO-OC*) strategy employs weekly returns between Monday open and Friday close (Friday close and Monday open) as formation period returns, and the next following Monday open to Friday close returns as trading period returns.

We report summary statics for weekly reversal-strategies based on international stocks in Table 8. The empirical evidence is similar to our core analysis as the *CO-OC* strategy remains the best performing weekly short-term reversal strategy with an annualized Sharpe ratio ranging from 8.02 for the US stock market to 4.48 for the UK stock market, and is largely uncorrelated with its competing strategies. Summary statistics for weekly reversal strategy based on exchange traded futures are presented in Table 9, and the evidence remains qualitatively identical.

Robustness V: news announcements. So and Wang (2014) provide evidence that short-term return reversals are more pronounced during earnings announcements relative to non-announcement periods. Their findings suggest that market makers demand higher compensation prior to earning announcements as they are averse to inventory imbalances and liquidity provision through the release of anticipated earnings news. More recently, Lucca and Moench (2015) find evidence of large excess returns for the US and other major international equity markets in anticipation of monetary policy decisions made at scheduled meetings of the Federal Open Market Committee (FOMC), when the volatility and volume also spike.

Following this literature, we check whether the excess returns of our *CO-OC* strategy are largely earned around the FOMC meetings and report our results in Table 10 for both international stock markets and exchange traded futures. Overall, we find qualitatively no difference between FOMC and non-FOMC announcement days. For instance, the average excess return is 1.60% (1.68%) per day with an annualized Sharpe ratio of 24.58 (24.13) on FOMC (non-FOMC) announcement days when we inspect the *CO-OC* strategy for the US equity market. Similarly, we uncover an average excess returns of 0.21% (0.26%) per day with an annualized Sharpe ratio of 3.06 (4.00) on FOMC (non-FOMC) announcement days when we consider the *CO-OC* strategy for equity index futures.

Additional robustness checks. We examine our main results using a variety of additional data and find no qualitative changes of our findings. We report these additional results in the Internet Appendix: (i) we use volatility indices and volatility futures in Table IA.1; (ii) we employs equity index, interest rate, commodity and currency Exchange Traded Funds (ETFs) in Table IA.2; (iii) we report the average return of *CO-OC* strategy in different calendar day, month and year of the US stock sample in Figure IA.1. In sum, our findings suggest that the reversal strategy based on overnight information (*CO-OC*) has higher return than other reversal strategies. Moreover, the reversal strategy *OO-OO* based on open-to-open returns outperforms the conventional *CC-CC* one that uses close-to-close returns.

4 Autocorrelation Structure

After showing the short-term reversal strategy results, especially the significantly high return of *CO-OC* strategy, a natural concern is that how long does overnight-intraday reversal effect last. In this section, we test the autocorrelation structure of overnight and intraday returns. We run the following multivariate Fama-MacBeth regression:[8]

$$r^{oc}_{i,t} = \beta_0 + \sum_{1}^{20} \beta_{k,t} \times r^{oc}_{i,t-k} + \sum_{1}^{20} \gamma_{k,t} \times r^{co}_{i,t-k} + \epsilon_{i,t} \tag{6}$$

[8]The results are quantitatively and qualitatively similar if we run univariate regression on each lagged variables. In addition, except for the first lag of overnight return r^{co}, the estimates of other variables in the cross-section regression shows low autocorrelation level, therefore, Fama-MacBeth methodology is harmless. For the first lag of r^{co}, we use pooled OLS regression while the standard errors are clustered by time and asset (Petersen, 2009). In futures samples, for the limited numbers of contracts for each asset classes, we run pooled OLS regression while the standard errors are clustered by time and asset (Petersen, 2009)

We run intraday return on the lagged intraday and overnight returns from 1 day to 20 days. The t-statistics are shown in Figure 1 and Figure 2, the coefficients are not shown since they are equal to scaled t-statistics. In Figure 1, the first lag of overnight return shows a large negative t-statistic, which supports the high returns of *CO-OC* strategies. The other lagged overnight returns and intraday returns have diverse patterns across different international equity markets. In the US sample, the lagged overnight returns have negative serial autocorrelations more than 20 days, in contrast to the results in Japan, where the overnight return reversal almost disappears after 7 days. The findings of intraday returns are intriguing as well. In Japan sample, except the first two lags, the intraday return shows positive serial autocorrelation with the lagged intraday returns. In contrast, there is no reversal or momentum effect of intraday return in UK sample, where the t-statistics are well located between the [-2, 2] interval after two lags.

Figure 2 depicts the t-statistics for the futures market. The first lag of overnight return has a high negative t-statistic in interest rate and commodity markets, while the t-statistics are slightly below 2 in equity index and currency markets. For other lagged overnight and intraday returns, there is no evidence of serial autocorrelation.

In sum, the overnight-intraday negative serial autocorrelations have diverse lasting periods in international equity markets, while in liquid futures market, the negative serial autocorrelation only lasts for one period.

5 Predictability: the Role of VIX

The VIX index is a natural predictor for the risk-taking behaviors of financial intermediaries, based on the implications from Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Adrian and Shin (2010). Nagel (2012) shows that the return of the reversal strategy is highly predictable with the VIX index. He explains that VIX index may not be the underlying variable driving expected returns from liquidity provision, but as a proxy for the market's demand for liquidity and market maker's supply of liquidity.

As shown in Figure 3, the VIX index spikes at the market open, then shrinks fast in the first half hour. The high VIX level at the open is complementary to the high realized volatility at the open that documented in several papers, such as in Barclay and Hendershott (2003). This intraday pattern of VIX index is consistent with the high liquidity shocks measured by the short-term reversal strategy *CO-OC*, which accumulates most of the return in the first minute after open. We test the predictability power of VIX in the return of *CO-OC* strategy with the following formula:

$$\Delta return_t^{CO-OC} = \alpha + \beta_1 \Delta VIX_{t-1} + \beta_2 VIX_{t-1}^{night} + \epsilon \quad (7)$$

We use first differences of the VIX index and reversal return due to the high autocorrelation levels of the series. ΔVIX measures the change of close levels of the VIX index. Aside from the close level of VIX, we also measure the overnight increment (VIX^{night}), which is the difference between the open and previous close level of VIX index. The overnight volatility increment potentially captures the volatility shocks at the opens. In order to match the time of open and close in each equity market, we use the main volatility index in each area: CBOE S&P 500 implied volatility index (VIX); Europe: EURO STOXX 50 volatility (VSTOXX); Japan: Nikkei stock average volatility index (VNKY); UK: FTSE 100 implied volatility index (IVI). Cross-section return volatility (dispersion) is used as the proxy for volatility index for the futures contracts in each asset classes, since there is no corresponding volatility index. The cross-section return volatility has very high correlation level with the VIX index in stock market.

Table 11 reports the results of the regression. In Panel A, the coefficients of ΔVIX are insignificant in international equity markets, except it is weakly significant with a t-statistic of 1.92 in UK sample. The VIX^{night} has significant predictability power for the reversal return, with adjusted t-statistics are higher than 3 in US, Europe and UK stock samples. The adjusted R^2 are improved with the addition of VIX^{night} in the regression.

The results in futures are stronger than in stock markets. In Panel B of Table 11, the ΔVIX have high t-statistics in all asset classes, with the lowest of 7.31 in interest rate market. Similar to the findings in equity markets, the VIX^{night} has significant predictability for the return of *CO-OC* strategy, except in currency market. Adding VIX^{night}, the adjusted R^2 increases from 0.048 to 0.086 in equity index market, from 0.021 to 0.034 in interest rate market and from 0.038 to 0.059 in commodity market.

The results indicate the importance of overnight volatility increment in explaining the profitability of *CO-OC* strategy across equity markets and different asset classes. Our findings are complementary to Nagel (2012), who use the close level of VIX index to predict traditional reversal strategy, and the *CO-OC* strategies rely more on the overnight volatility information.

6 A Model of Periodic Market Closures: Hong and Wang (2000)

Hong and Wang (2000) model a continuous-time stock market with periodic closures in which the investors trade for hedging demand or speculative motive. The trading and returns under periodic market closures provide rational support for the empirical patterns of return and volatility dynamics in the overnight and intraday periods. In this paper, we use the symmetric information case in Hong and Wang (2000), where investors trade stocks to hedge the risk in private investment opportunities (liquidity trade). The stock market[9] is periodically closed, while the private investment opportunities move continuously. There are two investors in the model, they trade with each other and each serves as the market maker to satisfy the trade demand of the other investor. We want to test in the model if the time-varying hedging demand induced by market closure explains the overnight-intraday return reversal. The based idea is from Grossman and Miller (1988), where market liquidity is determined by the demand and supply of immediacy, and the liquidity is linked to short-term reversal of returns.

In the model, the price in the periodic equilibrium is

$$P_t = F_t - (\lambda_0 + \lambda_1 Y_{1,t} + \lambda_2 Y_{2,t}) \qquad \forall t \in T \tag{8}$$

where F_t is the value of expected future dividends, an unconditional part (λ_0) is independent of the private investments, and a third part ($\lambda_1 Y_{1,t} + \lambda_2 Y_{2,t}$) depends on the expected returns of the private investments (Y_1, Y_2). The parameters λ_1 and λ_2 measure the sensitivities of stock price to returns of private investments. The third part depends on the correlation between the returns on the stock and the private investments, κ_{Dq}. Model details are in Internet Appendix.

In equilibrium, λ_1 and λ_2 are decreasing along the trading hours, especially, the $\lambda_1(open)$ is higher than $\lambda_1(close)$, and the $\lambda_2(open)$ is higher than $\lambda_2(close)$. It implies that the price is more sensitive to the shocks from private investments at the open than close. In real case of futures

[9]You can also think this is a futures market, where the private investment is the spot market. For instance, investors use the commodity futures contracts to hedge the risk of commodity price. The futures market is closed during weekend, while the spot commodity can be traded during weekend.

market, the accumulated orders during the closing period are all executed at the open, when thus has high imbalances. Based on the simulated stock returns, we run the autocorrelation regression (6) in the single return series. The result of t-statistics is shown in Figure 4.

The results in Figure 4 are qualitatively similar to those in Figure 1 and Figure 2. Firstly, the first lag of overnight return (r^{co}) has a large negative t-statistic, while the t-statistics of intraday returns (r^{oc}) are insignificant or weakly significant. Secondly, the lagged overnight returns have higher and longer reversals than intraday returns.

In Figure 5, we test the effect of liquidity shock on the overnight-intraday negative serial autocorrelation by changing the two key parameters: σ_Y and κ_{Dq}. In the first case, we change the volatility (σ_Y) of the private investments. The more volatile of the private investment, the higher pressure on the hedging activity of investors. The two left panels in Figure 5 show the difference between high and low volatility cases. The t-statistics in the high volatility case are more negative and significant than those in the low volatility case. Thus the high liquidity trading demand leads to high overnight-intraday reversal. The similar pattern observed in the second case, where we change the correlation of the returns of stock and private investment κ_{Dq}. The higher κ_{Dq} indicates higher exposure to the private investment, which induce higher hedging demand.

The trading under the periodic market closures therefore provides theoretical support to the overnight-intraday negative serial autocorrelation.

7 Reversal Based Liquidity Measure

Campbell, Grossman, and Wang (1993)) link the volume-related return reversal to the liquidity effect. Pastor and Stambaugh (2003) construct a liquidity measure depended on this volume-related return reversal, and show it is a state variable important for asset pricing. The key formula in Pastor and Stambaugh (2003) is

$$r^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,t} sign(r^e_{i,d,t}) \times \upsilon_{i,d,t} + \epsilon_{i,d+1,t} \tag{9}$$

The returns are all based on close prices. Basically, the coefficients γ measures the volume-related reversal. There are several issues arising from the daily volume and daily return. Most of the trading volume is accumulated during the trading hours, while the overnight trading volume account for small proportion of the total volume, especially in the early sample period. Consequently, the market liquidity measure in formula (9) is more likely to measure the liquidity condition during the trading hours. It implies that the volume-related return reversal should use the intraday return. A natural hypothesis is that the liquidity measure based on intraday return should be close to the measure based on close-to-close return, even the intraday returns have no reversal effect in US sample shown in Table 2. We test this idea through decomposing the liquidity measure into two parts[10]:

$$r^{e,oc}_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r^{oc}_{i,d,t} + \gamma_{i,t} sign(r^{e,oc}_{i,d,t}) \times \upsilon_{i,d,t} + \epsilon^{oc}_{i,d+1,t} \tag{10}$$

$$r^{e,co}_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r^{co}_{i,d,t} + \gamma_{i,t} sign(r^{e,co}_{i,d,t}) \times \upsilon_{i,d,t} + \epsilon^{co}_{i,d+1,t} \tag{11}$$

Following the steps in Pastor and Stambaugh (2003), we form the tradable long-short portfolios based on the stocks' exposure to the historical liquidity measures. Figure 6 shows the cumulative returns based on these three measures. In line with the hypothesis, the tradable factor based on intraday return liquidity measure (red line) captures the original Pastor and Stambaugh (2003) liquidity factor, while the overnight part shows insignificant return. In sum, for the market liquidity measure, the intraday return element is the important component. The overnight-intraday reversal is more likely induced by firm specific liquidity.

8 Conclusion

In this paper, we study the effects of market closures on short-term reversals in asset prices. We find that a naïve overnight-intraday reversal strategy delivers an average excess return and a Sharpe ratio that are five time larger than those generated by a conventional short-term reversal strategy in US stock market. This patter is consistent over time, and across both major international stock markets and exchange traded futures written on equity indices, interest rates, commodities and currencies. Our results seem to suggest that market structure imposes non-

[10]Due to the lack of volume data in each overnight and intraday period, we use the daily volume to proxy the volume in each part based on the assumption that the volume in each period holds constant proportion in short period. Since we aggregate the γ cross-sectionally in each month, the assumption should be harmless.

trivial frictions on the asset prices, even in the most liquid markets.

Extending the work in Nagel (2012), we find that the increment of the uncertainty, measured by VIX index, during the overnight period adds explanatory power for the returns of *CO-OC* strategies in different equity markets and other asset classes, aside from the uncertainty level at the close.

Based on the continuous-time model with periodic market closures as in Hong and Wang (2000), we show that overnight-intraday reversal patterns are consistent with an equilibrium in a periodically closed market. The model provides rational explanations for the reversal patterns.

Lastly, the diverse patterns of overnight and intraday returns have implications for the reversal-based market liquidity measure as in Pastor and Stambaugh (2003). The tradable factor based on intraday return liquidity measure captures the return of the original Pastor and Stambaugh (2003) liquidity factor, while the overnight part shows insignificant return. The overnight-intraday reversal is more likely induced by firm specific liquidity characteristics.

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Table 1: Short-term Reversal Strategies: Description

This table describes the short-term reversal strategies examined in the next tables: (i) *CC-CC* uses close-to-close daily returns $r^{cc}_{i,t-1}$ on day t-1 as formation period return (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 $r^{co}_{i,t}$ on day t 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: $r^{co}_{i,t} = \frac{P^{o}_{i,t}}{P^{c}_{i,t-1}} - 1$	open-to-close: $r^{oc}_{i,t} = \frac{P^{c}_{i,t}}{P^{o}_{i,t}} - 1$

Table 2: Short-term Reversal Strategies: International Stocks

This table presents descriptive statistics of short-term reversal strategies (see Table 1 for a description) based on international stock market returns: The strategies are rebalanced daily from January 1993 to December 2014, and returns are expressed in percentage per day. The Table also reports the j-th percentile Q_j, the j-th order autocorrelation coefficient AC_j, the annualized Sharpe ratio $SR \times \sqrt{252}$, and the sample correlation $corr$ between the overnight-intraday short-term reversal strategy CO-OC and the alternative ones. t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Open and close prices are collected from the CRSP database for the United States, and Datastream for all other countries.

	CC-CC	OO-OO	OC-OC	CO-OC	CC-CC	OO-OO	OC-OC	CO-OC
	United States				Europe (France and Germany)			
mean	0.330	0.625	-0.171	1.675	0.231	0.782	-0.206	1.017
t-stat	[16.57]	[28.09]	[-14.65]	[46.52]	[17.40]	[26.70]	[-18.39]	[43.51]
st. dev	0.917	0.979	0.759	1.093	0.870	1.539	0.742	0.952
skew	0.819	1.481	1.248	0.783	0.244	1.278	0.267	2.088
kurt	12.039	25.192	25.899	9.446	9.849	9.361	9.752	16.149
Q_5	-0.940	-0.635	-1.192	0.083	-1.048	-1.146	-1.296	-0.029
Q_{95}	1.605	1.922	0.816	3.216	1.561	3.670	0.901	2.651
SR $\times\sqrt{252}$	5.521	9.963	-3.795	24.163	4.023	7.960	-4.630	16.794
AC_1	0.182	0.170	0.058	0.453	0.001	0.106	0.047	0.251
AC_{21}	0.169	0.161	0.056	0.400	0.017	0.066	0.010	0.160
corr	0.253	0.225	-0.008	1.000	0.108	0.086	0.066	1.000
	Japan				United Kingdom			
mean	0.257	0.709	0.038	0.740	-0.240	0.447	-0.662	1.935
t-stat	[16.19]	[31.62]	[4.32]	[39.05]	[-9.31]	[13.71]	[-27.37]	[39.64]
st. dev	0.861	1.103	0.623	0.712	1.203	1.480	1.105	1.755
skew	0.172	1.066	0.400	1.520	-1.245	1.198	-1.302	2.092
kurt	9.503	9.004	9.053	11.002	19.507	11.282	13.511	16.184
Q_5	-1.045	-0.774	-0.853	-0.194	-2.051	-1.530	-2.363	0.008
Q_{95}	1.583	2.704	0.987	1.932	1.482	2.716	0.790	4.611
SR $\times\sqrt{252}$	4.546	10.043	0.695	16.251	-3.302	4.676	-9.671	17.408
AC_1	0.050	0.159	-0.021	0.315	0.122	0.225	0.192	0.362
AC_{21}	0.066	0.096	0.000	0.195	0.133	0.076	0.124	0.199
corr	0.218	0.151	0.185	1.000	-0.054	0.128	-0.264	1.000

Table 3: Short-term Reversal Strategies: Futures Contracts

This table presents descriptive statistics of short-term reversal strategies (see Table 1 for a description) based on exchange trade futures. The strategies are rebalanced daily from July 1982 to December 2014, and returns are expressed in percentage per day. The Table also reports the *j-th* percentile Q_j, the *j-th* order autocorrelation coefficient AC_j, the annualized Sharpe ratio $SR \times \sqrt{252}$, and the sample correlation *corr* between the overnight-intraday short-term reversal strategy *CO-OC* and the alternative ones. t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Open and close prices for futures traded on the Chicago Mercantile Exchange are obtained from TickData.

	CC-CC	OO-OO	OC-OC	CO-OC	CC-CC	OO-OO	OC-OC	CO-OC
	Equity Index				Interest Rate			
mean	0.087	0.201	0.024	0.252	-0.014	0.014	-0.011	0.055
t-stat	[5.20]	[9.36]	[1.67]	[13.18]	[-2.38]	[2.32]	[-2.13]	[11.85]
st. dev	1.199	1.311	1.069	0.980	0.504	0.513	0.467	0.399
skew	0.529	0.681	0.652	1.324	-0.196	0.079	-0.030	0.306
kurt	11.029	12.314	15.908	23.478	7.260	7.202	7.458	7.799
Q_5	-1.784	-1.729	-1.578	-1.101	-0.808	-0.798	-0.769	-0.570
Q_{95}	1.951	2.263	1.665	1.753	0.760	0.805	0.723	0.713
SR $\times\sqrt{252}$	1.149	2.429	0.363	4.078	-0.427	0.418	-0.370	2.198
AC_1	-0.031	0.018	-0.027	0.084	-0.023	-0.020	-0.013	0.006
AC_{21}	0.013	0.017	-0.009	0.062	0.025	0.009	0.008	-0.021
corr	0.013	0.039	0.012	1.000	-0.010	0.011	-0.008	1.000
	Commodity				Currency			
mean	-0.172	0.002	-0.031	0.170	0.007	0.020	-0.003	0.042
t-stat	[-9.29]	[0.08]	[-1.92]	[10.84]	[0.92]	[2.59]	[-0.39]	[6.76]
st. dev	1.581	1.725	1.408	1.403	0.668	0.675	0.565	0.534
skew	-0.206	0.044	0.043	0.340	0.002	-0.124	0.062	-0.202
kurt	4.436	5.032	4.528	4.739	11.177	7.767	11.084	12.361
Q_5	-2.800	-2.722	-2.308	-2.042	-0.997	-1.012	-0.841	-0.752
Q_{95}	2.317	2.761	2.182	2.499	1.007	1.070	0.827	0.856
SR $\times\sqrt{252}$	-1.730	0.015	-0.351	1.929	0.172	0.481	-0.072	1.262
AC_1	0.010	-0.013	0.010	-0.021	-0.039	-0.023	-0.034	-0.022
AC_{21}	-0.010	0.007	-0.006	0.003	0.002	0.016	0.023	0.048
corr	0.143	-0.015	0.119	1.000	0.001	0.017	-0.014	1.000

Table 4: Short-term Reversal Strategies: Sub-periods

This table presents descriptive statistics of short-term reversal strategies (see Table 1 for a description) for two different sub-periods. *Panel A* reports daily-rebalanced strategies based on international stock markets for the periods January 1993 through December 2006, and January 2007 through December 2014. *Panel B* refers to daily-rebalanced strategies that use exchange traded futures for the periods July 1982 through December 2006, and January 2007 through December 2014. The excess returns are expressed in percentage per day. The Table also reports the annualized Sharpe ratio $SR \times \sqrt{252}$, and the sample correlation *corr* between the overnight-intraday short-term reversal strategy *CO-OC* and the alternative ones. *t*-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Open and close stock prices are collected from the CRSP database for the US and Datastream for the other countries. Open and close prices for futures traded on the Chicago Mercantile Exchange are obtained from TickData.

	Panel A: International Stocks							
	CC-CC	OO-OO	OC-OC	CO-OC	CC-CC	OO-OO	OC-OC	CO-OC
	1993-2006				2007-2014			
	United States							
mean	0.434	0.778	-0.256	2.034	0.146	0.358	-0.023	1.047
t-stat	[17.09]	[29.38]	[-19.09]	[57.73]	[6.53]	[13.66]	[-1.40]	[25.85]
SR $\times\sqrt{252}$	7.342	12.146	-5.718	33.376	2.421	6.303	-0.683	16.070
corr	0.293	0.135	0.072	1.000	0.071	0.190	0.049	1.000
	Europe (France and Germany)							
mean	0.188	0.521	-0.229	0.941	0.307	1.240	-0.164	1.151
t-stat	[11.54]	[18.66]	[-17.15]	[33.21]	[14.63]	[27.57]	[-8.68]	[33.86]
SR $\times\sqrt{252}$	3.365	6.760	-5.458	16.161	5.096	10.179	-3.422	18.090
corr	0.151	0.139	0.079	1.000	0.032	-0.008	0.038	1.000
	Japan							
mean	0.383	0.727	0.060	0.856	0.037	0.676	0.000	0.535
t-stat	[21.23]	[27.63]	[6.01]	[38.96]	[1.88]	[18.15]	[-0.02]	[21.39]
SR $\times\sqrt{252}$	7.087	11.286	1.311	19.819	0.481	8.426	-0.258	11.463
corr	0.243	0.223	0.141	1.000	0.090	0.054	0.235	1.000
	United Kingdom							
mean	-0.504	0.373	-0.818	2.111	0.222	0.576	-0.391	1.629
t-stat	[-19.30]	[8.25]	[-26.69]	[31.23]	[8.04]	[17.57]	[-15.36]	[39.14]
SR $\times\sqrt{252}$	-6.963	3.542	-11.513	16.757	3.023	7.605	-6.512	21.708
corr	-0.015	0.146	-0.283	1.000	-0.023	0.109	-0.131	1.000
	Panel B: Futures							
	1982-2006				2007-2014			
	Equity Index							
mean	0.070	0.155	0.020	0.166	0.108	0.260	0.030	0.364
t-stat	[2.91]	[5.98]	[0.51]	[7.39]	[5.02]	[7.63]	[1.46]	[12.32]
SR $\times\sqrt{252}$	0.809	1.708	0.274	2.508	1.906	3.718	0.524	6.683
corr	-0.017	-0.039	-0.019	1.000	0.081	0.190	0.075	1.000
	Interest Rate							
mean	-0.020	0.014	-0.015	0.053	0.004	0.012	-0.001	0.061
t-stat	[-3.31]	[2.24]	[-2.91]	[10.40]	[0.28]	[0.91]	[-0.07]	[5.77]
SR $\times\sqrt{252}$	-0.718	0.477	-0.591	2.306	0.090	0.309	-0.028	2.028
corr	0.059	-0.005	0.110	1.000	-0.109	0.036	-0.160	1.000
	Commodity							
mean	-0.163	0.037	0.031	0.133	-0.203	-0.110	-0.229	0.290
t-stat	[-7.56]	[1.68]	[1.80]	[7.74]	[-5.55]	[-2.91]	[-6.42]	[8.28]
SR $\times\sqrt{252}$	-1.629	0.334	0.368	1.548	-2.053	-1.045	-2.341	3.027
corr	0.167	-0.021	0.168	1.000	0.079	0.010	0.011	1.000
	Currency							
mean	-0.001	0.024	-0.008	0.038	0.025	0.013	0.009	0.052
t-stat	[-0.09]	[2.56]	[-1.41]	[5.16]	[1.66]	[0.86]	[0.58]	[4.12]
SR $\times\sqrt{252}$	-0.021	0.588	-0.257	1.258	0.536	0.280	0.190	1.301
corr	0.046	-0.003	0.019	1.000	-0.062	0.045	-0.049	1.000

Table 5: Short-term Reversal Strategies: Sub-samples

This table presents descriptive statistics of short-term reversal strategies (see Table 1 for a description) for different sub-samples of US stocks. The strategies are rebalanced daily from January 1993 to December 2014, and returns are expressed in percentage per day. The Table also reports the *j-th* percentile Q_j, the *j-th* order autocorrelation coefficient AC_j, the annualized Sharpe ratio $SR \times \sqrt{252}$, and the sample correlation *corr* between the overnight-intraday short-term reversal strategy *CO-OC* and the alternative ones. *t*-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Open and close prices are collected from the CRSP database for the United States, and Datastream for all other countries.

	CC-CC	OO-OO	OC-OC	CO-OC	CC-CC	OO-OO	OC-OC	CO-OC
	Small Stocks				Large Stocks			
mean	0.628	0.970	-0.223	2.328	0.077	0.264	-0.091	0.781
t-stat	[20.20]	[31.36]	[-16.65]	[55.17]	[6.59]	[17.67]	[-7.92]	[32.41]
st. dev	1.049	1.034	0.773	1.230	0.938	1.035	0.824	1.058
skew	0.983	1.154	1.510	0.201	0.729	1.864	1.065	1.659
kurt	7.552	15.731	21.611	6.060	15.021	27.354	26.045	18.266
Q_5	-0.822	-0.437	-1.332	0.408	-1.252	-1.027	-1.192	-0.654
Q_{95}	2.369	2.612	0.832	4.090	1.382	1.641	1.006	2.283
SR $\times\sqrt{252}$	9.341	14.721	-4.788	29.909	1.130	3.885	-1.962	11.550
AC_1	0.392	0.384	0.075	0.524	0.002	-0.002	0.030	0.158
AC_{21}	0.356	0.351	0.086	0.465	0.038	0.024	0.040	0.118
corr	0.368	0.397	-0.107	1.000	0.086	-0.010	0.123	1.000
	S&P500 Stocks				S&P100 Stocks			
mean	0.077	0.215	-0.002	0.429	0.046	0.190	0.000	0.347
t-stat	[5.97]	[13.85]	[-0.20]	[23.07]	[3.06]	[11.69]	[0.01]	[19.18]
st. dev	1.014	1.089	0.868	1.116	1.205	1.309	1.025	1.313
skew	0.756	1.618	1.211	1.050	0.668	1.257	0.939	0.511
kurt	14.408	17.932	19.276	11.473	16.215	20.983	18.616	14.782
Q_5	-1.351	-1.236	-1.183	-1.189	-1.703	-1.601	-1.452	-1.371
Q_{95}	1.579	1.831	1.223	2.147	1.724	1.997	1.399	2.249
SR $\times\sqrt{252}$	1.036	2.977	-0.237	5.957	0.469	2.181	-0.164	4.073
AC_1	-0.021	-0.010	0.015	0.041	-0.062	-0.042	-0.013	-0.028
AC_{21}	0.012	-0.001	0.023	0.005	0.017	-0.005	0.022	-0.002
corr	0.060	-0.039	0.151	1.000	0.045	-0.034	0.125	1.000

Table 6: Short-term Reversal Strategies: Bid and Ask Quotes

This table presents descriptive statistics of the overnight-intraday reversal strategy (see Table 1 for a description) based on S&P500 stocks. We use bid quotes in *Panel A*, ask quotes in *Panel B*, and mid quotes in *Panel C*. The strategies are rebalanced daily from January 2011 to December 2014, and returns are expressed in percentage per day. The Table also reports the *j-th* percentile Q_j, the *j-th* order autocorrelation coefficient AC_j, the annualized Sharpe ratio $SR \times \sqrt{252}$, and the sample correlation *corr* between the overnight-intraday short-term reversal strategy *CO-OC* and the alternative ones. *t*-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Bid and ask quotes are obtained from the TAQ database.

	CC-CC	OO-OO	OC-OC	CO-OC
	Panel A: Bid Quote			
mean	0.031	0.398	-0.222	1.262
t-stat	[1.54]	[13.37]	[-11.35]	[20.55]
st. dev	0.644	0.679	0.487	1.041
skew	1.490	0.271	0.048	1.173
kurt	24.557	11.246	5.579	15.365
Q_5	-0.895	-0.536	-0.990	-0.198
Q_{95}	0.967	1.477	0.524	2.999
SR $\times\sqrt{252}$	0.508	9.064	-7.575	19.091
AC_1	0.071	0.172	0.143	0.360
AC_{21}	-0.032	0.014	0.028	0.232
corr	0.005	0.218	-0.160	1.000
	Panel B: Ask Quote			
mean	0.029	0.348	-0.197	1.152
t-stat	[1.45]	[12.95]	[-11.01]	[21.89]
st. dev	0.615	0.656	0.469	0.951
skew	0.343	0.327	0.096	1.707
kurt	10.456	11.289	5.659	23.732
Q_5	-0.891	-0.573	-0.931	-0.156
Q_{95}	0.959	1.373	0.549	2.691
SR $\times\sqrt{252}$	0.464	8.155	-7.034	19.046
AC_1	0.055	0.138	0.138	0.316
AC_{21}	-0.036	-0.004	-0.011	0.173
corr	-0.010	0.179	-0.109	1.000
	Panel C: Mid Quote			
mean	0.027	0.127	-0.065	0.432
t-stat	[1.37]	[5.91]	[-4.25]	[14.83]
st. dev	0.607	0.607	0.462	0.766
skew	0.062	-0.297	0.002	0.291
kurt	8.338	8.448	6.179	10.001
Q_5	-0.894	-0.781	-0.773	-0.674
Q_{95}	0.958	1.066	0.655	1.641
SR $\times\sqrt{252}$	0.427	3.036	-2.604	8.738
AC_1	0.059	0.089	0.066	0.091
AC_{21}	-0.038	-0.072	-0.037	0.004
corr	0.032	0.065	0.062	1.000

Table 7: Short-term Reversal Strategies: Transaction data

This table presents descriptive statistics of the overnight-intraday reversal strategy (see Table 1 for a description) based transaction prices for the S&P 500 stocks. In *Panel A* the formation windows uses returns observed at 9:30am whereas the trading period starts between 9.30 am and 9.45 am. In *Panel B* (*Panel C*) the formation windows uses returns observed at 9:29 am (9.25 am). The strategies are rebalanced daily from January 2011 to December 2014, and returns are expressed in percentage per day. The Table also reports the *j-th* percentile Q_j, the *j-th* order autocorrelation coefficient AC_j, the annualized Sharpe ratio $SR \times \sqrt{252}$, and the sample correlation *corr* between the overnight-intraday short-term reversal strategy *CO-OC* and the alternative ones. *t*-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Transaction prices are from the TAQ database.

	Panel A: Formation period ends at 9.30 am (opening)							
Trading period starts at	9.30 am	9.31 am	9.32 am	9.33 am	9.34 am	9.35 am	9.40 am	9.45 am
mean	0.359	0.112	0.108	0.105	0.088	0.089	0.050	0.042
t-stat	[10.98]	[3.81]	[3.74]	[3.74]	[3.31]	[3.38]	[2.19]	[1.99]
st. dev	0.964	0.885	0.868	0.840	0.804	0.809	0.716	0.667
skew	0.416	0.590	0.579	0.793	0.791	0.733	0.345	0.560
kurt	8.120	9.438	10.634	9.953	9.070	9.719	7.586	6.223
Q_5	-1.035	-1.159	-1.155	-1.129	-1.187	-1.088	-0.997	-0.998
Q_{95}	1.926	1.534	1.437	1.417	1.379	1.328	1.120	1.117
SR $\times\sqrt{252}$	5.746	1.818	1.778	1.787	1.524	1.548	0.872	0.734
AC_1	0.022	-0.013	-0.006	0.000	-0.001	-0.008	-0.022	-0.026
AC_{21}	-0.035	-0.008	-0.010	-0.012	-0.009	-0.010	-0.035	-0.038
	Panel B: Formation period ends at 9.29 am (pre-opening)							
mean	0.340	0.109	0.106	0.104	0.087	0.088	0.049	0.041
t-stat	[10.39]	[3.78]	[3.69]	[3.72]	[3.30]	[3.37]	[2.19]	[2.03]
st. dev	0.960	0.880	0.867	0.838	0.801	0.806	0.714	0.664
skew	0.376	0.544	0.564	0.765	0.765	0.696	0.278	0.496
kurt	8.074	9.357	10.682	9.813	8.967	9.637	7.449	5.998
Q_5	-1.047	-1.170	-1.141	-1.120	-1.133	-1.076	-1.011	-1.017
Q_{95}	1.922	1.542	1.469	1.440	1.372	1.327	1.109	1.123
SR $\times\sqrt{252}$	5.441	1.781	1.742	1.762	1.503	1.526	0.856	0.735
AC_1	0.018	-0.023	-0.014	-0.010	-0.011	-0.020	-0.032	-0.041
AC_{21}	-0.036	-0.009	-0.014	-0.015	-0.013	-0.012	-0.039	-0.040
	Panel C: Formation period ends at 9.25 am (pre-opening)							
mean	0.310	0.112	0.125	0.126	0.108	0.108	0.039	0.029
t-stat	[8.09]	[3.31]	[3.72]	[3.92]	[3.55]	[3.62]	[1.56]	[1.27]
st. dev	1.127	1.041	1.027	0.986	0.943	0.946	0.752	0.684
skew	0.512	0.695	0.686	0.872	0.828	0.647	-0.976	-0.555
kurt	9.841	11.227	13.363	10.946	10.260	10.482	15.608	11.983
Q_5	-1.333	-1.367	-1.266	-1.270	-1.268	-1.265	-0.991	-0.922
Q_{95}	2.053	1.692	1.676	1.636	1.528	1.519	1.156	1.078
SR $\times\sqrt{252}$	4.217	1.549	1.766	1.854	1.638	1.626	0.592	0.415
AC_1	0.004	-0.034	-0.030	-0.035	-0.030	-0.049	0.004	0.010
AC_{21}	-0.017	0.007	-0.002	0.001	0.000	-0.002	-0.055	-0.065

Table 8: Short-term Reversal Strategies: Weekly international stocks

This table presents descriptive statistics of weekly reversal strategy (similar to those described in Table 1) based on international stock markets. The strategies are rebalanced weekly from January 1993 to December 2014, and returns are expressed in percentage per week. The Table also reports the *j-th* percentile Q_j, the *j-th* order autocorrelation coefficient AC_j, the annualized Sharpe ratio $SR \times \sqrt{52}$, and the sample correlation *corr* between the overnight-intraday short-term reversal strategy *CO-OC* and the alternative ones. t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Open and close prices are collected from the CRSP database for the United States, and Datastream for all other countries.

	CC-CC	OO-OO	OC-OC	CO-OC	CC-CC	OO-OO	OC-OC	CO-OC
	United States				Europe (France and Germany)			
mean	0.699	0.878	0.445	1.870	0.666	1.029	0.289	1.363
t-stat	[12.81]	[16.42]	[10.49]	[23.44]	[14.23]	[17.42]	[7.16]	[20.61]
st. dev	1.718	1.623	1.661	1.633	1.607	1.910	1.573	1.640
skew	1.303	0.996	1.154	0.541	0.658	0.691	0.219	1.039
kurt	11.834	9.973	14.111	9.524	7.533	6.183	7.062	7.592
Q_5	-1.512	-1.305	-1.802	-0.540	-1.667	-1.849	-2.147	-0.864
Q_{95}	3.313	3.357	3.040	3.924	3.221	4.140	2.713	4.179
SR $\times\sqrt{52}$	2.711	3.665	1.700	8.020	2.749	3.685	1.079	5.757
AC_1	-0.051	-0.046	-0.136	0.269	-0.042	0.007	-0.051	0.131
AC_4	0.073	0.080	0.042	0.164	0.070	0.090	0.065	0.073
corr	0.001	0.186	-0.032	1.000	0.008	0.071	-0.002	1.000
	Japan				United Kingdom			
mean	0.641	1.103	0.409	1.049	0.410	0.680	0.240	1.409
t-stat	[10.14]	[16.54]	[8.62]	[17.56]	[7.62]	[10.60]	[4.51]	[16.67]
st. dev	1.691	1.888	1.586	1.399	1.823	2.005	1.775	2.185
skew	0.943	1.047	0.844	1.203	0.234	0.696	0.315	1.691
kurt	7.599	8.174	7.931	9.402	11.184	10.715	9.267	12.282
Q_5	-1.808	-1.606	-1.960	-0.970	-2.047	-1.995	-2.434	-1.462
Q_{95}	3.411	4.032	2.766	3.154	3.224	3.741	2.866	4.724
SR $\times\sqrt{52}$	2.506	4.010	1.620	5.132	1.410	2.254	0.758	4.475
AC_1	0.081	0.049	-0.044	0.152	-0.063	-0.011	-0.046	0.083
AC_4	0.083	0.048	0.038	0.134	-0.014	0.025	0.001	0.043
corr	0.194	0.153	0.183	1.000	0.066	0.073	0.005	1.000

Table 9: Short-term Reversal Strategies: Weekly futures

This table presents descriptive statistics of weekly reversal strategy (similar to those described in Table 1) based on exchange traded futures. The strategies are rebalanced weekly from July 1982 to December 2014, and returns are expressed in percentage per week. The Table also reports the *j-th* percentile Q_j, the *j-th* order autocorrelation coefficient AC_j, the annualized Sharpe ratio $SR \times \sqrt{52}$, and the sample correlation *corr* between the overnight-intraday short-term reversal strategy *CO-OC* and the alternative ones. *t*-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Open and close prices for futures traded on the Chicago Mercantile Exchange are obtained from TickData.

	CC-CC	OO-OO	OC-OC	CO-OC	CC-CC	OO-OO	OC-OC	CO-OC
	Equity Index				Interest Rate			
mean	0.089	0.267	0.057	0.379	0.055	0.073	0.038	0.128
t-stat	[1.09]	[3.45]	[0.66]	[4.18]	[1.94]	[2.46]	[1.30]	[4.46]
st. dev	2.563	2.285	2.643	2.325	1.107	1.165	1.135	1.036
skew	0.836	1.069	0.714	0.684	0.515	0.920	0.638	0.879
kurt	12.353	9.080	10.408	7.978	6.127	11.694	8.418	12.151
Q_5	-3.750	-3.353	-3.646	-3.120	-1.612	-1.573	-1.576	-1.422
Q_{95}	4.134	4.410	3.987	3.894	1.853	1.951	1.887	1.802
SR $\times\sqrt{52}$	0.251	0.842	0.157	1.176	0.358	0.454	0.244	0.894
AC_1	-0.169	-0.010	-0.159	0.062	0.007	-0.020	0.002	-0.042
AC_4	-0.016	0.109	0.024	0.041	0.009	0.004	0.015	-0.060
corr	-0.081	0.039	-0.040	1.000	0.020	-0.048	0.054	1.000
	Commodity				Currency			
mean	-0.077	0.072	-0.012	0.173	0.071	0.084	0.048	0.169
t-stat	[-0.86]	[0.76]	[-0.14]	[1.94]	[2.00]	[2.30]	[1.38]	[4.45]
st. dev	3.777	3.841	3.746	3.714	1.415	1.372	1.362	1.354
skew	-0.187	-0.236	-0.242	-0.049	-0.380	0.176	-0.278	0.408
kurt	5.640	5.302	5.682	5.109	14.394	8.625	12.907	5.065
Q_5	-6.270	-6.024	-6.013	-5.875	-1.904	-1.950	-1.933	-1.996
Q_{95}	5.821	6.223	5.796	5.905	2.364	2.237	2.318	2.356
SR $\times\sqrt{52}$	-0.147	0.135	-0.024	0.337	0.360	0.442	0.256	0.897
AC_1	0.052	0.084	0.047	0.031	0.028	0.054	0.048	0.009
AC_4	0.026	0.026	0.028	-0.026	0.008	0.023	0.011	0.049
corr	0.037	0.034	0.025	1.000	0.043	0.061	0.042	1.000

Table 10: Short-term Reversal Strategies: FOMC announcement

This table presents descriptive statistics of short-term reversal strategies (see Table 1 for a description) for FOMC and non-FOMC announcement days. *Panel A* reports daily-rebalanced strategies based on international stock markets for the periods January 1993 through December 2006, and January 2007 through December 2014. *Panel B* refers to daily-rebalanced strategies that use exchange traded futures for the periods July 1982 through December 2006, and January 2007 through December 2014. The excess returns are expressed in percentage per day. The Table also reports the annualized Sharpe ratio $SR \times \sqrt{252}$, and the sample correlation *corr* between the overnight-intraday short-term reversal strategy *CO-OC* and the alternative ones. t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Open and close stock prices are collected from the CRSP database for the US and Datastream for the other countries. Open and close prices for futures traded on the Chicago Mercantile Exchange are obtained from TickData.

	Panel A: International Stocks							
	FOMC Announcement				non-FOMC Announcement			
	CC-CC	OO-OO	OC-OC	CO-OC	CC-CC	OO-OO	OC-OC	CO-OC
	United States							
mean	0.396	0.703	-0.131	1.601	0.323	0.617	-0.175	1.683
t-stat	[7.61]	[12.63]	[-4.04]	[18.15]	[15.67]	[26.66]	[-14.44]	[45.37]
SR $\times\sqrt{252}$	6.955	12.874	-3.166	24.576	5.378	9.711	-3.858	24.132
corr	0.168	0.398	-0.152	1.000	0.262	0.211	0.006	1.000
	Europe (France and Germany)							
mean	0.292	0.863	-0.125	1.018	0.225	0.774	-0.214	1.017
t-stat	[7.69]	[10.34]	[-3.64]	[15.62]	[16.07]	[25.42]	[-18.08]	[42.40]
SR $\times\sqrt{252}$	5.135	9.461	-2.853	14.803	3.909	7.820	-4.820	17.046
corr	0.075	0.053	-0.001	1.000	0.112	0.090	0.074	1.000
	Japan							
mean	0.264	0.745	0.021	0.747	0.257	0.705	0.040	0.739
t-stat	[5.76]	[11.73]	[0.65]	[16.00]	[15.52]	[30.58]	[4.34]	[37.97]
SR $\times\sqrt{252}$	4.571	10.563	0.243	16.243	4.543	9.989	0.744	16.250
corr	0.095	0.216	0.262	1.000	0.231	0.144	0.177	1.000
	United Kingdom							
mean	-0.274	0.440	-0.700	2.003	-0.236	0.447	-0.659	1.928
t-stat	[-3.25]	[4.49]	[-8.67]	[13.65]	[-9.11]	[13.45]	[-27.86]	[40.09]
SR $\times\sqrt{252}$	-3.066	4.216	-8.731	16.188	-3.343	4.731	-9.805	17.565
corr	-0.080	0.186	-0.379	1.000	-0.050	0.121	-0.248	1.000
	Panel B: Futures							
	Equity Index							
mean	0.101	0.229	0.060	0.213	0.085	0.198	0.021	0.256
t-stat	[1.49]	[2.73]	[1.14]	[3.64]	[5.07]	[9.12]	[0.94]	[13.10]
SR $\times\sqrt{252}$	1.087	2.578	0.750	3.055	0.999	2.270	0.149	4.003
corr	-0.054	0.120	-0.029	1.000	0.021	0.030	0.017	1.000
	Interest Rate							
mean	0.021	0.080	0.024	0.053	-0.016	0.008	-0.014	0.055
t-stat	[0.72]	[3.87]	[1.06]	[2.66]	[-2.79]	[1.41]	[-2.66]	[11.25]
SR $\times\sqrt{252}$	0.285	1.961	0.403	1.607	-0.858	-0.071	-0.835	1.788
corr	-0.024	0.054	-0.071	1.000	-0.009	0.007	-0.002	1.000
	Commodity							
mean	-0.170	-0.057	-0.051	0.165	-0.172	0.006	-0.030	0.171
t-stat	[-2.32]	[-0.81]	[-0.77]	[2.88]	[-9.00]	[0.28]	[-1.81]	[10.54]
SR $\times\sqrt{252}$	-1.781	-0.607	-0.659	1.753	-1.841	-0.045	-0.457	1.812
corr	0.105	-0.041	0.099	1.000	0.146	-0.013	0.120	1.000
	Currency							
mean	0.084	0.076	0.083	0.064	0.001	0.016	-0.010	0.041
t-stat	[2.66]	[2.91]	[2.99]	[2.95]	[0.08]	[1.90]	[-1.64]	[6.13]
SR $\times\sqrt{252}$	1.654	1.606	1.917	1.630	-0.239	0.118	-0.581	0.887
corr	-0.032	0.039	0.025	1.000	0.004	0.015	-0.018	1.000

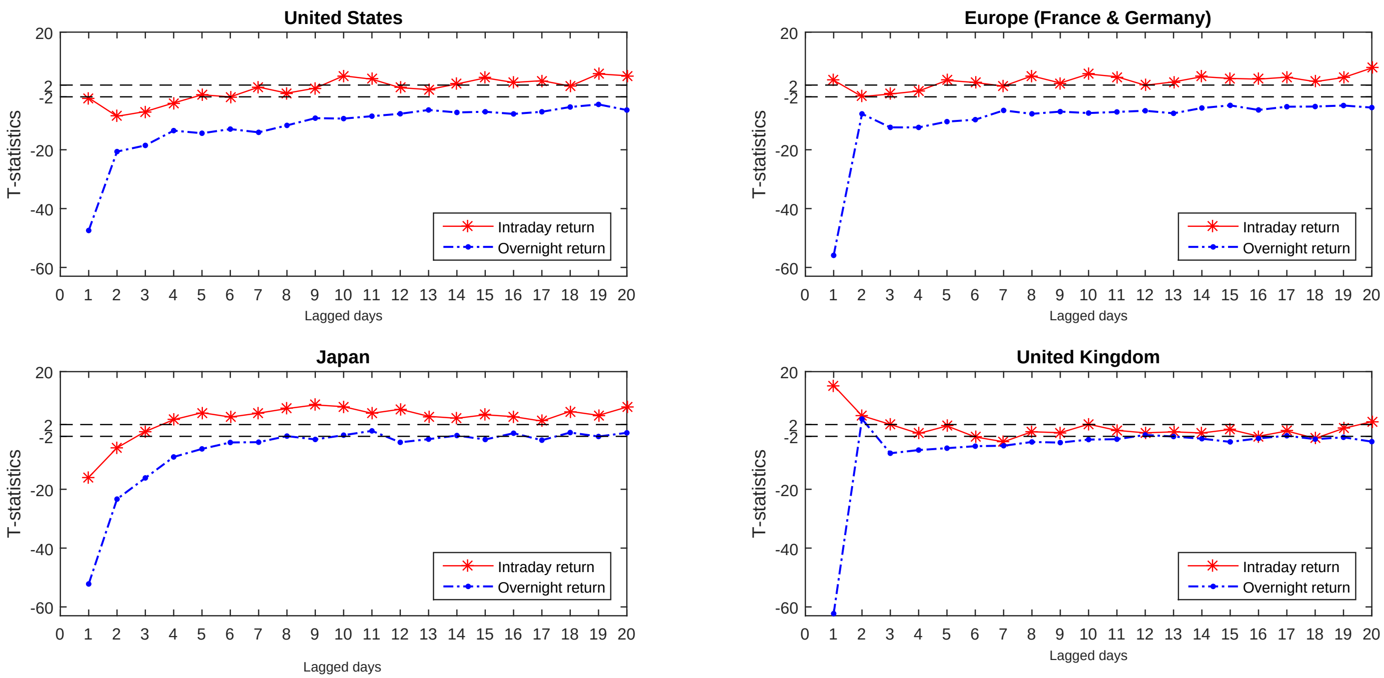
Table 11: Predictability: the role of VIX

This table reports the results of the regression: $\Delta return_t^{CO-OC} = \alpha + \beta_1 \Delta VIX_{t-1} + \beta_2 VIX_{t-1}^{night} + \epsilon$. We use the following volatility index for each equity market: US: CBOE S&P 500 implied volatility index (VIX); Europe: EURO STOXX 50 volatility (VSTOXX); Japan: Nikkei stock average volatility index (VNKY); UK: FTSE 100 implied volatility index (IVI). ΔVIX is the change of VIX close quote. VIX^{night} is the difference between open quote and previous close quote. For futures, VIX is proxied by the cross-section return dispersion. t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets.

Dependent Variable: $\Delta CO - OC$				
Panel A: International Stocks				
	United States		Europe	
intercept	0.000	-0.000	0.000	0.000
	[0.00]	[-1.78]	[0.04]	[-0.15]
ΔVIX	0.000	0.000	0.000	0.000
	[1.38]	[1.76]	[1.46]	[1.55]
VIX^{night}		0.001		0.001
		[3.04]		[3.36]
Adj_R^2	0.001	0.013	0.001	0.007
	Japan		United Kingdom	
intercept	0.000	0.000	0.000	0.000
	[0.02]	[0.55]	[-0.04]	[-0.03]
ΔVIX	0.000	0.000	0.000	0.000
	[-0.20]	[-0.16]	[1.92]	[2.00]
VIX^{night}		0.001		0.000
		[1.65]		[3.63]
Adj_R^2	-0.000	0.001	0.002	0.008

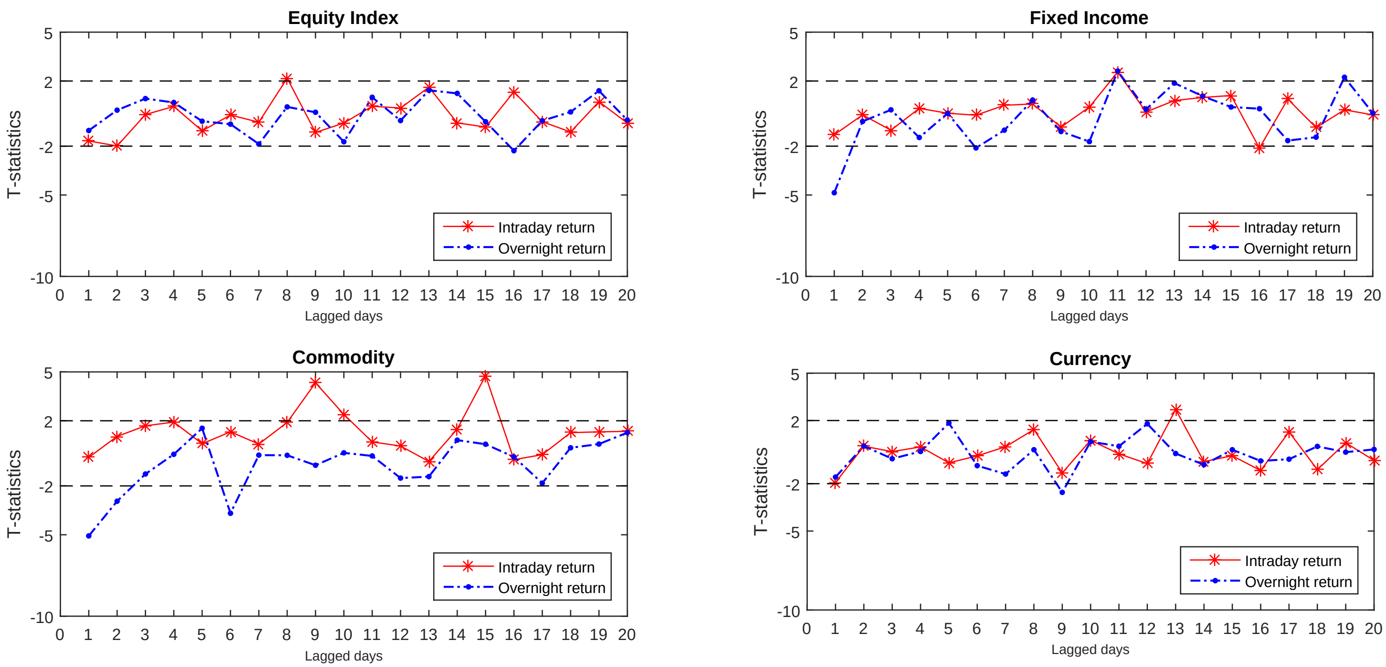
Panel B: Futures				
	Equity Index		Interest Rate	
intercept	0.000	0.000	0.000	0.000
	[0.16]	[0.15]	[-0.09]	[-0.13]
ΔVIX	0.226	0.255	0.149	0.151
	[8.01]	[9.48]	[7.31]	[7.59]
VIX^{night}		0.283		0.269
		[6.83]		[4.85]
Adj_R^2	0.048	0.086	0.021	0.034
	Commodity		Currency	
intercept	0.000	0.000	0.000	0.000
	[-0.16]	[-0.17]	[0.03]	[0.03]
ΔVIX	0.189	0.195	0.201	0.206
	[13.44]	[14.17]	[8.76]	[9.36]
VIX^{night}		0.217		0.045
		[9.57]		[1.58]
Adj_R^2	0.038	0.059	0.062	0.063

Figure 1: Autocorrelation Structure: International Stocks



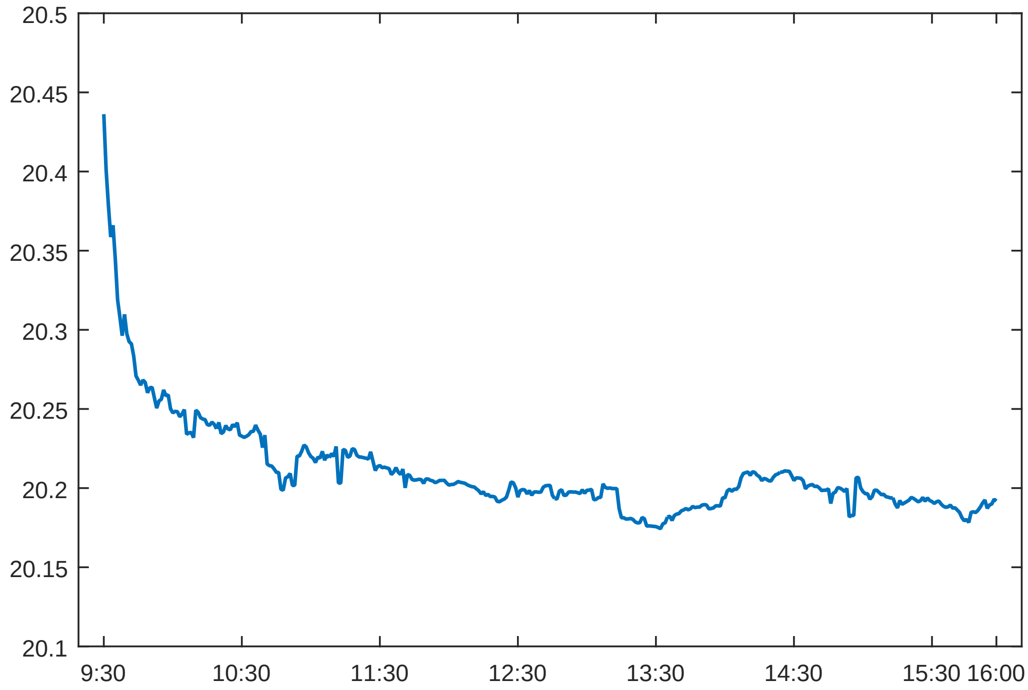
This figure plots the average Fama-MacBeth coefficients of the autocorrelation test: $r_{i,t}^{oc} = \beta_0 + \sum_1^{20} \beta_{k,t} * r_{i,t-k}^{oc} + \sum_1^{20} \gamma_{k,t} * r_{i,t-k}^{co} + \epsilon_{i,t}$. The t-statistic for the first lag (r^{co}) is computed using standard errors that are clustered by time and asset, in order to account for the time-series dependence of the estimates in the first step. The sample is from January 1993 to December 2014.

Figure 2: Autocorrelation Structure: Futures



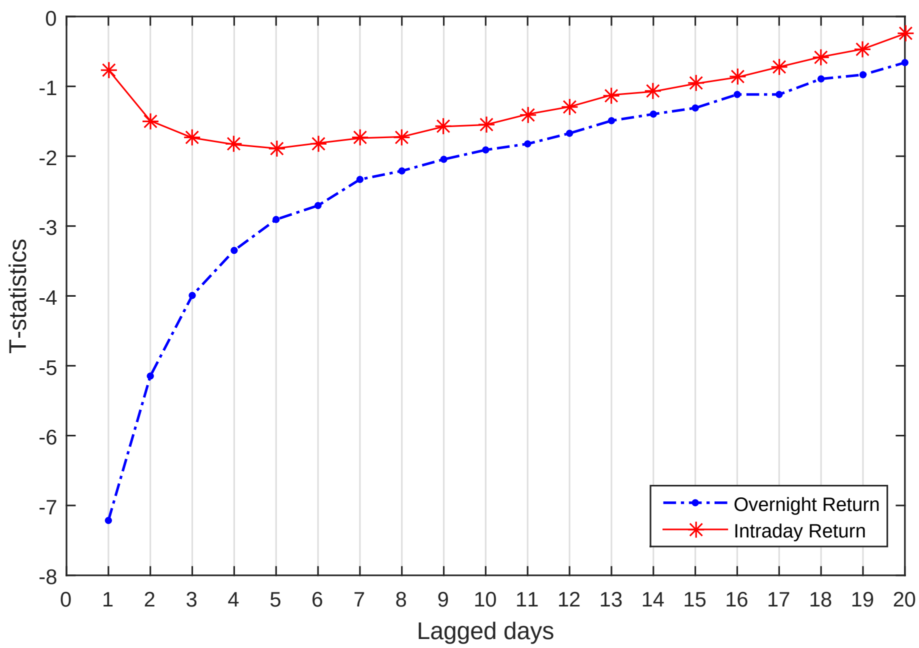
This figure plots the pooled OLS coefficients of the autocorrelation test: $r^{oc}_{i,t} = \beta_0 + \sum_1^{20} \beta_{k,t} * r^{oc}_{i,t-k} + \sum_1^{20} \gamma_{k,t} * r^{co}_{i,t-k} + \epsilon_{i,t}$. The t-statistic are computed using standard errors that are clustered by time and asset, in order to account for the time-series dependence of the estimates. The sample is from July 1982 to December 2014.

Figure 3: Intraday Dynamics of VIX



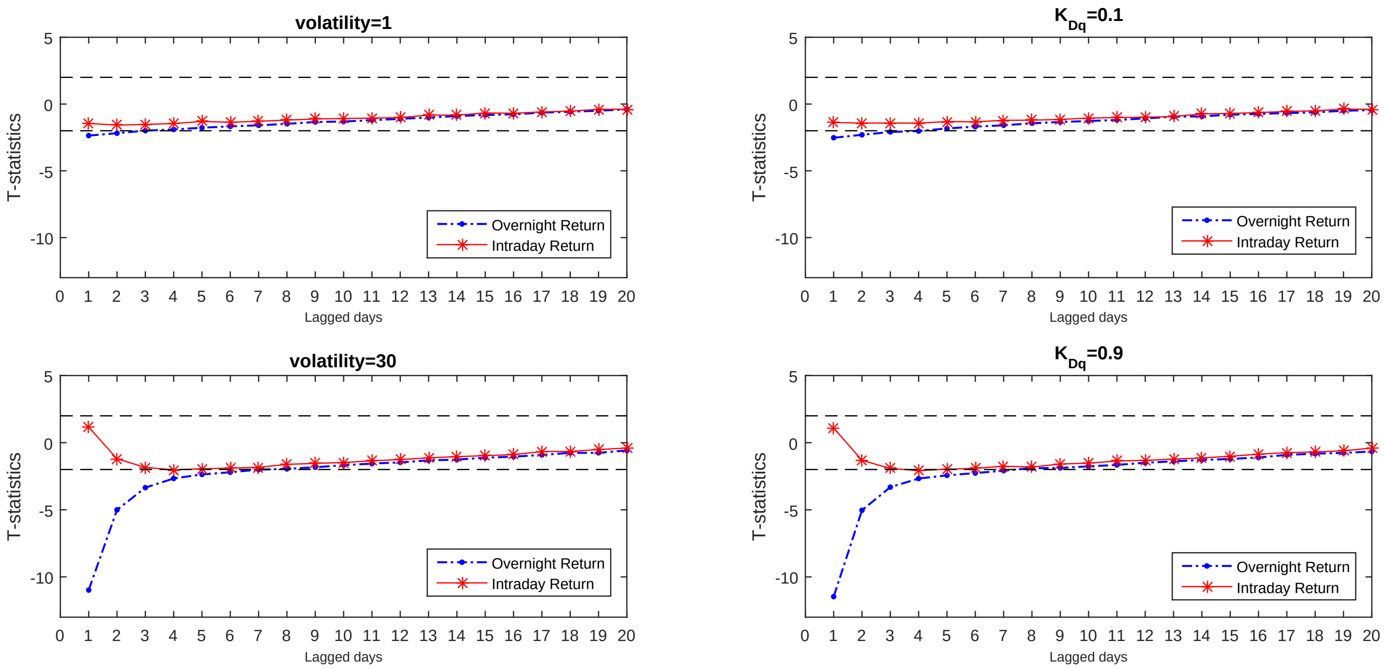
This figure plots average intraday minute levels of VIX index from January 1993 to December 2013.

Figure 4: Autocorrelation Structure: Simulation



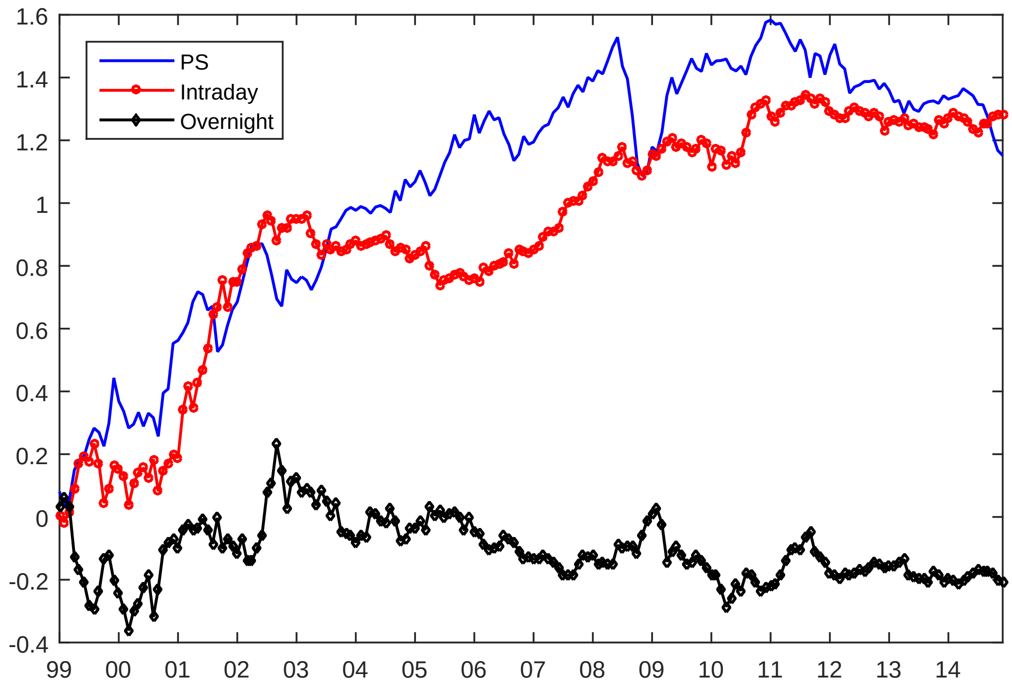
This figure plots the average coefficients of the simulated autocorrelation test based on the model in Hong and Wang (2000). The regression formula is: $r_t^{oc} = \beta_0 + \sum_1^{20} \beta_k * r_{t-k}^{oc} + \sum_1^{20} \gamma_k * r_{t-k}^{co} + \epsilon_t$. The model parameters are set at the following values: The lengths of open and close periods are $T = 0.4$ and $N = 0.6$, $\gamma = 1000$, $r = 0.001$, $\sigma_D = \sigma_G = 0.08$, $\sigma_q = 0.5$, $\sigma_y = 0.25$, $\sigma_1 = \sigma_2 = 7$, $\kappa_{Dq} = 0.65$, $\kappa_{12} = 0$.

Figure 5: Autocorrelation Structure: the role of liquidity shock



This figure plots the average coefficients of the simulated autocorrelation test based on the model in Hong and Wang (2000). The regression formula is: $r_t^{oc} = \beta_0 + \sum_1^{20} \beta_k * r_{t-k}^{oc} + \sum_1^{20} \gamma_k * r_{t-k}^{co} + \epsilon_t$. The model parameters are set at the following values: The lengths of open and close periods are $T = 0.4$ and $N = 0.6$, $\gamma = 1000$, $r = 0.001$, $\sigma_D = \sigma_G = 0.08$, $\sigma_q = 0.5$, $\sigma_y = 0.25$,$\kappa_{12} = 0$. We choose different values for the volatility σ_1 and σ_2 and the stock's exposure to the real investment opportunity κ_{Dq},

Figure 6: Pastor-Stambaugh Liquidity Factor



This figure reports the cumulative return of the traded Pastor-Stambaugh liquidity factor. The traded factor is the value-weighted return on the 10-1 portfolio from a sort on historical liquidity betas.The blue curve shows the return of Pastor-Stambaugh factor. The red circle line depicts the return of liquidity factor based on the measure with intraday return: $r^{e,oc}_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r^{oc}_{i,d,t} + \gamma_{i,t} sign(r^{e,oc}_{i,d,t}) \times \upsilon_{i,d,t} + \epsilon^{oc}_{i,d+1,t}$. The black diamond depicts the return of liquidity factor based on the measure with overnight return: $r^{e,co}_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r^{co}_{i,d,t} + \gamma_{i,t} sign(r^{e,co}_{i,d,t}) \times \upsilon_{i,d,t} + \epsilon^{co}_{i,d+1,t}$.

Internet Appendix to

"Market Closure and Short-Term Reversal"

(not for publication)

Abstract

This appendix presents supplementary results not included in the main body of the paper.

IA.A A model of periodic market closure: Hong and Wang (2000)

Basic Setting

The economy is defined on a continuous time-horizon with a single commodity, which is also used as a numeraire.

- The underlying uncertainty is characterized by an n-dimensional standard Wiener process, $\mathbf{w_t}$.
- Two types of investors, with proportion ω and $1-\omega$, denoted by i=1,2.
- **Investment opportunities**: public (risk-free money market and a risky stock), private investment technologies only available to individual investors in each group. Payoffs as following:
  - Risk-free rate of return r.
  - Each share of the stock pays a cumulative dividend D_t where

$$D_t = \int_0^t (G_s ds + \mathbf{b_D} d\mathbf{w_s}); \tag{IA.A.1}$$

$$G_t = G_0 + \int_0^t (-a_G G_s ds + \mathbf{b_G dw_s}); \tag{IA.A.2}$$

  - Investor i's private technology yields a cumulative excess return $q_{i,t}$, where

$$q_{i,t} = \int_0^t (Y_{i,s} ds + \mathbf{b_q} d\mathbf{w_s}); \tag{IA.A.3}$$

$$Y_{i,t} = Y_{i,0} + \int_0^t (-a_Y Y_{i,s} ds + \mathbf{b_i dw_s}); \tag{IA.A.4}$$

  Here, i=1,2, a_G, a_Y are positive constant, $\mathbf{b_D}, \mathbf{b_G}, \mathbf{b_q}, \mathbf{b_1}, \mathbf{b_2}$ are constant matrices.

  - The system $G_t, Y_{1,t}, Y_{2,t}$ follow Gaussian Markov process, which determines the distribution of future payoffs on stock and private technologies. For convenience, let $\mathbf{Z_t} = [G_t, Y_{1,t}, Y_{2,t}]'$.

$$\mathbf{Z_t} = \mathbf{Z_0} + \int_0^t -\mathbf{a_z Z_s} ds + \mathbf{b_Z dw_s}); \tag{IA.A.5}$$

  where $\mathbf{Z_0} = [G_0; Y_{1,0}; Y_{2,0}]$, $\mathbf{a_Z} = [[\mathbf{a_G}, \mathbf{0}, \mathbf{0}]; [\mathbf{0}, \mathbf{a_Y}, \mathbf{0}]; [\mathbf{0}, \mathbf{0}, \mathbf{a_Y}]]$, and $\mathbf{b_Z} = [\mathbf{b_G}; \mathbf{b_1}; \mathbf{b_2}]$

- The investors can continuously invest in private technologies and money market, while the stock market is open periodically and the price is denoted as P_t.

- **Periodic Stock Market**: $[t_k, n_k]$ denote the k-th trading period, and (n_k, t_{k+1}) is the k-th non-trading period, where k=1,2...... Length of trading period T ($n_k - t_k = T$) and non-trading period N ($t_{k+1} - n_k$=N) are constant. $T = \cup_k [t_k, n_k]$ is the set of times of trading periods, and $N = \cup_k [n_k, t_{k+1}]$ is set of times the stock market is closed.

- **Information**: All investors observe realized dividends and prices. Class 1 investors observe all state variables $(G_t, Y_{1,t}, Y_{2,t})$, but class 2 investors only observe $(Y_{2,t})$. Additionally, a set of public signal by $\mathbf{U_t}$ where

$$\mathbf{U_t} = \mathbf{U_0} + \int_0^t \mathbf{a_U Z_s} ds + \mathbf{b_U dw_s}); \tag{IA.A.6}$$

  $\mathbf{U_0}$ is joint normal with $G_0, Y_{1,0}, Y_{2,0}$, and $\mathbf{a_U}, \mathbf{b_U}$ are constant matrices.

- **Endowments, Policies, and Preferences**: let $c_{i,t}$ ($t \in [0, \infty)$) be his consumption, $y_{i,t}$ ($t \in [0, \infty)$) be the investment in private technology, and $\theta_{i,t}$ ($t \in T$) the number of stock shares he holds at time t, and they are adapted to information $I_{i,t}$. All investors have the following expected utility:

$$E[-\int_t^\infty e^{-\rho(s-t)-\gamma c_{i,s}} ds | I_{i,t}] \tag{IA.A.7}$$

- **Distributional Assumptions**:
  Assume

$$\mathbf{w_t} = [w_{D,t}; w_{G,t}; w_{1,t}; w_{2,t}; w_{q,t}; \mathbf{w_{U,t}}]$$

  and

$$\mathbf{b_D} = \sigma_D[1, 0, 0, 0, 0, \mathbf{0}]; \mathbf{b_G} = \sigma_G[0, 1, 0, 0, 0, \mathbf{0}]; \mathbf{b_q} = \sigma_q[\kappa_{Dq}, 0, 0, 0, \sqrt{1 - \kappa_{Dq}^2}, \mathbf{0}];$$

$$\mathbf{b_1} = \sigma_1[0, 0, \kappa_-, \kappa_+, \mathbf{0}]; \mathbf{b_2} = \sigma_2[0, 0, \kappa_+, \kappa_-, 0, \mathbf{0}]; \mathbf{b_U} = \sigma_U[0, 0, 0, 0, 0, \mathbf{0}];$$

  where $\kappa_{Dq} \in (-1, 1)$ and $\kappa_\pm = \frac{1}{2}(\sqrt{1 + \kappa_{12}} \pm \sqrt{1 - \kappa_{12}})$

- **Additional Notation**:

Define the expected value of future dividends discounted by risk-free rate under full information,

$$F_t = E_t[\int_t^{\infty} e^{-r(s-t)dD_s}] = \frac{1}{r + a_G} G_t \tag{IA.A.8}$$

Also define

$$dQ_t = dP_t + dD_t - rP_t dt \tag{IA.A.9}$$

to be the instantaneous excess return when market is open and $e = E[dQ_t]/dt$, $\sigma_Q^2 = E[(dQ_t)^2]/dt$ its first two unconditional moments.

$$R_{s,t} = P_t - P_s + \int_s^t D_\tau d\tau \tag{IA.A.10}$$

where $s, t \in T$

Definition of Equilibrium

Investor i's financial wealth consist of two parts: the balance in a money-market account $W_{i,t}^0$ and the stock position $\theta_{i,t}$. During the day, the stock market is open, investor can freely adjust his stock position and money-market account to finance consumption and investment in private technology, and the total financial wealth is: $W_{i,t} = W_{i,t}^0 + \theta_{i,t} P_t$. During the night, the budget constraint is by $W_{i,t}^0$, and the overnight stock position θ_{i,n_k} is an additional state variable. Each investors' optimization problem can now be expressed:

$$t \in T_k : J_{i,t} = \sup_{\{c_i, y_i, \theta_i\}} E[-\int_t^{n_k} e^{-\rho(s-t) - \gamma c_{i,t}} ds + J^*_{i,n_k^+} | I_{i,t}] \tag{IA.A.11}$$

$$s.t. \quad dW_{i,t} = (rW_{i,t} - c_{i,t})dt + \theta_{i,t} dQ_t + y_{i,t} dq_{i,t}$$

$$t \in N_k : J^*_{i,t} = \sup_{\{c_i, y_i\}} E[-\int_t^{t_{k+1}} e^{-\rho(s-t) - \gamma c_{i,t}} ds + J_{i,t_{k+1}} | I_{i,t}] \tag{IA.A.12}$$

$$s.t. \quad dW_{i,t}^0 = (rW_{i,t}^0 - c_{i,t})dt + \theta_{i,n_k} dD_t + y_{i,t} dq_{i,t}$$

where $J_{i,t}, J^*_{i,t}$ denote value function during day and night, and t^-, t^+ the time right before and after t. At the open and close, the boundary conditions are:

$$J_{i,n_k} = E[J^*_{i,n_k^+}|I_{i,n_k}] \qquad J^*_{i,t^-_{k+1}} = E[J_{i,t_{k+1}}|I_{i,t^-_{k+1}}] \tag{IA.A.13}$$

The stock market clears:

$$\omega\theta_{1,t} + (1-\omega)\theta_{2,t} = 1 \qquad \forall t \in T \tag{IA.A.14}$$

Definition 1:

A periodic equilibrium is defined by the stock price function $P(\bullet;t)$ and the policy functions $c_i(\bullet;t), y_i(\bullet;t), \theta_i(\bullet;t)$, $i = 1,2$, such that (a) the policies maximize expected utility, (b) the stock market clears, (c) the price function and policy functions are periodic in t with periodicity $T+N$.

This paper restrict to the linear equilibrium in which price function is linear in the sufficient statistics for $I_{i,t}$.

Conjecture of the Equilibrium

The conjectured price function is linear in the conditional expectations of both investors:

$$P_t = \boldsymbol{\lambda_1} E_{1,t}[\mathbf{Z_t}] + \boldsymbol{\lambda_2} E_{2,t}[\mathbf{Z_t}] - \lambda_0 \qquad \forall t \in T \tag{IA.A.15}$$

where $\boldsymbol{\lambda_i} = [\lambda_{iG}, -\lambda_{i1}, -\lambda_{i2}]$ $(i = 1,2)$, defined on T, is deterministic but time-dependent with periodicity $T+N$. Define $\widehat{G}_t = E_{2,t}(G_t)$ and $\widehat{Y}_{1,t} = E_{2,t}[Y_{1,t}]$. Then the price function is:

$$P_t = \lambda_{1G}G_t - \lambda_{11}Y_{1,t} - \lambda_{12}Y_{2,t} + \lambda_{2G}\widehat{G}_t - \lambda_{21}\widehat{Y}_{1,t} + \lambda_{22}Y_{2,t} - \lambda_0 \tag{IA.A.16}$$

Characterization of the Equilibrium To characterize the equilibrium, we take the price function (16) as given and derive teach investor's expectations and policies and conditions for market clearing.

- **Conditional Expectations**

  Investor i receives a vector of signals $\mathbf{S_{i,t}}$: $\mathbf{S_{1,t}} = [\mathbf{U_t}; D_t; P_t; G_t; Y_{1,t}; Y_{2,t}; q_{1,t}]$ and $\mathbf{S_{2,t}} = [\mathbf{U_t}; D_t; P_t; Y_{2,t}; q_{2,t}]$. Thus, $I_{i,t} = \{\mathbf{S_{i,t}} : \mathbf{0} \leq \mathbf{s} \leq \mathbf{t}\}$. Since $\mathbf{Z_t}$ and $\mathbf{S_{i,t}}$ are jointly Gaussian, the distribution of $\mathbf{Z_t}$ conditional on $\{\mathbf{S_t}\}$ is Gaussian, fully characterized by its mean and variance. Let $Z_{i,t} = E_{i,t}[\mathbf{Z_t}]$ and $\mathbf{o_i}(t) = E_{i,t}[(\mathbf{Z_t} - \mathbf{Z_{i,t}})(\mathbf{Z_t} - \mathbf{Z_{i,t}})']$.

  Lemma 1:

$$\forall t > s: \qquad \mathbf{Z_{i,t}} = e^{-\mathbf{a_Z}(t-s)}\mathbf{Z_{i,s}} + \int_s^t e^{-\mathbf{a_Z}(t-\tau)}\mathbf{k_i}(d\mathbf{S}_{\mathbf{i},\tau} - E_{i,\tau}[d\mathbf{S}_{\mathbf{i},\tau}]) \tag{IA.A.17}$$

$$\forall t > s: \mathbf{o_i}(t) = \mathbf{o_i}(s) + \int_s^t \mathbf{g_{i,o}} d\tau \tag{IA.A.18}$$

  where $\mathbf{k_i}$ and $\mathbf{g_{i,o}}$ are deterministic. $\mathbf{o_i}$ evolves deterministically over time. The periodic solution to the investors' expectations requires that:

$$\mathbf{o_i}(t_{k+1}) = \mathbf{o_i}(t_k), \qquad k = 0, 1, 2.... \tag{IA.A.19}$$

- **Optimal Policies**

  Define $\mathbf{X_t} = [1, Y_{1,t}, Y_{2,t}, G_t - \widehat{G}_t, Y_{1,t} - \widehat{Y}_{1,t}]'$ as a sub_vector of the state variables and let $\mathbf{X_{i,t}} = E_{i,t}[\mathbf{X_t}]$ denotes the conditional expectation. The price function can be rewritten as follows:

$$P_t = F_t - \lambda X_t = F_{i,t} - \lambda_i X_{i,t} \qquad \forall t \in T \tag{IA.A.20}$$

  where $\lambda = [\lambda_0, \lambda_1, \lambda_2, \frac{1}{r+a_G} - \lambda_G, 0]$, $F_{i,t} = E_{i,t}(F_t)$, $\lambda_1 = \lambda$ and $\lambda_2 = [\lambda_0, \lambda_1, \lambda_2, 0, 0]$.

$$\forall t > s: \qquad \mathbf{X_{i,t}} = \mathbf{X_{i,0}} + \int_0^t \{-\mathbf{a_{i,X}}\mathbf{X}_{i,s} ds + \mathbf{k_{i,X}}(d\mathbf{S}_{i,s} - E_{i,s}[d\mathbf{S}_{i,s}])\} \tag{IA.A.21}$$

  and

$$\forall t \in T: \qquad Q_t = \int_0^t \{\mathbf{a}_{i,Q}\mathbf{X}_{i,t} ds + \mathbf{k}_{i,Q}(d\mathbf{S}_{i,s} - E_{i,s}[d\mathbf{S}_{i,s}])\} \tag{IA.A.22}$$

  Lemma 3

Given the price function (20) and the solution to investors' expectation, investor i's value function has the form:

$$\begin{cases} t \in T_k : & J_{i,t} = -exp\{-\rho t - r\gamma W_{i,t} - \frac{1}{2}\mathbf{X'}_{i,t}\upsilon_i \mathbf{X}_{i,t}\} \\ t \in N_k : & J^*_{i,t} = -exp\{-\rho t - r\gamma W^*_{i,t} - \frac{1}{2}\mathbf{X'}^*_{i,t}\upsilon_i \mathbf{X}^*_{i,t}\} \end{cases} \tag{IA.A.23}$$

where $W^*_{i,t} = W^0_{i,t} + \theta_{i,n_k} F_{i,t}$, $\mathbf{X}^*_{i,t} = [\mathbf{X}_{i,t}; \theta_{i,n_k}]$, υ_i is a symmetric matrix, given by

$$\forall s < t : \qquad \upsilon_i(s) = \upsilon_i(t) + \int_t^s \mathbf{g}_{i,\upsilon} d\tau \tag{IA.A.24}$$

and

$$\upsilon_i(t_k) = \upsilon_i(t_{k+1}) \tag{IA.A.25}$$

with $\mathbf{g}_{i,\upsilon}$ being deterministic. The optimal policies are

$$t \in [t_k, n_k] : \begin{cases} \begin{bmatrix} \theta_{i,t} \\ y_{i,t} \end{bmatrix} = \begin{bmatrix} \mathbf{h}_{i,\theta} \\ \mathbf{h}_{i,y} \end{bmatrix} \mathbf{X}_{i,t} \\ c_{i,t} = -\frac{1}{r} ln\gamma + rW_{i,t} + \frac{1}{2\gamma}\mathbf{X}'_{i,t}\upsilon_i \mathbf{X}_{i,t} \end{cases} \tag{IA.A.26}$$

$$t \in (n_k, t_{k+1}) : \begin{cases} y_{i,t} = [\mathbf{h}_{i,y}, h_i]\mathbf{X}^*_{i,t} \\ c_{i,t} = -\frac{1}{r} ln\gamma + rW^*_{i,t} + \frac{1}{2\gamma}\mathbf{X}'^*_{i,t}\upsilon_i \mathbf{X}^*_{i,t} \end{cases}$$

where $\mathbf{h}_{i,\theta}$, $\mathbf{h}_{i,y}$ and h_i are functions of λ_i, $\mathbf{o}_i$, υ_i.

Given λ and resulting $\mathbf{o}_i$, Lemma 3 expresses investor i's optimal policies as functions of υ_i, which is in (24), a (vector-form) first-order ODE with boundary condition (25).

- **Market Clearing**

  Stock market clearing condition requires:

$$\omega\lambda_1\mathbf{h}_{1,\theta} + (1-\omega)\mathbf{h}_{\mathbf{2},\theta}\tau = [\mathbf{1}, \mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}] \qquad \forall \mathbf{t} \in T_k \tag{IA.A.27}$$

where $\tau = [[\lambda, 0, 0, 0, 0]; [0, \lambda_1, 0, -\lambda_G, 0]; [0, 0, \lambda_1, 0, 0]]$. The periodic condition requires

$$\lambda(t_k) = \lambda(t_{k+1}) \tag{IA.A.28}$$

Given $\mathbf{h}_{i,\theta}$, equation (27) defines first-order ODE for λ and boundary condition is (28).

Computation of the Equilibrium

The periodic equilibrium now reduces to solving a system of first-order ODE's for $\mathbf{o_i}$, υ_i and λ, subject to periodicity conditions (19), (25) and (28).

In general, the actual values of $\mathbf{o_i}$, υ_i and λ can only be solved numerically. We need start with the solution at $\omega = 1$ and then obtain solutions for values of ω close to one. Iteratively, we arrive at the solutions for desired valued of ω.

The Case of Symmetric Information

This case can be obtained from the general model by letting $\mathbf{U_0} = \mathbf{Z_0}$, $\mathbf{a_U} = [[1, 0, 0]; [0, 1, 0]; [0, 0, 1]]$ and $\mathbf{b_U} = 0$. $G_t, Y_{1,t}, Y_{2,t}$ then become public information.

The stock price under symmetric information is

$$P_t = F_t - (\lambda_0 + \lambda_1 Y_{1,t} + \lambda_2 Y_{2,t}) \qquad \forall t \in T \tag{IA.A.29}$$

It is given by the value of expected future dividends (F_t) minus a risk discount ($\lambda_0 + \sum_i \lambda_i Y_{i,t}$). The risk discount consists of two parts: (a) an unconditional part (λ_0) that is independent of the returns on the private investments and (b) a conditional part that depends on the expected returns on the private investments. The unconditional part derives primarily from the uncertainty in future dividends. The conditional part of the risk discount depends on the correlation between the returns on the stock and the private technologies, κ_{Dq}.

The stock position during the day is

$$\theta_{i,t} = h_{i,\theta}^{(0)} + h_{i,\theta}^{(1)} Y_{1,t} + h_{i,\theta}^{(2)} Y_{2,t} \tag{IA.A.30}$$

The stock position consists of three parts: for instance, as for investor 1, the first component $h_{1,\theta}^{(0)}$ gives the unconditional stock position, the second component $h_{1,\theta}^{(1)} Y_{1,t}$ arises from his hedging trade as he adjusts his stock position to hedge the risk of his private investments, and the third components $h_{1,\theta}^{(2)} Y_{2,t}$ is his market-making activity.

Discrete Simple Returns

Market closures give rise to time variation in investors' hedging trade. In the following discussions, we use numerical examples to illustrate the main implications of the model. We use the same parameter setting as in Hong and Wang (2000). In particular, we set $\sigma_1 = \sigma_2$ and $\omega = 0.5$ to main the symmetry between the two class of investors. The lengths of open and close periods are $T = 0.4$ and $N = 0.6$. The other parameters in the benchmark case is: $\gamma = 1000$, $r = 0.001$, $\sigma_D = \sigma_G = 0.08$, $\sigma_q = 0.5$, $\sigma_y = 0.25$, $\sigma_1 = \sigma_2 = 7$,$\kappa_{Dq} = 0.65$, $\kappa_{12} = 0$.

Table IA.1: Short-term Reversal Strategies: Implied Volatility

This table presents descriptive statistics of the four short-term reversal strategies volatility index and VIX futures. The strategy *CC-CC* forms the signal based on close-to-close return, and trades in the next close-to-close return. The strategy *OO-OO* forms the signal based on open-to-open return, and trades in the next open-to-open return. The strategy *OC-OC* forms the signal based on open-to-close return, and trades in the next open-to-close return. The strategy *CO-OC* forms the signal based on close-to-open return, and trades in the next open-to-close return. The mean, standard deviation, value at quantile 5% and 95% are expressed in percentage per day. The table also reports the autocorrelation coefficient with one day lag and one month lag (AC_1, AC_{21}), the annualized Sharpe ratio (SR). t-statistics are based on Newey and West (1987) standard errors with Andrews (1991). The *corr* measures the correlation between the return of *CO-OC* strategies with other three strategies' returns. The strategies in index level are rebalanced daily from January 1992 to December 2014. The strategies in VIX futures are rebalanced daily from March 2004 to October 2015.

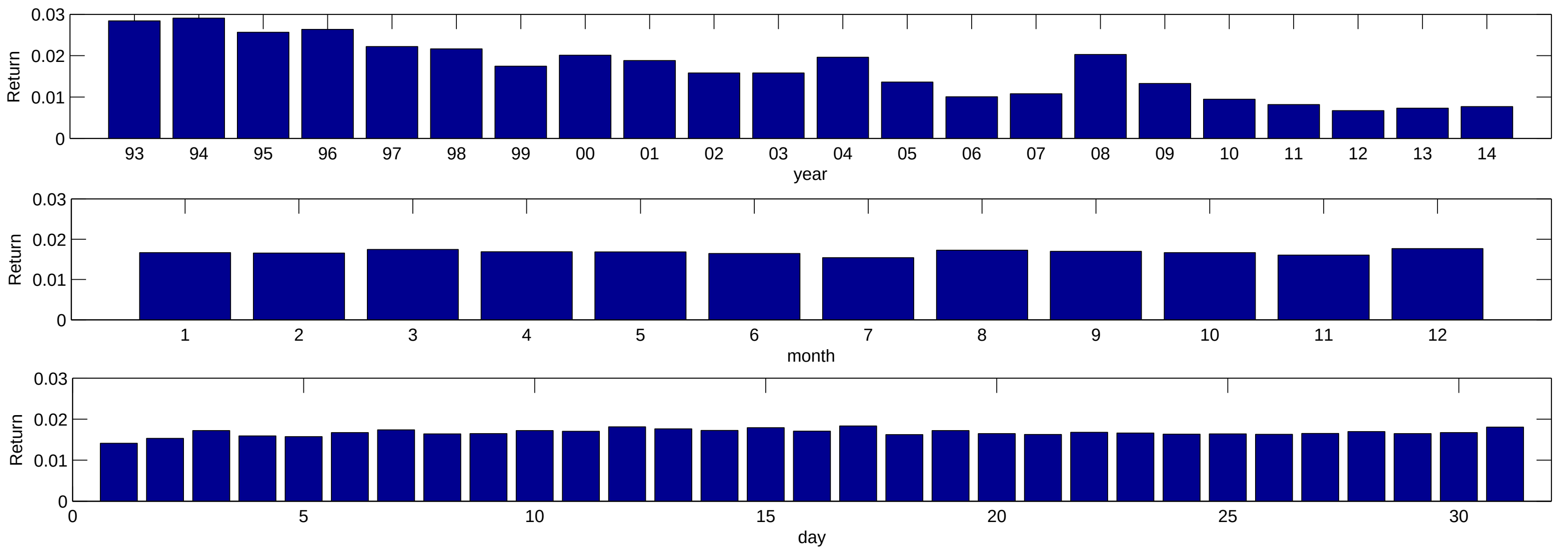
	CC-CC	OO-OO	OC-OC	CO-OC
	Implied Volatility Indices			
mean	1.006	1.948	-0.437	2.304
t-stat	[21.82]	[25.34]	[-6.30]	[33.12]
st. dev	3.726	4.836	4.228	3.850
skew	3.409	1.175	-1.499	1.391
kurt	91.900	10.876	44.723	16.832
Q_5	-3.763	-4.316	-6.243	-2.322
Q_{95}	6.026	10.081	5.221	8.417
SR $\times\sqrt{252}$	4.287	6.394	-1.642	9.503
AC_1	-0.053	0.042	0.103	0.089
AC_{21}	-0.012	0.016	0.025	0.048
corr	-0.114	0.045	-0.252	1.000
	VIX Futures			
mean	0.190	0.459	-0.075	0.741
t-stat	[4.19]	[10.17]	[-1.76]	[15.73]
st. dev	2.503	2.279	2.267	1.981
skew	0.678	0.487	0.507	-0.291
kurt	11.462	9.963	10.457	15.363
Q_5	-3.492	-2.804	-3.465	-1.947
Q_{95}	3.988	3.987	3.404	3.663
SR $\times\sqrt{252}$	1.207	3.198	-0.523	5.938
AC_1	0.026	0.055	0.009	0.076
AC_{21}	0.009	0.008	-0.004	0.035
corr	-0.192	0.070	-0.178	1.000

Table IA.2: Short-term Reversal Strategies: ETFs

This table presents descriptive statistics of the four short-term reversal strategies in ETFs that covers equity index, interest rate, commodity and currency. The strategy *CC-CC* forms the signal based on close-to-close return, and trades in the next close-to-close return. The strategy *OO-OO* forms the signal based on open-to-open return, and trades in the next open-to-open return. The strategy *OC-OC* forms the signal based on open-to-close return, and trades in the next open-to-close return. The strategy *CO-OC* forms the signal based on close-to-open return, and trades in the next open-to-close return. The mean, standard deviation, value at quantile 5% and 95% are expressed in percentage per day. The table also reports the autocorrelation coefficient with one day lag and one month lag (AC_1, AC_{21}), the annualized Sharpe ratio (SR). t-statistics are based on Newey and West (1987) standard errors with Andrews (1991). The *corr* measures the correlation between the return of *CO-OC* strategies with other three strategies' returns. The strategies are rebalanced daily from March 1999 to December 2014.

	CC-CC	OO-OO	OC-OC	CO-OC	CC-CC	OO-OO	OC-OC	CO-OC
	Equity Index				Fixed Income			
mean	0.075	0.111	0.028	0.156	0.034	0.075	0.005	0.077
t-stat	[6.02]	[7.61]	[2.39]	[11.47]	[1.28]	[2.75]	[0.19]	[3.23]
st. dev	0.831	0.909	0.784	0.725	1.181	1.223	1.048	1.018
skew	0.832	1.356	1.955	2.417	0.424	-0.222	-0.005	-0.244
kurt	17.963	28.024	40.963	37.091	9.927	12.478	11.546	16.961
Q_5	-1.011	-0.994	-0.994	-0.687	-1.706	-1.611	-1.457	-1.183
Q_{95}	1.328	1.363	1.168	1.118	1.783	2.017	1.580	1.589
SR $\times\sqrt{252}$	1.303	1.819	0.436	3.260	0.412	0.927	0.022	1.153
AC_1	-0.045	-0.041	-0.050	0.033	0.004	-0.063	-0.064	-0.034
AC_{21}	-0.004	0.025	-0.003	0.028	-0.014	-0.037	-0.034	0.012
corr	0.008	-0.017	0.110	1.000	-0.122	-0.018	-0.086	1.000
	Commodity				Currency			
mean	0.394	0.573	0.028	0.843	0.046	0.041	0.003	0.044
t-stat	[6.56]	[9.69]	[0.49]	[10.52]	[1.85]	[1.45]	[0.16]	[1.99]
st. dev	1.929	1.655	1.550	1.940	1.222	1.324	0.792	0.846
skew	-0.578	0.471	-0.100	6.390	0.170	-0.080	-1.050	0.412
kurt	18.258	5.092	8.362	91.838	7.392	11.232	15.272	15.309
Q_5	-2.380	-1.928	-2.185	-1.109	-1.976	-1.931	-1.143	-1.143
Q_{95}	3.356	3.502	2.662	3.198	1.980	2.092	1.218	1.272
SR $\times\sqrt{252}$	3.245	5.497	0.290	6.897	0.536	0.445	-0.030	0.751
AC_1	-0.058	-0.029	0.036	0.011	-0.033	-0.007	0.027	0.090
AC_{21}	-0.003	-0.010	-0.054	-0.004	-0.033	-0.014	-0.016	0.040
corr	0.087	-0.014	-0.079	1.000	-0.003	0.021	0.1189	1.000

Figure IA.1: Calendar Effect



This figure reports the average return of *CO-OC* strategy in different calendar day, month and year, of the US stock sample.