The Overnight Drift
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Abstract
This paper documents large positive returns to holding U.S. equity futures overnight during the opening hours of European markets. These returns are not explained by liquidity risk, volatility risk, tail events, or overnight news. Instead, consistent with models of inventory risk and demand for immediacy, we demonstrate a strong relationship with market sell-offs from the previous intraday session. Moreover, price reversals are strongest at the opening of European markets, when overnight trading volumes peak. Finally, the timing of overnight returns shifts predictably in response to exogenous variation in the arrival time of Asian investors due to daylight savings time asynchronicities.

Key words: overnight returns, immediacy, volatility risk, inventory risk

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To view the authors’ disclosure statements, visit https://www.newyorkfed.org/research/staff_reports/sr917.html.
Since the advent of electronic trading in the late 1990’s, U.S. S&P 500 index futures have traded close to 24 hours a day. In this paper, we document that, despite the 24 hour nature of the market, returns do not accrue linearly over the 24 hours. In fact, the largest positive returns accrue between 2:00 a.m. and 3:00 a.m., the opening of European markets in U.S. Eastern Time terms, averaging 3.6% on an annualised basis. Focusing on returns during this hour, we show that positive average returns are highly statistically significant, consistently present throughout the 1998 – 2019 sample, accompanied by substantial trading volume, and do not cluster on any particular day of the week or month of the year. We dub this positive average return the ‘overnight drift’, and argue that this pattern of returns is driven by overnight resolution of order imbalances at the end of the preceding U.S. trading day.

Models of immediacy, such as Grossman and Miller (1988), show that risk-averse market makers profit by providing liquidity to investors who arrive asynchronously to the market, generating mean reversion in prices as market makers absorb shocks to their inventories.1 To understand how inventory management concerns can lead to the overnight drift, suppose there is selling pressure during the day, translating into an overall negative order imbalance by the end of regular trading hours. Market makers become net buyers, bearing inventory risk until they are able to sell to new market participants arriving overnight; however, they demand compensation for this in terms of positive expected returns. In other words, they must expect to be able to sell this inventory at a higher price than at which they acquired it. As new participants arrive overnight, market makers offload their inventory and prices gradually rise.

We conduct a number of tests, showing that inventory risk borne by market makers overnight can explain the overnight drift. First, sorting days based on end-of-trading-day order imbalance, we show that positive overnight returns occur only on nights following market sell-offs (negative end-of-day order imbalances). When order imbalances are in the bottom tercile (most negative order imbalances), contemporaneous closing returns are on average −81% p.a. The subsequent overnight returns average 7.6% p.a. during Asian hours and 12.4% p.a. during European hours, such that the overnight reversal bounces back by 20%. Of the 20% reversal, returns earned around the opening of European markets between 2:00 a.m - 3:00 a.m ET (1:30 a.m - 3:30 a.m)

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1The CME does not designate ‘specialist’ market makers in e-mini futures. Instead, effective market makers are any participant willing to post limit orders on both sides of the order book and hence supplying liquidity (immediacy) to market takers.
ET) equal 7.5% (13.5%). Price reversals following market *rallies* are much more modest: When order imbalances are in the top tercile (most positive order imbalances), contemporaneous closing returns are on average 81% p.a. but the subsequent overnight returns average −1.5% p.a. during Asian hours, and 5.1% p.a. during European hours, and there is no reversal effect between 2:00 a.m - 3:00 a.m ET. Thus, although market sell-offs and market rallies at U.S. close are similar in magnitude (though, naturally, of opposite sign), positive closing order imbalances lead to much smaller price reversals than negative closing imbalances, generating an unconditional positive overnight drift. We speculate that this asymmetry is related to time-varying risk aversion, which arguably increases during bad states (market sell-offs) more so than during good states.

Second, we investigate the relationship between end-of-day order imbalance and subsequent overnight returns more formally by estimating high frequency predictability regressions of returns on end-of-day order imbalance, and find statistically and economically significant loadings on the hours when London and Frankfurt financial markets open. Thus, high frequency returns become predictable as market makers transact with new participants arriving overnight, trading away order imbalances remaining from the previous U.S. trading day. We also show that this high frequency predictability can be re-cast in different terms, with closing returns predicting both subsequent overnight order flows and overnight returns, and end-of-day order imbalance also predicting order flow reversals during the night. Finally, consistent with the hypothesis that asymmetry in price reversals following market sell-offs and market rallies is related to time-varying risk aversion, we show that the relationship between end-of-day order imbalance and subsequent overnight returns is amplified when market sell-offs are accompanied by increases in implied volatility, as measured by the VIX.

Third, our hypothesis that the overnight drift is caused by end-of-day demand for immediacy is supported by a novel natural experiment. First, we show that e-mini trading has been increasing in Asian trading hours throughout the sample, suggesting that end-of-day order imbalances can be resolved earlier in the overnight session in the second half of our sample. We document that, post-2010, a secondary overnight drift does in fact emerge at precisely the Tokyo financial market open. This stands in contrast to pre-2010 when there was virtually no trade during these hours and we observed no return predictability at the Tokyo open. Next, we exploit the time difference between the U.S. and Japan: While the U.S. observe daylight savings time (DST), Japan does not.
Thus, seen from the perspective of a U.S. trader, the timing of Japanese market opening changes exogenously from 7 p.m. in winter to 8 p.m. in summer.\textsuperscript{2} Indeed, accounting for DST, return predictability around Tokyo open shifts forward by one hour when moving from winter to summer time, so that exogenous variation in the time of arrival of liquidity traders leads to predictable variation in the returns earned overnight.

A natural question is why do price reversals not happen immediately upon overnight market opening but instead take time to resolve. The answer is that, even though overnight volumes have grown steadily over our sample period, the close of regular trading at 16:15 EST marks the only time of the day when volumes jump discontinuously down. Even in recent years volumes during Asian open hours remain substantially below volume at the U.S. close: between 2009 - 2019 trading volumes in regular Asian hours (18:00 - 2:00 a.m.) accounted for 15\% of closing volumes between 15:15 and 16:15. Indeed, if we recast the trading day in volume time instead of clock-time, returns increase linearly in signed volume until around 60,000 contracts are traded, corresponding to the average number of contracts traded by 3 a.m. In other words, it takes market makers roughly 60,000 transactions to offset end-of-day order imbalances as of the previous day, with this re-balancing occurring earlier during the night as trading increases during Asian market hours. We show that the linearity in the relationship between signed volume and returns in volume-time terms persists even after we condition on market sell-offs, emphasizing the importance of studying inventory management motives in volume time.

Finally, we explore alternative explanations for the unconditional overnight drift. Summarizing, we reject explanations based on contemporaneous liquidity and volatility effects, tail events, as well as the arrival of overnight news such as international macro, central bank, or U.S. after hours earnings announcements. The overnight drift is thus unlikely to be related to risk compensation related to announcement premia. We furthermore document that end-of-day order imbalance in the e-mini futures market predicts subsequent overnight returns in both the e-mini and the VIX futures contracts, while end-of-day order imbalance in the VIX futures market does not. Thus, although contemporaneously overnight returns in the e-mini and VIX futures are related through the leverage effect, overnight returns in both markets are predicted by end-of-day imbalance in the e-mini market, making the “resolution of uncertainty” hypothesis an unlikely explanation for

\textsuperscript{2}The Tokyo Stock Exchange trades from 9.00 a.m. to 3.00 p.m. in Japanese Standard Time.
the overnight drift.

We conclude by studying a set of trading strategies that exploit overnight price reversals in the post-2005 sample period. Pre-transaction costs, a trading strategy that goes long the S&P 500 futures between 2:00 a.m. and 3:00 a.m. earns large positive returns equal to 3.7% p.a. with a Sharpe ratio of 1.14, but accounting for bid-ask spreads reduces strategy returns to −0.8% p.a. Extending the trading interval to the sub-period between 1:30 a.m and 3:30 a.m increases pre-transaction returns to 5.8% and post-transaction costs remains barely profitable with returns of 1.3% p.a. and a Sharpe ratio of 0.1. This is exactly what would be predicted by models of inventory risk: market makers position their limit order books to incentivize trades that bring their inventory closer to their targets, making the contrarian trade – where a client would earn the bid-ask spread – non-profitable. However, conditioning on date $t-1$ order imbalance, we consider a ‘buy-the-dip’ strategy that goes long the S&P 500 between between 1:30 a.m and 3:30 a.m only on trading days following market sell-offs. Trading approximately 50% of days, this strategy generates (post transaction cost) returns equal to 4.2% p.a with a Sharpe ratio of 1.2, which is five times larger than a passive (no transaction costs) position in the market over the same sample period. More generally, the presence of the overnight drift implies that the timing of portfolio adjustments should be an important consideration for a wide range of asset managers.

**Related Literature:** In the time-series, numerous studies have documented that equities earn a substantial proportion of their returns during the overnight period compared to the regular U.S. trading-hours (for example, Cliff, Cooper, and Gulen, 2008 or Kelly and Clark, 2011).\(^3\) In work subsequent to ours, Bondarenko and Muravyev (2020) replicate our finding that the lion’s share of CTC equity futures returns are earned around the opening hours of European markets. However, by ignoring in the impact of heterogeneously timed market participation and time trends in volumes, these authors misinterpret evidence on inventory management.

In the cross-section, Heston, Korajczyk, and Sadka (2010) study high frequency periodicity in firm level returns documenting persistent intraday return reversals, which the authors argue arise because investors have predictable demand for immediacy at certain points within the day. Lou,

Polk, and Skouras (2017) document firm level reversal patterns between intraday and overnight returns: overnight (intraday) returns predict subsequent overnight (intraday) returns positively, while overnight (intraday) returns predict subsequent intraday (overnight) negatively. The authors link this pattern to a ‘tug of war’ between retail investors trading at the beginning of the day and institutional investors who trade at the end of the day. Bogousslavsky (2018), on the other hand, studies institutional constraints and overnight risk in the cross-section of intraday pricing anomalies. Consistent with limits to arbitrage theory, a mis-pricing factor earns positive returns throughout the day but negative returns on market close when arbitragers are forced to close their positions. Hendershott, Livdan, and Rösch (2018) also study intraday versus overnight return components in the cross-section and present evidence that the CAPM holds overnight. These authors argue their findings are consistent with short lived beta-related price effects at market open and close.

In contrast to these studies, we focus on high-frequency movements in returns to U.S. equity index futures, allowing us to uncover the overnight drift, which we argue arises because of rational inventory management by risk-averse market makers. Moreover, exploiting data that spans the 24-hour trading day we can test the implications of inventory management models by exploiting exogenous variation in the arrival time of clients due to asynchronicity in Daylight Savings Time management between U.S. and Japan and Australia.

Theoretical models on intraday patterns have focused on price discovery and learning at market openings (Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990; Biais, Hillion, and Spatt, 1999; Hong and Wang, 2000). In contrast, we motivate our empirical design from a literature that studies demand for immediacy and inventory risk (Ho and Stoll, 1981; Grossman and Miller, 1988; Vayanos, 1999, 2001; Rostek and Weretka, 2015). A common prediction of these models links price reversals to temporary order imbalances absorbed by liquidity providers. Indeed, the Duffie (2010) presidential address reviews price dynamics with ‘slow-moving’ capital and highlights that ‘Even in markets that are extremely active, price dynamics reflect slow capital when viewed from a high-frequency perspective.’

The nature of our data set enables us to measure liquidity demand (order imbalance) at the market close and study variation in high frequency demand for liquidity faced by dealers. Our

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4For a textbook treatment we refer the reader to Foucault, Pagano, Roell, and Röell (2013).
empirical findings complement the literature on the investors’ demand for liquidity such as, the return to liquidity-providing trading strategies (Nagel, 2012), liquidity demand by mutual funds (Coval and Stafford, 2007; Da, Gao, and Jagannathan, 2011; Rinne and Suominen, 2016) or by hedge funds (Jylhä, Rinne, and Suominen, 2014; Choi, Shachar, and Shin, 2019).

The rest of the paper is organized as follows. We describe the high-frequency futures data in Section I. We present the our main contribution in Section II. Section III describes a motivating framework and tests predictions arising from inventory risk models linking order imbalances to returns. Section IV tests alternative explanations for the overnight drift based on volatility risk, liquidity risk, the arrival of overnight news, and the resolution of uncertainty. We examine the profitability of a trading strategy based on the overnight drift in Section V. Section VI concludes.

I. Data

Our primary focus is data on intraday trades and quotes for S&P 500 futures contracts. The initial S&P 500 futures contract was introduced by the CME in 1982, trading both by open outcry and electronically during regular hours concurrent with trading in the cash market. This ‘big’ futures contract (henceforth SP) was originally quoted with a multiplier of $500 per unit of underlying, so that if the index trades, for example, at $500, the value of the SP contract is $250,000. As the index level rose over time, the SP contract became expensive to trade at this multiplier and the contract multiplier was cut to $250 times the index on November 3, 1997. In September 1993, the SP contract began trading electronically outside regular hours via the CME GLOBEX electronic trading platform. The S&P 500 e-mini futures contract (henceforth ES) was introduced on September 9, 1997 and is quoted at fifty times the index, i.e. one-fifth of the big SP contract. The ‘e’ in e-mini is for electronic as trading takes place only on the CME GLOBEX platform which facilitates global trade for (almost) 24-hours a day 5-days a week. The two futures contracts have quarterly expiries on the third Thursday in March, June, September and December. The most traded contract is almost always the front contract (the contract closest to expiry). Only when the front contract is close to expiry is the back contract (the contract second closest to expiry)

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5Regular trading hours are defined by the open outcry or pit session which trades between 9:30-16:15 (ET)
6The minimum tick size was also cut to 0.25. See Karagozoglu, Martell, and Wang (2003) for a discussion on how this change affected market liquidity and volatility.
more traded. This is because market participants roll their positions in advance of the expiry. We always use the most traded contract.

We use tick-by-tick data on trades and quotes from Thomson Reuters Tick History (TRTH), with complementary data obtained directly from the CME. The trades dataset includes the trade price, trade size and trade time. The quotes dataset includes quote price, quote size and quote time, with the first five levels of the order book available at all times. All trades and quotes are time-stamped to the millisecond, using Universal Time (UT). The UT timestamps are converted to U.S. Eastern Time (ET), so we can define the intraday (ID) and overnight (ON) trading sessions relative to the opening hours of the U.S. cash equity market. We identify the direction of trades by comparing the trade price to the most recent quoted prices of top level of the limit order book: Buy (sell) orders must trade at the best available ask (bid) price. Our sample period with 24 hour trading starts in January 1998 and ends in December 2018. Market depth for the first 5 levels of the order book is available since 2009.

Panel (a) of figure 1 displays within-the-month average daily trading volume for the SP and ES contracts where the ES is further split by volumes within ON and ID trading sessions. We measure volume as the total number of contracts traded in the most liquid contract, multiplying the volume for the SP contract by 5 (10 prior to 1998) to make its volume comparable to the ES. The figure shows that, since the advent of electronic trading, volume in the SP has trended down over time. Instead, the trading volume in the ES (plotted in red for ON and blue for ID) was growing through the financial crisis but has since stabilized at around 1-2 million contracts traded per day with 15% of trading taking place during the ON session. Turning to panel (b), we see that, while the annual volume traded ON as a percentage of overall volume was small and constant at around 2% until the years 2002, it increased linearly to around 15% in 2010 and has remained flat at that level since then. In 2018, with the level of the index above 2000, using the index multiplier of 50, this corresponds to more than $15 billion traded through the e-mini contract daily during the overnight session.

[ Insert figure 1 ]
II. Returns around the clock

Exact trading times on CME platforms have changed over time but today trades are executed continuously from Sunday (18:00; 6 p.m.) – Friday (17:00; 5 p.m.), with a daily maintenance break between 16:15 – 16:30 (4:15 p.m. – 4:30 p.m.). This section studies intraday returns computed from the most liquid e-mini contract, which is almost always the front month contract, except in expiration months when contracts are rolled. Returns are computed from both volume weighted average prices (VWAPs) and from mid quotes of best bid-offers. The sample period is January 5, 1998 – December 31, 2018.

A. Main result

The $n$-th log return on day $t$ is defined as

$$r_{t,n}^N = p_{t, n/N} \cdot N - p_{t, n-1/N} \cdot N$$

for $n = 1, \ldots, N$, where $p_{t, n/N}$ denotes the log price at time $n/N$ on day $t$ and $N$ is the number of return observations throughout the day. $n = 0$ and $n = N$ corresponds to 18:00 ET when a new trading day begins as defined by the CME. We work interchangeably with hourly returns ($N = 24$), 15-minute returns ($N = 96$), 5-minute returns ($N = 288$), and 1-minute returns ($N = 1440$).

The grey bars in figure 2 display hour-by-hour returns averaged across all trading days in our sample. Estimates are annualized and displayed in percentage points. Over the last 20 years, $ON$ returns have been large and positive between the hours of 12 a.m. (midnight in New York) and 3 a.m. Thirty minutes prior to the opening of the cash market in the U.S. at 9:30 a.m., equity returns display initially large negative returns which become smaller in magnitude but remain persistently negative until 12 p.m. The $ID$ period is then characterized by a flat return profile until 3:00 p.m. followed by a sequence of large positive returns until the closing bell at 4:15 p.m.

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7Between November 1994 and December 2012 the trading week began on Sunday at 18:30 ET (6:30 p.m.) and closed on Friday at 16:15 ET (4:15 p.m.). The trading day (other than Sundays) ran from 18:00 (6 p.m.) one day to 17:30 (5:30 p.m.) the following day with maintenance break between 16:15 – 16:30 (4:15 p.m. – 4:30 p.m.). From December 2012 to December 2015 trading began half an hour earlier on Sundays (18:00 ET, 6 p.m.) and closed one hour later Fridays (17:15 ET, 5:15 p.m.). There was also a maintenance break from 23:00 to 00:00 (11 p.m. to 12 a.m.) on Tuesday through Friday from October 1998 to September 2003.

8Our last observation on Fridays is at 18:00. Our first observation on Sunday is at 18:01. Thus the weekend return is incorporated into the first overnight return on Mondays.
This return pattern is surprising. The red line in figure 2 plots the cumulative average return profile one would expect if information arrived continuously and returns followed linearly, while the black line plots the actual average realized cumulative returns. The gross CTC return is 4.3%, which equals the average yearly return on the S&P 500 index cash over this sample period. More than half of this return is generated during the ON session: between 16:15 p.m. and 9:30 a.m. equity returns average 2.6% p.a. More striking than this, a significant proportion of this return, averaging 3.6% p.a., occurs in the window between 2 a.m. and 3 a.m., a return sequence we dub the ‘overnight drift’ (OD). Figure A.2 in the online appendix (OA) displays a more granular perspective, showing a persistent sequence of positive returns is clearly visible in almost every interval between 1:30 a.m. and 3:00 a.m., confirming that the drift between 2 a.m. and 3 a.m. is not driven by within hour outliers but represents a continuous drift over this interval of the day. Between the hours of 9:00 a.m. and 10:00 a.m., we observe a sequence of negative returns averaging −3.0% p.a.; we dub this sequence ‘opening returns’ (OR).

B. Summary statistics

Stacking hourly returns in the vector $\mathbf{r}$ and denoting $D$ as a dummy matrix containing appropriately located 0 and 1’s, we estimate the $1 \times 24$ vector of mean returns $\mu$ via the projection $\mathbf{r} = D\mu^T + \varepsilon$. Table I reports estimates for $\mu$ and HAC robust standard errors. We also report median returns, standard deviations, skewness and kurtosis estimates. Returns are computed from both VWAPs and mid quotes and denoted in basis points.

Consider first panels (a) and (b), which collect ON return statistics. Using traded prices, the average return for the hours {01-02, 02-03} is equal to {0.54, 1.48} basis points per hour per day, respectively, with corresponding $t$-statistics equal to {3.24, 7.09}. Using quotes, these returns are similar in magnitude. These are the only overnight hours statistically significant at conventional levels.

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9. The monthly correlation between S&P 500 value weighted cash index returns obtained from CRSP and our close-to-close returns is > 98%.

10. This finding is consistent with previous studies that document return differences between trading day and night sessions. In particular, Cliff, Cooper, and Gulen (2008) and Kelly and Clark (2011) show that overnight returns are systematically larger than intraday returns.
Median returns computed from VWAPs are also positive for the hours \{01-02, 02-03\} and equal to \{0.46, 0.88\} basis points per day. Due to the minimum tick size, median returns computed from quotes are almost always zero during the night. Indeed, table A.2 (OA) shows that, for the hours \{01-02, 02-03\}, approximately \{13%, 9%\} of days produce zero returns computed from quotes. However, even the median quote return for the \textit{OD} hour is large and positive equal to 0.80 basis points per day. Median returns are lower than mean returns, implying that the return distribution in this hour is positively skewed. We find return skewness during the \textit{OD} hour equal to 0.20 from VWAPS and 0.62 from quotes, which compares to daily \textit{CTC} return skewness of −0.27 and −0.16, respectively.

Consider now panels (c) and (d), which collect \textit{ID} estimates. The opening hour 9-10 returns, computed from trades (quotes) are strongly negative, equal to -1.47 (-1.21) basis points per hour per day with a \textit{t}-statistic of 3.49 (2.53). The remaining \textit{ID} returns are flat and statistically indistinguishable from zero.

Table A.2 in the online appendix reports additional non-parametric tests which reject the null of a random walk hypothesis around the \textit{OD} hours but not for the \textit{OR}, while table A.3 (OA) confirms \textit{OD} returns are special, in the sense that they are statistically different than all other hourly returns.

\[ \text{Insert table I here} \]

\textbf{C. Calendar effects}

We now study the time-variation in the overnight drift across days of the week, months of the year, and throughout each year in our sample.

\textbf{C.1. Day of the week}

Panel (a) of figure 3 plots cumulative 5-minute returns sampled for each trading day of the week. In terms of close-to-close returns, \(r^{\text{THU}}_{\text{CTC}} \gg r^{\text{TUE}}_{\text{CTC}} \sim r^{\text{WED}}_{\text{CTC}} > r^{\text{FRI}}_{\text{CTC}} > r^{\text{MON}}_{\text{CTC}}\); however, the differences in weekday \textit{CTC} returns are not statistically different from each other. Considering the \textit{OD}, it is clearly visible in each day of the week, and displays far less dispersion than close-to-close returns, suggesting that it is a systematic phenomenon. Panel (a) of Table II tests this claim formally.
using a regression dummy framework as above. In all days of the week, the 2 a.m. - 3 a.m.
return is positive and significant at the 1% level, except for Thursdays, which is significant at
the 5% level. Excluding Thursdays, the magnitude of the returns is also quite close and ordered
\[ r_{OD}^{WED} > r_{OD}^{MON} > r_{OD}^{FRI} > r_{OD}^{TUE} > r_{OD}^{THU}. \]

Panel (b) of Table II, on the other hand, shows that the OR is always negative but only
statistically significant on Thursdays and Fridays with mean returns equal to −3.01 and −2.82
basis points per hour per day, with t-statistics equal to −2.84 and −2.44, respectively. Figure A.4 in
the OA reports three pieces of suggestive evidence as to why the OR occurs only on Thursdays and
Fridays: Firstly, we observe more U.S. macro announcements released at 8:30 a.m. on Thursdays
and Fridays. Generally, we experience large positive returns leading up to announcements, as has
been documented in the literature (see, for example, Savor and Wilson, 2013). We conjecture
that (short-lived) price-reversals following the macro announcements partly explain the negative
opening returns. Secondly, we do not observe many FOMC announcements on Thursdays and
Fridays and we also know that returns typically are positive in the hours leading up to FOMC
announcements which subsequently do not revert (Lucca and Moench, 2015). Thirdly, we observe
most negative earnings announcements days are Thursdays and Fridays.

In summary, while the OR is concentrated in the final days of the week, the OD is systemat-
ically positive and significant in each day of the week. Consistent with these findings, the OR is
only weakly related to the OD, which can be seen from a daily regression of opening returns on
previous period overnight drift returns, controlling for date \( t - 1 \) opening returns:

\[
    r_{t}^{OR} = -1.82 + 0.13 r_{t}^{OD} - 0.01 r_{t-1}^{OR},
\]

where point estimates are reported above t-statistics in parenthesis. We see that the OR has a
weak positive relation to the OD, so the OR is not a price reversal of the OD.

\[ \text{[ Insert figure 3 and table II here ]} \]

\section*{C.2. Month of the year}

Panel (b) of figure 3 plots average cumulative 5-minute returns across the trading day for the
futures contract roll months March, June, September and December. While ID returns display
significant variation, in particular $OR$ are large and negative in September equal to $-3.46\%$, opening returns are either slightly positive or negative in other months. The $OD$, however, is clearly visible in all months.

More formally, Table III reports the statistical significance within each calendar month. Consistent with Figure 3, the $OD$ drift is positive in all months of the year and statistically significant at conventional levels in 9 out of 12 months.

C.3. Year-by-year

Panel (c) of Figure 3 examines the economic and statistical importance of returns year by year for $OD$ versus $OR$ return. The $OD$ drift is positive in 19 out of 21 years in our sample. Moreover, the $OD$ is only negative in the recessionary years of 2002 and 2008. Panel (c) of Figure 3 also reports the $(1 - p)$ values from a $t$-test of $OD / OR$ returns versus the null hypothesis of zero. At the 10% level, the $OD$ is significant in 16 out of 21 years in our sample. In contrast, the $OR$ return is only statistically different than zero in 6 years. Moreover, the negative $OD$ are concentrated in recessionary years and, in particular, around the busting of the dot-com bubble. Splitting the sample year-by-year highlights the consistency of the $OD$ drift compared to other trends in intraday returns that we can observe from figure 2.

III. Inventory Management and Price Reversals

Buyers and sellers in financial markets arrive asynchronously, which generates transient imbalances between buy and sell volumes. Liquidity suppliers offer immediacy to incoming traders by absorbing imbalances and subsequently trading them away. However, in doing so, they bear inventory risk and require compensation for this. This point is discussed by numerous studies.\footnote{Important early contributions include Stoll (1978), Ho and Stoll (1981), Ho and Stoll (1983), Grossman and Miller (1988), Biais (1993), and more recently Brunnermeier and Pedersen (2009). There also exists a related literature studying price formation with large risk averse investors; for example see Vayanos (1999, 2001) or more recently Rostek and Weretka (2015).}

Motivated by this literature, consider the following stylized example. Assume bad news during regular U.S trading hours results in selling pressure at market close. These orders transact at the
best available bids and, consequently, execute at successively lower prices down the order book. As the market is selling off, prices drop below fundamental values because risk-averse market makers bear inventory risk.\textsuperscript{12} The risk-averse market makers are compensated for bearing that extra risk through high expected returns, earned when they offload their extra inventory to new customers arriving overnight.

Models of this type provide an intuitive link between liquidity provision, demand for immediacy and price formation, and a wealth of empirical evidence exists on return reversals that arise as a result of order imbalance.\textsuperscript{13}

\section*{A. Intraday Volume Patterns}

Before discussing an inventory management explanation for the findings above, consider figure 4 which depicts intraday and overnight volume patterns. To account for the increasing trend in trade over time, for each day we compute the volume in every 5 minute interval weighted by the average volume that occurred in a 5 minute interval on that day. A number above ‘1’ means there is more volume during a given 5 minute interval compared to the average 5 minute volume for that day and vice-versa for a number below ‘1’. Panel (a) shows that most trade occurs around the opening and close of the U.S cash market. Panel (b) zooms in on the overnight session showing three U-shaped trading patterns: between 18:00 and 2:00 a.m. (Asia), between 2:00 a.m. and 3:00 a.m. (European opening), and between 3:00 a.m. and 8:30 a.m. which coincides with scheduled U.S macro announcements.

A notable feature of figure 4 is that the only downward jump in intraday volume is at U.S close, which from an inventory management perspective makes this a particularly risky point in time. Table IV highlights this by reporting overnight average trading volumes as a percentage of closing trading volumes. Specifically, we compute the hourly volumes between 18:00 and 4 a.m. divided by the closing volume between 15:15 and 16:15, and then average this ratio. Estimates are reported as percentages. Consistent with figure 1, we see that overnight volumes were a small fraction of intraday volumes (closing volumes in this case) in the first half of the sample. Volumes

\textsuperscript{12}Micro-foundations for market maker risk aversion can arise from a multitude of sources, including regulatory limits on position size, constraints on market maker leverage, and margin requirements. Intuitively, the more binding these constraints are, the larger would be the effective risk aversion of the market maker.

\textsuperscript{13}See Hendershott and Menkveld (2014) and the references therein.
in Asian hours were effectively zero and European hours marked the first point of trade during the
calendar day in the e-mini. Asian trading volumes increased in the second half of the sample, so
that closing volumes were only 50 times larger than during a typical Asian hour. The final rows
report yearly averages for the last 5-years of our sample. Here we see the rise in the fraction of
overnight trade as a proportion of closing volumes has been particularly dramatic, approximately
doubling in Australasian and Asian hours but has remained comparatively flat during the opening
of European hours.

B. End-of-day Order Imbalance

The volume pattern discussed above has implications for asset prices due to heterogeneously timed
participation by different groups trading a global market. Traders holding positions during regular
U.S hours are exposed to end-of-day (EOD) order imbalances, which are problematic because
volumes in the subsequent overnight period are known to be comparatively small, making them
difficult to trade away. Studying this idea, we propose a novel of measure of order imbalance
measured as closing signed volume relative to total closing volume

\[ RSV_t = \frac{\text{Signed Volume}_{t}^{\text{close}}}{\text{Total Volume}_{t}^{\text{close}}} \in [-1, 1], \]  

(3)

where Signed Volume\(_{t}^{\text{close}} = \#\text{buys} - \#\text{sells}\) and Total Volume\(_{t}^{\text{close}} = \#\text{buys} + \#\text{sells}\) sampled
during the closing hour between 15:15 – 16:15 (3:15 p.m. – 4:15 p.m.). Measuring relative signed
volume, as opposed to absolute signed volume, accounts for the increasing trend in total volume
during the sample period. However, the results that follow are quantitively similar using absolute
signed volume.

Panel (a) of figure 5 plots the distribution of \(RSV_t\). It is symmetric around zero with more
than half of all observations being within ±5%. A 1-standard deviation shock to \(RSV_t\) is 5.5%;
with index level at 2500 (e.g., in the years 2017 and 2018) corresponds to an EOD order imbalance
of 2.0 billion dollars.

We sort days into three buckets with equal number of observations based on \(RSV_t\). Panel (a) of
table V provides summary statistics of for \(RSV_t\) and information on 48-hours of adjacent returns.
Considering the bottom tercile of \(RSV_t\) (market sell-offs), we observe a mean \(RSV_t\) equal -7.1%,
associated with a -81.2% p.a return in the last hour of trading, which accounts for the bulk of the -113.1% negative close-to-close return on that day. The subsequent day CTC return rebounds positively equal to 22.7% p.a, and, importantly for an inventory risk explanation, the reversal is almost completed during overnight hours, with returns in Asian hours equal to 7.6% p.a. and returns in European hours equal to 12.4%. Returns earned during the OD hour account for a substantial proportion of the total CTC reversal, equal to 7.5%. This result is in line with the basic idea of Grossman and Miller (1988)-style models, which imply that, conditional on an order imbalance, prices revert as new participants enter the market and market makers offload their inventories.

Panel (b) of figure 5 visualizes table V and dissects the unconditional result of figure 2. Here we clearly see the reversals are concentrated at the opening of Asian and European markets, and that returns quickly flatten off after the initial hours of European trade. Considering the top tercile of $RSV_t$ (market rallies), we do not observe overnight reversals: positive OD returns occur only on days when the closing $RSV$ were negative, which gives rise to positive unconditional overnight returns discussed in section II above.

Panel (b) of table V reports overnight trading patterns conditional on our three sets of closing $RSV_t$’s. Specifically, we compute relative signed volumes for Asian, EU, OD, and CTC hours following equation 3. Following market sell-offs, in the bottom tercile, $RSV_t$ during Asia, EU, and OD hours are large and positive equal to 0.9%, 1.78%, and 6.6%, respectively. In the middle tercile, we also observe small negative $RSV_t$ during Asia hours and small positive $RSV_t$ during during EU and OD time. Following market rallies, in the upper tercile, we do in fact observe negative $RSV_t$’s in Asia and EU hours. Thus, consistent with the idea that market makers adjust quotes to induce mean reversion in their inventories: return patterns in panel (a) are mirrored by quantities of trade in panel (b).

C. Return Predictability in High Frequency

Quantifying the impact of EOD order imbalance on overnight expected returns, we regress future high frequency realized returns on closing $RSV$ from the preceding trading day. Panel (a) of Table

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14Asian trading hours are defined as 18:00 - 2:00 and EU trading hours are defined as 2:00 - 8:00.
VI reports the estimated coefficients from regressions of hourly returns with the overnight session (18:00 – 6:00 a.m), measured in basis points, on order flow imbalance at the end of the preceding trading day

\[ r_{t,n}^H = \mu_n + \beta_n^{RSV} RSV_{t-1} + \epsilon_{t,n}, \quad \text{for } n = 1, ..., 12, \]  

(4)

together with \(t\)-statistics computed from robust standard errors clustered within each month.

As predicted by models of market maker inventory risk, we observe a strong negative relation between the closing order imbalance and returns. The relation is strongest between 2 a.m. – 4 a.m., which are the hours that straddle the opening of European markets (overnight volumes are displayed in figure 4). The estimates are both economically and statistically significant, with a 10 percentage point decrease (a sell-off) in closing relative signed volume corresponding to a 1.66 (1.88) basis point increase in returns between 2 a.m. – 3 a.m. (3 a.m. – 4 a.m).

We also investigate the standard inventory risk prediction that price reversals should be amplified in states of high volatility. Testing this, we interact \(RSV\) with the level of the VIX index at the close of the previous day

\[ r_{t,n}^H = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{VIX} VIX_{t-1}^{close} + \beta_n^{RSV \times VIX} RSV_{t-1}^{close} \times VIX_{t-1}^{close} + \epsilon_{t,n} \]  

(5)

for \(n = 1, ..., 12\). Panel (b) of Table VI reports the estimates, showing that ex-ante volatility has a strong amplification effect on the relationship between order imbalance and overnight returns between 2 a.m. – 4 a.m.: Assuming \(RSV_{t-1}^{close} = -10\%\) and \(VIX_{t-1}^{close} = 20\%\) (the average \(VIX\) level throughout the sample period is 20.1\%) we see that the total effect of order flow from 2 a.m. – 3 a.m. is \(15.80 \cdot (-0.1) - 1.63 \cdot (-0.1) \cdot 20 = 1.68\) basis points. If the \(VIX\) level is at its historical minimum of 10\%, the effect of order flow is close to zero and, if the \(VIX\) level is 30\%, the effect is 3.31 basis points.

D. Asymmetry

Figure 5 (a) also shows that returns are negative between 2–3 a.m. when \(RSV\) was positive but the relationship is asymmetric in the sense that the reaction following negative \(RSV\) days
is significantly stronger, consistent with panel (b) of figure 2 which displays an unconditionally positive drift. The regression estimates of equation 5 provide a potential rationale for this finding. In the theory of Brunnermeier and Pedersen (2009), which builds on Grossman and Miller (1988), market liquidity and funding liquidity interact in flight-to-quality episodes. Consistent with the regression estimates, capital required for trading evaporates when market returns are negative and, at the same time, the level of the VIX tends to be high in these states of the world ($RSV_{t-1}^{close}$ and $VIX_{t-1}^{close}$ are negatively correlated), which explains why we observe large price reversals after negative but not positive demand shocks.

E. Daylight savings tests

The results so far highlight that large negative order imbalances at the end of the U.S. trading are subsequently resolved during the overnight trading session, as new customers arrive into the market. The 24-hour nature of the e-mini market allows us to provide additional evidence on this explanation by conducting a novel test that exploits exogenous variation, from the perspective of U.S.-based market makers, in the arrival time of Asia-based clients. Specifically, we exploit the fact that while both U.S. and Europe observe daylight savings time (DST), Japan does not. From the perspective of U.S.-based market makers, clients based in Japan arrive at 7 p.m. ET during U.S. winter months (DST off) and at 8 p.m. ET during U.S. summer months (DST on). Thus, DST changes represents exogenous variation in the arrival time of Japan-based clients.

Panel (a) of figure 8 shows that prior to 2010, when e-mini trading during Asian open hours was small, there is no change in volume around Tokyo opening, regardless of whether the U.S. is observing DST.\footnote{The spike at 18:30 (6:30 p.m.) ET occurs because the futures market used to open at 18:30 on Mondays from 1998 to 2012. The drop in trading volume from 23:00 (11:00 p.m.) ET to 00:00 (12:00 a.m.) ET appears because futures trading was closed in this hour from 1998 to 2003 on Tuesdays to Fridays.} Panel (b) of figure 8 shows that, during the second half of our sample, when the trading volume during Asian opening hours is non-negligible, there is a spike in e-mini trading volume at 7 p.m. ET at Tokyo open when DST is not active (red line) and when DST is active, the increase in volume occurs instead at 8 p.m. ET, which corresponds the opening of the Tokyo stock exchange (TSE) in the U.S. summer and U.S. winter. Notice, also, a secondary spike in trading volume at 22:30 (10:30 p.m.) ET when the TSE re-opens after its lunch break during U.S. winter months and at 23:30 (11:30 p.m.) ET when the TSE re-opens after the lunch break during
the U.S. summer months.\textsuperscript{16} 

We now test more formally whether the arrival time of Asia-based clients translates into a change in the timing of returns overnight. Table VII reports the estimated coefficients from a regression of hourly overnight returns (18:00 – 6:00 a.m.), measured in basis points, on order flow imbalance at the end of the preceding trading day, a dummy for U.S. DST, and an interaction between the two

\[
\begin{align*}
H_{t,n} &= \mu_n + \beta_{n}^{RSV} RSV_{t-1,close} + \beta_{n}^{DST} 1_{DST,t} + \beta_{n}^{RSV \times DST} RSV_{t-1,close} \times 1_{DST,t} + \varepsilon_{t,n} \quad (6)
\end{align*}
\]

for \(n = 1, \ldots, 12\), where the dummy variable takes on a value of 1 in summer time (DST active) and 0 in winter time (DST not active), with daylight savings seen from a U.S. perspective. We estimate the regression for two samples: for the years 1998-2009 when trading during Asian hours was negligible and for the years 2010-2019 when trading had picked up. Consider first panel (b), which reports the results for the second half of the sample.

Consistent with the hypothesis that DST creates exogenous variation in the arrival time of Asia-based clients, the coefficient on the interaction term \(\beta_{n}^{RSV \times DST}\) switch from positive to negative between 18:00 ET – 20:00 ET. To see this, consider first U.S. winter time when the DST dummy equals 0, Australia opens at 18 ET, TSE opens at 19 ET and there are no major market openings at 20 ET. Here, the effect of \(RSV\) is \(\beta_{n}^{RSV} = \{-27.01; -14.00; 0.25\}\) for the hours 18-19, 19-20 and 20-21. In U.S. summer time, when the DST dummy equals 1, there are no major market openings at 18 ET, TSE opens at 20 and Australia opens at 19 or 20.\textsuperscript{17} Now, we find the effect of \(RSV\) by summing \(\beta_{n}^{RSV} + \beta_{n}^{RSV \times DST}\) = \{-2.38; -13.08; -10.25\} and, indeed, we see that the effect of \(RSV\) shifts in accordance with DST.

Comparing panels (a) and (b) of table VII shows that these results are much stronger in the post-2010 sample, confirming that the DST difference is only relevant when there is a significant volume of trade during the Asian open hours.

\textsuperscript{16}For an in-depth discussion of the TSE lunch break and its effects on trading on the NIKKEI, see Lucca and Shachar (2014).

\textsuperscript{17}Australia does not switch to winter (summer) time at exactly the same date where the U.S. switches to summer (winter) time. Therefore, seen from a U.S perspective, Australia opens at 19 p.m. for short periods during the spring and fall.
We can likewise exploit the fact that DST is observed both in Europe and the U.S.\textsuperscript{18} to construct a placebo test. In unreported results (available on request) we find, consistent with DST being (almost) synchronized between Europe and the U.S., the coefficient on the interaction between closing order imbalance and the DST dummy are not significant for any of the trading time intervals.

Summarizing, the increase in trading activity during Asian trading hours suggests that, post-2010, market makers are able to offload larger parts of their inventory at TSE open instead of waiting for the London open. Consistent with this hypothesis, in unreported results (also available on request), we find that the relationship between closing order flow and returns at London open are indeed weaker after 2010.

\begin{center}
[ Insert table VII here ]
\end{center}

\textbf{F. Market Depth}

We can also trace the dynamics of the limit order book itself in response to large closing order imbalances. Figure 6 displays the market depth measured as the average number of contracts available for the first five levels of the order book. Figure 7 displays the average difference in ask depth and bid depth for the first 5 levels with trading days sorted into groups based on the RSV of the preceding trading day. The figure displays the bottom quartile (most negative preceding RSV) and top quartiles (most positive preceding RSV) for sample period is 2009-2019.

We find that following days with negative closing RSV, the limit order book is deeper on the ask side (#ask quotes > #bid quotes) – market makers post more sell-side quotes to offload the inventory accumulated during the previous trading day.\textsuperscript{19} Similarly, following days with positive RSV, the limit order book is deeper on the bid side, as market makers post more buy-side quotes to close the negative inventory gap from the previous day. Importantly, these differences in the limit order book depth all but disappear after European market openings at 3 a.m. U.S. ET, again suggesting that market makers take advantage of the earliest possible opportunity – the

\textsuperscript{18}The standard time difference between New York and London is five hours but throughout our sample period the U.S. and Europe have switched to DST at different times, typically 1 week apart. This gives us 200 trading days where the time difference was four hours and 45 trading days where the time difference was six hours. Indeed, we see that the spike in e-mini trading volume and the overnight drift at London open switches by 1 hour according to the time difference.

\textsuperscript{19}Negative closing RSV from the clients’ side implies positive market maker inventory.
Asian and European trading sessions – to rebalance large inventory deviations at the end of the previous U.S. trading day, as would be predicted in standard inventory risk models.

\[ \text{[ Insert figure 6 and 7 here ]} \]

\section*{G. Volume Time}

As argued above, market makers cannot manage inventory imbalances if the trade activity is zero. On the other hand, when trading activity is high, markets markers can quickly revert inventories to zero. Thus, it is natural to measure the time elapsed in terms of the trading volume. Specifically, we consider \textit{volume time} which advances one increment for every single contract traded and thus equals the cumulative trading volume. Volume time is a type of \textit{activity time}, like tick time, advancing slowly when few contracts are traded (Asian hours) and quickly when many contracts are traded (U.S. hours). By definition, trade activity is constant in volume time and we therefore expect order imbalances to revert linearly to zero in volume time. Thus, we also expect price reversals induced by inventory management to be linear when measured in volume time. Models of immediacy and inventory risk, such as Grossman and Miller (1988), are implicitly set in volume time where it is assumed that a fixed number of trades occur in each period. This is why price reversals occur linearly in such models.

Figure 9 displays the cumulative log returns and the cumulative signed volume in both clock time and volume time and sorted by closing order imbalance ($R_{close}^{t-1}$) on the previous trading day. Since we want to study cumulative signed volumes we start in 2010 when overall volume have stabilized.\footnote{Results are similar for 1998-2009. However, because total trading volume was smaller, order imbalances were quantitatively smaller as well. Thus, when measured in volume time, price reversals happened much quicker in the early part of the sample period.} Following negative closing order imbalance days, both signed volume and returns increase essentially monotonically, with most of the close-to-close return earned by the time that around 60,000 contracts are traded, or in other words, around the time when European markets open: On average, for 2010-2018, 48,000 contracts are traded by 2:00 a.m., 57,000 contracts are traded by 3:00 a.m. and 200,000 contracts (the last observation in the plots) are traded by 8:33 a.m. Corresponding positive closing order imbalance represent a smaller absolute market dislocation than negative closing order imbalance, and order flow moves more slowly following positive closing
SV days, reaching a peak of around -750 contracts, as compared to the peak of 1,500 contracts following negative RSV days.

Summarising, in additional to the evidence presented above, as one would expect in a standard inventory models, returns and signed volume accrue in a linear fashion when plotted in volume time. This is opposed to the clock time plots where returns are largest when trading volume spikes at Tokyo open and EU open.

[ Insert figure 9 here ]

IV. Alternative Explanations

We now explore alternative explanations for the overnight return patterns discussed above.

A. Volatility Risk

Figure 10(a) which depicts average realized intraday volatility (squared log returns) from 1998-2018 sampled at a 1-minute frequency. The intraday volatility displays the well-known U-shaped pattern for Asian, European and US trading hours where volatility is high at the beginning and at the end of each trading period (see e.g. Andersen, Bondarenko, Kyle, and Obizhaeva, 2018). Across trading periods, the level of volatility is lowest during Asian trading hours and highest during US trading hours, relative to the average trading volume across the 3 periods. Comparing average levels for each session, we find that US hours volatility is more than twice as large as Asian hours volatility and therefore considerably larger than estimates of return volatility using close-to-close prices. The large spike in volatility at 8:30 is caused by the spike in volume observed just after US macro announcements. Figure 10(b) plots time series of the realized volatility for each of the three trading periods. The volatility is always lowest during Asian hours and highest during US hours but the difference has diminished over time as trading volume in the overnight session has picked up. The 3 time series are highly positively correlated, indicating that volatility increases on the same days for all three trading periods.

Importantly, we do not observe an obvious link between realised quantities of risk and returns.
More formally, we run the regression

$$ r_t^{OD} = -0.29 + 0.19 \, \text{vol}_t^{OD} + \varepsilon_t $$

(7)

where $\text{vol}_t^{OD}$ is the date $t$ sum of squared log returns measured through the OD window between 2:00 a.m. and 3:00 a.m..

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B. Overnight Liquidity

To measure liquidity risk we construct hourly estimates of 1) Kyle (1985) lambda (based on returns sampled at the 1-min frequency), 2) the Amihud price impact measure and 3) the bid-ask spread. Figure 11 depicts the average intraday patterns of these measures as well as their time series for the Asian, European and U.S. trading hours. As expected, intraday illiquidity is lowest during U.S. trading hours where the trading activity is highest and illiquidity is highest during Asian hours when the trading activity is at its lowest. The bid-ask spread is very close to the minimum tick size (0.25 index points) at all times during the trading day. All liquidity measures experience large changes throughout the sample period. Most notably, the overnight illiquidity (Asian and European hours) has decreased strongly as overnight trading activity has picked up, and today is much closer to the illiquidity level in regular U.S. trading hours. Secondly, the illiquidity increases during times of crises, as one would expect.

Considering all three measures, we do not observe intraday patterns which could rationalize the OD returns with theories of liquidity risk. We see average intraday bid-ask spreads are almost always trading at the minimum tick size, equal to 0.25 index points. The spread is only significantly higher after 16.30 when trading resumes after the maintenance break and volumes are close to zero (see figure 4). The jumps in the bid-ask spread at 8:30 am. and 10:00 a.m. corresponds to the U.S. macro announcements which are released at these times.

In addition, since we observe the aggregate limit order book for the market, we can also measure intraday illiquidity by computing the depth of the market. Market depth is computed as the number of contracts available in each 5 minute interval, and is reported for the first five levels
on each side of the order book. Figure 6 shows the intraday depth averaged across all days in the 2009-2018 sample. Here we observe that, at each level, the depth of the bid is equal to the depth of the ask. We also note there are three depth regimes differentiated by Asia, European and U.S. trading hours. Depth is flat in Asian hours and rises throughout European hours. At U.S. open, depth increases steeply, remains relatively flat during the regular U.S. hours and then spikes at U.S. close before dropping in the overnight market. However, we also see the the overnight market remains highly liquid. For example, until 2.00 a.m. at the top level (L1) there are, on average, 100 contracts available, which in dollar terms with the S&P level at 2000 is equal to $10 million at the bid or ask. Considering all levels, L1 - L5 depth rises to $80 million. Indeed, a highly liquid overnight market is consistent with the large overnight volumes traded in this market, which as noted in the introduction, have averaged in excess of $15 billion daily.

[ Insert figure 11 here ]

C. Overnight News

We now consider if overnight news released after the U.S. cash market close are not immediately incorporated into prices during Asian hours but instead accumulate and are resolved at European open when trading volumes increase. Indeed, a large fraction of U.S. corporate earnings announcements are released after U.S. market close. Furthermore, Asian and European macro or central bank information released during the U.S. overnight session may signal news about U.S. growth prospects. We study this conjecture by examining hour-by-hour returns conditional on U.S. earnings announcements., and U.S., Japanese or European macro- and central bank announcements.

C.1. Earnings Announcements

We test if firm-specific announcements predict intraday returns. Previous literature (see e.g. Bernard and Thomas, 1989; Sadka, 2006, and the subsequent literature) has documented a positive (negative) drift in stock prices of individual firms following a positive (negative) earnings

\footnote{Although we note that ES volumes in Asian hours are substantial in Dollar terms; equal to 18% of total overnight overnight volume between 2010 and 2018.}
announcement surprise. The earnings data is obtained from I/B/E/S and Compustat. Following Hirshleifer, Lim, and Teoh (2009), for each firm $i$ and on day $t$ we define the earnings surprise as

$$ES_{i,t} = \frac{A_{i,t} - F_{i,t} - P_{i,t}}{P_{i,t}},$$

where $A$ is the the actual earnings per share (EPS) as reported by the firm, $F$ is the most recent median forecast of the EPS and $P$ is the stock price of the firm at the end of the quarter. As I/B/E/S updates the professional forecasters’ expectations on a monthly basis, the shock is the difference between the actual earnings and forecasters expected earnings approximately 1 month prior to the announcement date. Scaling the shock $A - F$ by the stock price implies that firm shocks are equally weighted.\(^{22}\) We define the daily earnings surprise of the S&;P 500 index, $ES_t$, as the daily sum of all $ES_i$.\(^{23}\)

Figure 12 plots the time series of $ES_t$. The shocks are periodic on a quarterly basis and generally positive ($\sim 75\%$ of all shocks are positive). Notably, we see large negative shocks during the financial crisis and almost exclusively positive shocks following the crisis.

To test this conjecture formally, we sort all trading days based on $ES_t$. We choose only announcements that are published after U.S. close (4 p.m. ET). This is because the effect of announcements published early in the day should be incorporated into the price on that day, while announcements that occur after $CTO$ hours could affect returns in these hours. Table VIII reports the average returns for day $t+1$ after sorting on $ES_t$. We sort all trading days into 5 groups based on $ES_t$. In group 1, $ES_t < 0$. For group 2-4, $ES_t$ is positive and increasing by group. Group 5 is for days where $ES_t$ is unobserved, i.e. not a single firm announced their earnings prior to these days (this was 46.57 % of all trading days). The table contains a number of interesting findings. First, we see a strong monotonic positive relation between earnings shocks and $CTC$ returns across groups. Second, no news days have the highest CTC return, equal to 4.52 % p.a, with a $t$-statistic of 1.83, and in this sense “no news is good news”. Third, negative shocks are not incorporated into the price until the U.S. market opens, while positive shocks are incorporated immediately during the $CTO$ period. However, most importantly for the focus of this paper, we do not detect a post close information effect: the $OD$ is not driven by earnings announcements as

\(^{22}\)EPS is earnings per share outstanding, implying that EPS$/P$ is earnings per market cap.

\(^{23}\)We also test specifications of $ES_{S&P500}^S$ where firms are value weighted and result are similar.
it is positive and significantly different from zero for all 5 set of days.

[Insert figure 12 and table VIII here]

C.2. Macro and Central Banks

From Bloomberg’s Economic Calendar we collect dates and times for

- U.S.: Non-farm Payrolls; CPI Ex Food and Energy; GDP QoQ.
- EU: Unemployment Rate; PPI MoM; Industrial Production SA MoM.
- U.K.: Jobless Claims Change; CPI Ex Food and Energy; QoQ.
- Japan: Jobless Rate; PPI MoM; Industrial Production MoM.

Announcement times are generally close to 8:30 a.m. ET in the U.S., 2:00 a.m. ET in the Eurozone, 4:30 a.m. ET in the U.K., and 19:50 (7:50 p.m.) ET in Japan.

For central banks, we collect announcement dates and times from the websites of the following central banks: (i) FOMC; (ii) the ECB; (iii) the BoE; (iv) the BoJ. FOMC target rate announcements are released at or very close to 2:15 p.m. ET. ECB target announcements are at 6:45 a.m. ET, followed by a press conference at 7:30 a.m. ET. BoE announcement days often coincide with ECB days and the announcements are at 7:00 a.m. ET. Finally, BoJ announcements do not occur at a regular time but target rate decisions are generally announced between 22.00 and 1.00 a.m. ET. Our sample period is January 1998 to December 2018.

We test the effect of announcements on hourly subinterval returns in a regression framework with dummy variables which take a ‘1’ on days with an announcement and ‘0’ otherwise. More specifically, the dummy takes a value of 1 if the announcement occurs within the current calendar day. Thus, Japanese and European macro announcements are contemporaneous with the overnight return, while U.S. announcements occur subsequent to the overnight returns. The regression we estimate is

$$r_{i,n}^H = a^n + b^n_{1} \mathbb{1}_{U.K.} + b^n_{2} \mathbb{1}_{EU} + b^n_{3} \mathbb{1}_{JP} + b^n_{4} \mathbb{1}_{U.S.} + \epsilon^n_t,$$

where $\mathbb{1}_i$ is a macro or central bank announcement dummy for country $i$. 

25
Panel (a) of table IX reports estimates for macro announcements. The intercept during the OD hour (2-3 a.m) is estimated to be 1.35 bps with a t-statistic of 5.44, i.e. the drift is present on non-announcement days and thus not driven by macro announcements. Furthermore, none of the announcement dummies are statistically different from the non-announcement days in this hour. The U.K. macro dummy is economically large and significantly negative at 3 a.m (which is 8 a.m in London). More generally, we fail to detect an announcement effect in any of the overnight hours. U.S. announcements occur at 8:30 and indeed we see a large positive return of 3.67 bps with a t-statistics of 2.25.

Panel (b) of table IX reports estimates for central bank announcements. Again, the intercept is unaffected at 2-3 a.m and we obtain an estimate of 1.34 bps with a t-statistic of 6.10. The BoE dummy is economically large and significantly negative at 1 a.m (which is 6 a.m in London) The FOMC dummy is the only significantly positive estimate we obtain, equal to 1.55 with a t-statistic of 1.96. This implies that during the night on days preceding FOMC announcements, the 1-2 a.m return equals $0.47 + 1.55 = 2.02$ basis points, which is small compared to the pre-FOMC drift returns documented by Lucca and Moench (2015).

Summarizing, we fail to detect a relationship between the overnight drift and (i) earnings announcements that are released after the close of the cash market, during Asian hours, or (ii) overnight news from Asian or European central bank or macro announcements; thus, it is unlikely that the overnight drift is driven by risk compensation related to announcement premia.

C.3. Resolution of Uncertainty

The results directly above suggest that the overnight drift is unlikely to be related to an information effect. Recent literature (see e.g. Ai and Bansal, 2018 for the theoretical argument and Hu, Pan, Wang, and Zhu, 2019 for suggestive empirical evidence), however, has argued that resolution uncertainty, as measured by changes in the VIX, ahead of macroeconomic announcements could explain the pre-announcement drift of (Lucca and Moench, 2015). More recently, in work subsequent to ours, Bondarenko and Muravyev (2020) postulate uncertainty resolution at the open of
European markets as a possible explanation for the central empirical result of our paper (figure 2).

To investigate this hypothesis, we consider changes in volatility by computing intraday and overnight VIX futures (VX) returns. Panel (a) of figure 13 displays the average cumulative 5-minute log returns for the front month VX contract. The intraday VX returns are relatively flat during the U.S. hours. At the close of regular U.S. trading hours, in the run up to the maintenance break, VX returns are strongly negative, equal to -80% p.a. During regular Asian trading hours VX returns rebound, generating annualized returns of 40% between 18:00 and 1:00 am, and at the opening of European markets we again see negative VX returns, equal to 50% p.a between 2:00a.m. and 4:00 am.

Focusing on VX returns at European open, one can easily rationalize a contemporaneous negative co-movement with ES returns (absent a resolution of uncertainty conjecture) in terms of the the ‘leverage effect’, which is the well known empirical fact that equity volatility tends to fall (rise) when equity returns are (positive) negative. Panel (b) of figure 13 demonstrates the leverage effect in intraday data by computing the intraday 1-minute correlations between ES and VX futures returns ($r_{t}^{ES} \times r_{t}^{VX}$) for intervals where we observe quote updates and averaging these over all days in our sample. During both overnight and intraday periods the correlation is close to -80% which demonstrates that economic interpretations of resolution of uncertainty based on a contemporaneous VIX relationship is limited: “correlation does not imply causation”.

More interesting, is the question of whether end-of-day order imbalances in one futures contract predict overnight returns in the other contract. Table X answers this question by estimating two high frequency predictability regressions

$$ES{r}_{t,n}^{H} = \mu_{n} + \beta_{n}^{ESRV} ES{RSV}_{t-1}^{close} + \beta_{n}^{VXRSV} VX{RSV}_{t-1}^{close} + \epsilon_{t,n}, \text{ for } n = 1, \ldots, 12,$$

---

24 Investors wanting to manage risks around the clock can now trade VIX futures (VX) contracts in all time zones. VX futures are open nearly 23 hours a day, 5 days a week, trading electronically on the CBOE futures exchange. VX is closed daily from 4:15 to 4:30 PM and from 5:00 to 6:00 PM ET time. On Sundays, they start at 6:00 PM ET time. The link between the OD equity returns and uncertainty can be examined by computing intraday returns to the front month VX contract.

25 A common explanation for this phenomenon is due to Black (1976) and Christie (1982) who argue that companies become mechanically more leveraged as equity prices decline relative value of their debt and, as a result, their equity values become more volatile (as in Merton, 1974).
and

\[ VX r^H_{t,n} = \mu_n + \beta_n^{VXR} V X R S V_{t-1}^{\text{close}} + \beta_n^{ESR} E S R S V_{t-1}^{\text{close}} + \epsilon_{t,n}, \text{ for } n = 1, \ldots, 12. \]

Summarizing the table, while \( ES \) imbalances at U.S. close predict subsequent overnight returns in both the \( ES \) and the \( VX \) contracts, \( VX \) imbalances only predict overnight \( VX \) returns. Overnight \( ES \) returns between 2:00 a.m. and 3:00 a.m. are forecastable by closing \( ES \) order imbalance after controlling for \( VX \) order imbalances. \( VX \) returns, on the other hand, are predicted by \( ES \) order imbalances between 2:00 a.m. and 3:00 a.m. and then subsequently by \( VX \) order imbalances between 4:00 a.m. and 6:00 am. Moreover, the signs on the projection coefficients are consistent with the inventory risk explanations argued throughout the paper.

Thus, while \( ES \) and \( VX \) returns are contemporaneously mechanically linked through the leverage effect, overnight returns in both markets are predicted by end-of-day imbalances in the \( ES \), making the resolution of uncertainty hypothesis an unlikely explanation for the overnight drift.

[Insert figure 13 and table X here]

V. Trading Overnight Reversals

We conclude the paper by considering a set of trading strategies designed to exploit overnight price reversals, with-and-without transaction costs, and in doing so implicitly study how market makers adjust their spreads in response to inventory risk. The trading strategies we consider are stylized examples that expose an investor to holding the \( ES \) contract for a sub-period of each trading day compared to passively holding the \( ES \) contract. Returns on trading day \( j \) earned on a strategy that goes long the \( ES \) contract in the sub-period \([t_1, t_2]\) are computed as

\[ r_{j,[t_1,t_2]}^L = \frac{P_{j,t_2} - P_{j,t_1}}{P_{j,t_1}}, \quad (9) \]

where \( P \) denotes price of the \( ES \) contract. The analogous short position earns \( r^S = -r^L \). Mid quotes are used to compute returns excluding transaction costs. Including transaction costs,
returns are computed from quotes as
\[
\begin{align*}
    r_{j, [t_1, t_2]}^L &= \frac{P_{\text{bid}}_{j, t_2} - P_{\text{ask}}_{j, t_1}}{P_{\text{ask}}_{j, t_1}}, \quad r_{j, [t_1, t_2]}^S = -1 \times \frac{P_{\text{ask}}_{j, t_2} - P_{\text{bid}}_{j, t_1}}{P_{\text{bid}}_{j, t_1}},
\end{align*}
\]

We consider the following strategies:

- long CTC: \( t_1 = 16:15 \rightarrow t_2 = 16:15; \)
- long CTO: \( t_1 = 16:15 \rightarrow t_2 = 9:30; \)
- long OTC: \( t_1 = 9:30 \rightarrow t_2 = 16:15; \)
- long OD: \( t_1 = 02:00 \rightarrow t_2 = 03:00; \)
- long OD+: \( t_1 = 01:30 \rightarrow t_2 = 03:30 \)

We also consider a conditional trading strategy that “buys-the-dip”, denoted BtD, which holds the e-mini during the OD+ period but only on trading days following a negative order flow at market close (\( RSV_{t-1}^{\text{close}} < 0 \)). We report findings for the sample period 2005.1 — 2018.12 since as after this point the bid-ask spread during the overnight period reached its effective minimum of one tick size (=0.25 index points) around 2005. Full sample results are reported in the online appendix.

Table XI (a) reports summary statistics of the trading strategies when transaction costs are excluded. Holding the ES contract continuously (the CTC strategy) since 2005 has yielded an average yearly log return of 4.63\% with a Sharpe ratio of 0.21.\textsuperscript{26} The beta is equal to 1 by definition as we use the CTC return as a proxy for the market return. CTO returns have contributed a larger proportion to the total return earned by a passive investor holding the index than OTC returns: On an annualized basis, CTO returns averaged 2.33\% and OTC returns averaged 2.30\%.

A dissection of this magnitude is not particularly surprising in itself. However, it is surprising that the average CTO return is below the OD return component which averaged 3.68\%. The OD strategy has a Sharpe ratio of 1.14, which outperforms the market Sharpe ratio, and arises from a combination of high excess returns and low volatility during the overnight drift period. The best performing strategy is the conditional versions of OD+ which holds the e-mini on \( \sim 50\% \) of trading days. Returns from trading the BtD strategy are considerable larger than OD+ returns, which we interpret as additional evidence in support of the inventory risk prediction that past RSV should predict subsequently higher expected returns, as new agents arrive to

\textsuperscript{26}Sharpe ratios are computed from daily risk free rates implied by 4 week U.S. Treasury bills.
market and liquidity suppliers offload their long positions. In addition to larger returns, the BtD strategy return variance is significantly lower and thereby the Sharpe ratio higher. Specifically, $\text{RSV}^\text{close}_t < 0$ has a Sharpe ratio of 1.90 compared to 1.27 of $\text{OD}^+$.\footnote{The large number of zero returns is also what causes the large kurtosis. The positive skewness of BtD occurs because the $\text{RSV} < 0$ signal filters a significant fraction of the negative returns.}

Table XI (b) reports summary statistics post transaction costs. Returns on all strategies are significantly lower and none of the simple trading strategies are profitable over the full sample period. However, the BtD strategy remains profitable because it only pays the bid-ask spread on half the trading days when returns are higher. This is exactly what we would expect from an inventory management perspective. Market makers earn the bid-ask spread, buying at the bid at the end of the trading day on negative closing RSV days and selling at the ask during the overnight trading session. In general, market makers position their limit order books to incentivise trades that bring their inventory closer to their targets, making a contrarian trade – where a \textit{client} would earn the bid-ask spread – less profitable.

It is important to highlight that small yet persistent intraday return seasonalities can have large low frequency effects. To illustrate this point, figure 14 depicts the cumulative returns of the $\text{CTC}$, $\text{OD}$, $\text{OD}^+$ and BtD strategies for a one dollar investment in January 2005. The overnight strategies have performed exceptionally well in the sense that they never experience large negative returns. Remarkably, the BtD strategy has large positive returns during the financial crises even though the strategy never shorts the market. Panel (a) displays returns for a hypothetical investor who trades without costs. Trading the $\text{OD}$ ($\text{OD}^+$), a one dollar initial investment in 2005 generated a portfolio value of $1.60$ ($2.25$) in December 2018, and an even higher portfolio of $2.40$ trading the BtD strategy. Panel (b) of figure 14 displays cumulative returns including transaction costs. The $\text{CTC}$ return remains unchanged as it is a passive strategy (we only have to roll the contract at a quarterly basis and pay for the spread between the initial buy in 2005 and final sell in 2018). With transaction costs, the $\text{OD}$ is not profitable in practice. BtD still earns large positive returns and while it does not beat a passive position in the market, it has a significantly higher Sharpe ratio and does not experience large losses related to the business cycle.

Notice finally that, although the documented high frequency return patterns are not easily profitable, the persistent presence of the overnight drift suggests that the intraday timing of
portfolio adjustments should be an important consideration for asset managers and institutional investors.

[ Insert table XI and figure 14 here ]

VI. Conclusion

In this paper, we study returns on U.S. equity futures around the clock, documenting an overnight positive drift in returns accruing around the opening hours of global exchanges. We document that this overnight drift is negatively related to the signed volume at the close of the previous trading day, suggesting that market makers take the earliest available opportunity to bring their inventories back to neutral. Consistent with inventory management motives, we show that the timing of the overnight drift shifts together with exogenous changes in the time difference between U.S. and Japan due to differences in daylight savings time. Moreover, we document that prior to 2010, when trading volume during Tokyo opening hours was relatively low, the largest fraction of the overnight drift accrues during London opening hours. As trading in Asian hours has increased over time, the overnight drift has migrated to these hours. Thus, as the market for U.S. equity futures becomes more global, market makers have been able to offset closing-time order imbalances more quickly, demonstrating a positive role for financial market globalization.
References


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Cliff, Michael, Michael Cooper, and Huseyin Gulen, 2008, Return differences between trading and non-trading hours: Like night and day, Working paper.


Hendershott, Terrence, Dmitry Livdan, and Dominik Rösch, 2018, Asset pricing: A tale of night and day, .


Rinne, Kalle, and Matti Suominen, 2016, Short-term reversals, returns to liquidity provision and the costs of immediacy, SSRN abstract N. 1537923.


## VII. Tables

### (a) Overnight hourly returns: Trades

<table>
<thead>
<tr>
<th>Hour</th>
<th>18-19</th>
<th>19-20</th>
<th>20-21</th>
<th>21-22</th>
<th>22-23</th>
<th>23-24</th>
<th>24-01</th>
<th>01-02</th>
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<th>03-04</th>
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<th>07-08</th>
<th>08-09</th>
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<tbody>
<tr>
<td>Mean</td>
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<td>0.20</td>
<td>0.11</td>
<td>−0.09</td>
<td>−0.08</td>
<td>0.04</td>
<td>0.26</td>
<td>0.54</td>
<td>1.48</td>
<td>0.38</td>
<td>−0.06</td>
<td>0.16</td>
<td>0.24</td>
<td>0.17</td>
<td>0.10</td>
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<tr>
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<td>−0.49</td>
<td>−0.50</td>
<td>0.24</td>
<td>1.72</td>
<td>3.24</td>
<td>7.09</td>
<td>1.43</td>
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<td>1.13</td>
<td>0.79</td>
<td>0.33</td>
</tr>
<tr>
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<td>0.13</td>
<td>0.08</td>
<td>0.00</td>
<td>0.10</td>
<td>0.20</td>
<td>0.16</td>
<td>0.46</td>
<td>0.88</td>
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<td>0.24</td>
<td>0.29</td>
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</tr>
<tr>
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<td>−0.20</td>
<td>−0.32</td>
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<td>−0.05</td>
<td>0.20</td>
<td>0.17</td>
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<td>−0.08</td>
<td>0.08</td>
<td>−0.27</td>
<td>0.07</td>
</tr>
</tbody>
</table>

| Mean    | −0.22 | 0.33  | 0.11  | −0.03 | −0.07 | 0.11  | 0.32  | 0.42  | 1.44  | 0.30  | −0.11 | 0.05  | 0.60  | 0.05  | 0.08  |
| t-stat  | −0.74 | 1.77  | 0.51  | −0.17 | −0.43 | 0.88  | 2.26  | 2.79  | 7.22  | 1.11  | −0.43 | 0.23  | 2.49  | 0.18  | 0.21  |
| Median  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| Skew    | −1.47 | 0.95  | −0.64 | −1.04 | −3.61 | 0.31  | 1.00  | −0.63 | 0.62  | −0.04 | −0.70 | −0.41 | 1.39  | 1.05  | −0.33 |
| Kurt    | 75.30 | 46.89 | 66.04 | 44.06 | 81.29 | 27.95 | 43.92 | 38.77 | 32.99 | 17.73 | 16.28 | 19.69 | 22.02 | 62.60 | 25.30 |

### (b) Overnight hourly returns: Quotes

<table>
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<th>Hour</th>
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<th>10-11</th>
<th>11-12</th>
<th>12-13</th>
<th>13-14</th>
<th>14-15</th>
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<th>16-17</th>
<th>17-18</th>
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<td>−0.44</td>
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<td>0.04</td>
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</tr>
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<td>−1.61</td>
<td>1.10</td>
</tr>
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<td>0.79</td>
<td>1.96</td>
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<td>0.78</td>
<td>−0.62</td>
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<td>24.08</td>
<td>25.67</td>
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<td>39.74</td>
<td>17.96</td>
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<td>−0.27</td>
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<td>Kurt</td>
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<td>6.54</td>
<td>8.25</td>
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### (c) Intraday hourly returns: Trades

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<th>11-12</th>
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<th>13-14</th>
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<th>17-18</th>
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<td>0.04</td>
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</table>

### (d) Intraday hourly returns: Quotes

#### Table I. Summary Statistics

Summary statistics for S&P 500 e-mini futures hourly returns occurring overnight (panels (a) and (b)) and intraday (panel (c) and (d)). Panels (a) and (c) compute returns from volume-weighted average prices. Panels (b) and (d) compute returns using mid quotes at the top of the order book. Returns are computed from log price changes in the most liquid contract maturity (either the front or the back month contract). Mean, medians and standard deviations are displayed in basis point terms.
Table II. Day of Week Mean Returns

Mean returns are estimated for each day of the week by projecting hourly return series on a set of dummy variables, one for each hour of the day, for all days in the sample. Estimates are in basis points. \(t\)-statistics reported in parenthesis are computed from HAC robust standard errors.

### (a) Overnight hourly returns

<table>
<thead>
<tr>
<th>Hour</th>
<th>09-10</th>
<th>10-11</th>
<th>11-12</th>
<th>12-13</th>
<th>13-14</th>
<th>14-15</th>
<th>15-16</th>
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</thead>
<tbody>
<tr>
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<td>-0.32</td>
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<td>0.18</td>
<td>-0.20</td>
<td>-0.60</td>
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<tr>
<td>t-stat</td>
<td>(-0.33)</td>
<td>(-0.17)</td>
<td>(-2.06)</td>
<td>(0.35)</td>
<td>(-0.35)</td>
<td>(-1.05)</td>
<td>(0.11)</td>
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<tr>
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<td>0.16</td>
<td>0.09</td>
<td>-0.77</td>
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<tr>
<td>t-stat</td>
<td>(0.19)</td>
<td>(0.12)</td>
<td>(0.53)</td>
<td>(-0.68)</td>
<td>(-0.35)</td>
<td>(-0.69)</td>
<td>(0.11)</td>
<td>(0.14)</td>
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<tr>
<td>Wednesday</td>
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<td>1.85</td>
<td>1.06</td>
<td>-0.40</td>
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<td>-2.08</td>
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<tr>
<td>t-stat</td>
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<td>(-0.75)</td>
<td>(1.91)</td>
<td>(1.36)</td>
<td>(-0.40)</td>
<td>(1.59)</td>
<td>(-1.30)</td>
<td>(-0.00)</td>
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<tr>
<td>Thursday</td>
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<tr>
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<td>(-0.26)</td>
<td>(0.06)</td>
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<td>(-0.32)</td>
<td>(1.27)</td>
<td>(0.50)</td>
<td>(-0.75)</td>
</tr>
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<td>(0.61)</td>
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</tr>
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</table>
Table III. Month of Year Mean Returns

 Mean returns are estimated for each month of the year by projecting hourly return series on a set of dummy variables, one for each hour of the day, for all days in the sample. Estimates are in basis points. \( t \)-statistics are computed from HAC robust standard errors.

(a) Overnight hourly returns

(b) Intraday hourly returns
Table IV. Overnight Volumes as Percentage of Closing Volumes
This table reports overnight average trading volumes as a percentage of closing trading volumes. Specifically, for each overnight period we compute the hourly volumes for each of the overnight hours between 6 p.m. and 4 a.m. divided by the closing volume between 15:15 and 16:15, and then average this ratio of the sample period. Estimates are reported as percentages. The first two rows split our full sample period in half and the remaining rows report within year averages for the last 5-years of our sample.

<table>
<thead>
<tr>
<th>Hour</th>
<th>18-19</th>
<th>19-20</th>
<th>20-21</th>
<th>21-22</th>
<th>22-23</th>
<th>23-24</th>
<th>24-01</th>
<th>01-02</th>
<th>02-03</th>
<th>03-04</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998-2008</td>
<td>0.00</td>
<td>0.67</td>
<td>0.63</td>
<td>0.58</td>
<td>0.52</td>
<td>0.33</td>
<td>0.40</td>
<td>0.39</td>
<td>0.86</td>
<td>2.24</td>
</tr>
<tr>
<td>2009-2018</td>
<td>2.39</td>
<td>1.66</td>
<td>2.45</td>
<td>2.36</td>
<td>1.89</td>
<td>1.49</td>
<td>1.29</td>
<td>1.58</td>
<td>3.38</td>
<td>9.11</td>
</tr>
<tr>
<td>2015</td>
<td>2.42</td>
<td>1.44</td>
<td>2.26</td>
<td>2.13</td>
<td>1.80</td>
<td>1.45</td>
<td>1.22</td>
<td>1.51</td>
<td>3.74</td>
<td>9.40</td>
</tr>
<tr>
<td>2016</td>
<td>2.50</td>
<td>2.36</td>
<td>3.38</td>
<td>3.60</td>
<td>2.98</td>
<td>2.48</td>
<td>1.81</td>
<td>1.97</td>
<td>4.40</td>
<td>12.04</td>
</tr>
<tr>
<td>2017</td>
<td>2.83</td>
<td>1.80</td>
<td>2.90</td>
<td>2.59</td>
<td>1.84</td>
<td>1.37</td>
<td>1.23</td>
<td>1.54</td>
<td>3.02</td>
<td>7.86</td>
</tr>
<tr>
<td>2018</td>
<td>3.43</td>
<td>2.48</td>
<td>3.69</td>
<td>3.76</td>
<td>2.78</td>
<td>1.88</td>
<td>1.60</td>
<td>2.17</td>
<td>4.07</td>
<td>7.49</td>
</tr>
</tbody>
</table>
Table V. Average Returns Sorted on Closing Order Flow

We sort trading days into three sets, each with an equal number of observations, based on the closing order flow of the preceding trading day. Panel (a) reports average annualized returns of each group are reported for the contemporaneous $CTC$ returns and closing returns, for returns during Asian trading hours (18:00 – 02:00), for returns during European trading hours (02:00-08:00), for returns during the overnight drift hour (02:00 – 03:00) and for the subsequent close-to-close return. Panel (b) reports corresponding average relative signed volumes ($RSVs$) computed within each trading period.

```
<table>
<thead>
<tr>
<th>$RSV_{t-1}^{\text{close}}$</th>
<th>obs</th>
<th>min (%)</th>
<th>max (%)</th>
<th>mean (%)</th>
<th>$r_{t-1}^{CTC}$ (%)</th>
<th>$r_{t-1}^{\text{close}}$ (%)</th>
<th>$r_{t}^{\text{Asia}}$ (%)</th>
<th>$r_{t}^{EU}$ (%)</th>
<th>$r_{t}^{OD}$ (%)</th>
<th>$r_{t}^{CTC}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[-1, Q_1]$</td>
<td>1,728.00</td>
<td>-31.36</td>
<td>-4.10</td>
<td>-7.05</td>
<td>-113.07</td>
<td>-81.18</td>
<td>7.63</td>
<td>12.40</td>
<td>7.49</td>
<td>22.66</td>
</tr>
<tr>
<td>$(Q_1, Q_3]$</td>
<td>1,733.00</td>
<td>-4.10</td>
<td>4.48</td>
<td>0.16</td>
<td>8.80</td>
<td>9.01</td>
<td>0.06</td>
<td>3.88</td>
<td>3.49</td>
<td>-0.27</td>
</tr>
<tr>
<td>$(Q_3, 1]$</td>
<td>1,727.00</td>
<td>4.48</td>
<td>34.62</td>
<td>7.45</td>
<td>127.64</td>
<td>81.45</td>
<td>-1.54</td>
<td>5.12</td>
<td>-0.17</td>
<td>2.59</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$RSV_{t-1}^{\text{close}}$</th>
<th>$RSV_{t}^{\text{Asia}}$ (%)</th>
<th>$RSV_{t}^{EU}$ (%)</th>
<th>$RSV_{t}^{OD}$ (%)</th>
<th>$RSV_{t}^{CTC}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[-1, Q_1]$</td>
<td>0.93</td>
<td>1.64</td>
<td>6.57</td>
<td>-0.50</td>
</tr>
<tr>
<td>$(Q_1, Q_3]$</td>
<td>-0.42</td>
<td>0.38</td>
<td>0.93</td>
<td>-0.35</td>
</tr>
<tr>
<td>$(Q_3, 1]$</td>
<td>-1.75</td>
<td>-0.08</td>
<td>0.23</td>
<td>-0.18</td>
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</tbody>
</table>
```

(a)
<table>
<thead>
<tr>
<th></th>
<th>18-19</th>
<th>19-20</th>
<th>20-21</th>
<th>21-22</th>
<th>22-22</th>
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<th>01-02</th>
<th>02-03</th>
<th>03-04</th>
<th>04-05</th>
<th>05-06</th>
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<tbody>
<tr>
<td><strong>RSV</strong></td>
<td>-1.22</td>
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<td>-6.27</td>
<td>-1.38</td>
<td>2.33</td>
<td>0.34</td>
<td>-1.42</td>
<td>-5.90</td>
<td>-16.59</td>
<td>-18.81</td>
<td>4.34</td>
<td>1.34</td>
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<td></td>
<td>(-0.38)</td>
<td>(-1.97)</td>
<td>(-3.44)</td>
<td>(-0.67)</td>
<td>(1.45)</td>
<td>(0.21)</td>
<td>(-1.38)</td>
<td>(-3.26)</td>
<td>(-7.70)</td>
<td>(-6.38)</td>
<td>(1.00)</td>
<td>(0.58)</td>
</tr>
<tr>
<td><strong>const</strong></td>
<td>-0.18</td>
<td>0.27</td>
<td>0.07</td>
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<td>0.04</td>
<td>0.04</td>
<td>0.30</td>
<td>1.38</td>
<td>0.30</td>
<td>0.02</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.49)</td>
<td>(2.04)</td>
<td>(0.37)</td>
<td>(0.70)</td>
<td>(0.33)</td>
<td>(0.33)</td>
<td>(1.97)</td>
<td>(2.96)</td>
<td>(5.83)</td>
<td>(1.21)</td>
<td>(0.08)</td>
<td>(-0.04)</td>
</tr>
<tr>
<td><strong>R²(%)</strong></td>
<td>0.00</td>
<td>0.10</td>
<td>0.08</td>
<td>0.01</td>
<td>0.02</td>
<td>0.00</td>
<td>0.01</td>
<td>0.15</td>
<td>0.60</td>
<td>0.37</td>
<td>0.03</td>
<td>0.00</td>
</tr>
</tbody>
</table>

(a)

<table>
<thead>
<tr>
<th></th>
<th>18-19</th>
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<th>20-21</th>
<th>21-22</th>
<th>22-22</th>
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<th>01-02</th>
<th>02-03</th>
<th>03-04</th>
<th>04-05</th>
<th>05-06</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RSV</strong></td>
<td>-47.02</td>
<td>-3.61</td>
<td>17.39</td>
<td>-7.41</td>
<td>-7.88</td>
<td>2.00</td>
<td>-1.05</td>
<td>15.80</td>
<td>22.38</td>
<td>-4.08</td>
<td>-14.43</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.70)</td>
<td>(-0.39)</td>
<td>(1.37)</td>
<td>(-0.84)</td>
<td>(-0.78)</td>
<td>(-0.89)</td>
<td>(0.28)</td>
<td>(-0.09)</td>
<td>(1.13)</td>
<td>(2.44)</td>
<td>(-0.26)</td>
<td>(-0.96)</td>
</tr>
<tr>
<td><strong>VIX</strong></td>
<td>0.01</td>
<td>-0.01</td>
<td>0.08</td>
<td>-0.03</td>
<td>-0.01</td>
<td>0.03</td>
<td>0.05</td>
<td>-0.00</td>
<td>0.05</td>
<td>0.04</td>
<td>-0.08</td>
<td>-0.10</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(-0.48)</td>
<td>(1.58)</td>
<td>(-1.06)</td>
<td>(-0.34)</td>
<td>(0.81)</td>
<td>(1.66)</td>
<td>(-0.03)</td>
<td>(0.71)</td>
<td>(0.68)</td>
<td>(-0.91)</td>
<td>(-0.92)</td>
</tr>
<tr>
<td><strong>RSV × VIX</strong></td>
<td>2.33</td>
<td>-0.13</td>
<td>-1.17</td>
<td>0.29</td>
<td>0.52</td>
<td>0.50</td>
<td>-0.15</td>
<td>-0.25</td>
<td>-1.63</td>
<td>-2.08</td>
<td>0.40</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td>(2.50)</td>
<td>( -0.29)</td>
<td>(-1.70)</td>
<td>(0.65)</td>
<td>(0.98)</td>
<td>(0.92)</td>
<td>(-0.42)</td>
<td>(-0.36)</td>
<td>(-2.02)</td>
<td>(-3.92)</td>
<td>(0.44)</td>
<td>(0.94)</td>
</tr>
<tr>
<td><strong>const</strong></td>
<td>-0.28</td>
<td>0.52</td>
<td>-1.61</td>
<td>0.69</td>
<td>0.26</td>
<td>-0.61</td>
<td>-0.76</td>
<td>0.43</td>
<td>0.23</td>
<td>-0.52</td>
<td>1.55</td>
<td>2.06</td>
</tr>
<tr>
<td></td>
<td>(-0.20)</td>
<td>(1.01)</td>
<td>(-1.61)</td>
<td>(1.34)</td>
<td>(0.46)</td>
<td>(-0.84)</td>
<td>(-1.41)</td>
<td>(1.39)</td>
<td>(0.17)</td>
<td>(-0.48)</td>
<td>(1.07)</td>
<td>(0.97)</td>
</tr>
<tr>
<td><strong>R²(%)</strong></td>
<td>0.28</td>
<td>0.11</td>
<td>0.42</td>
<td>0.06</td>
<td>0.06</td>
<td>0.16</td>
<td>0.18</td>
<td>0.16</td>
<td>0.98</td>
<td>0.62</td>
<td>0.15</td>
<td>0.31</td>
</tr>
</tbody>
</table>

(b)

Table VI. Regression: overnight returns on closing signed volume

Panel (a) displays regression estimates of hourly overnight returns regressed on the relative signed volume leading up to the U.S. close period of the previous trading day:

$$r^H_{t,n} = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \epsilon_{t,n} \quad n = 1, \ldots, 12,$$

and Panel (b) repeats this regression but interacts relative signed volume with the level of the VIX from the close of the preceding day

$$r^H_{t,n} = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{VIX} VIX_{t-1}^{close} + \beta_n^{RSV×VIX} RSV_{t-1}^{close} \times VIX_{t-1}^{close} + \epsilon_{t,n}, \quad \text{for } n = 1, \ldots, 12,$$

Days where the time difference between London and New York is different from 5 hours are excluded. Estimates are in basis points. $t$-statistics reported in parenthesis are computed from robust standard errors clustered within each month.
<table>
<thead>
<tr>
<th></th>
<th>18-19</th>
<th>19-20</th>
<th>20-21</th>
<th>21-22</th>
<th>22-22</th>
<th>23-24</th>
<th>24-01</th>
<th>01-02</th>
<th>02-03</th>
<th>03-04</th>
<th>04-05</th>
<th>05-06</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSV</td>
<td>-5.30</td>
<td>-13.54</td>
<td>-7.60</td>
<td>-4.80</td>
<td>4.13</td>
<td>0.36</td>
<td>-2.27</td>
<td>-7.19</td>
<td>-20.16</td>
<td>-21.81</td>
<td>1.88</td>
<td>-0.33</td>
</tr>
<tr>
<td></td>
<td>(-1.39)</td>
<td>(-1.53)</td>
<td>(-1.45)</td>
<td>(-1.80)</td>
<td>(2.67)</td>
<td>(0.32)</td>
<td>(-0.75)</td>
<td>(-1.99)</td>
<td>(-9.55)</td>
<td>(-6.15)</td>
<td>(0.28)</td>
<td>(-0.09)</td>
</tr>
<tr>
<td>DST</td>
<td>-1.12</td>
<td>-1.09</td>
<td>0.11</td>
<td>-0.46</td>
<td>0.26</td>
<td>0.24</td>
<td>-0.47</td>
<td>-0.01</td>
<td>0.23</td>
<td>0.04</td>
<td>-1.10</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>(-1.29)</td>
<td>(-2.73)</td>
<td>(0.30)</td>
<td>(-1.25)</td>
<td>(0.69)</td>
<td>(0.72)</td>
<td>(-0.82)</td>
<td>(-0.02)</td>
<td>(0.32)</td>
<td>(0.05)</td>
<td>(-1.16)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>RSV × DST</td>
<td>11.59</td>
<td>15.89</td>
<td>1.41</td>
<td>4.36</td>
<td>-4.54</td>
<td>0.53</td>
<td>3.22</td>
<td>1.23</td>
<td>7.94</td>
<td>-2.98</td>
<td>-2.61</td>
<td>-1.73</td>
</tr>
<tr>
<td></td>
<td>(2.18)</td>
<td>(1.76)</td>
<td>(0.24)</td>
<td>(1.16)</td>
<td>(-2.12)</td>
<td>(0.28)</td>
<td>(1.06)</td>
<td>(0.29)</td>
<td>(2.33)</td>
<td>(-0.49)</td>
<td>(-0.25)</td>
<td>(-0.34)</td>
</tr>
<tr>
<td>const</td>
<td>0.63</td>
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<td>0.19</td>
<td>-0.18</td>
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<td>0.54</td>
<td>0.50</td>
<td>1.16</td>
<td>0.58</td>
<td>0.39</td>
<td>-0.23</td>
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<tr>
<td></td>
<td>(0.76)</td>
<td>(2.67)</td>
<td>(3.58)</td>
<td>(0.57)</td>
<td>(-0.62)</td>
<td>(0.15)</td>
<td>(1.01)</td>
<td>(2.05)</td>
<td>(2.95)</td>
<td>(1.05)</td>
<td>(0.63)</td>
<td>(-0.49)</td>
</tr>
<tr>
<td>R² (%)</td>
<td>0.10</td>
<td>0.35</td>
<td>0.12</td>
<td>0.08</td>
<td>0.04</td>
<td>0.02</td>
<td>0.05</td>
<td>0.18</td>
<td>0.62</td>
<td>0.70</td>
<td>0.08</td>
<td>0.01</td>
</tr>
</tbody>
</table>

(a) 1998 – 2010

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<th>20-21</th>
<th>21-22</th>
<th>22-22</th>
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<th>01-02</th>
<th>02-03</th>
<th>03-04</th>
<th>04-05</th>
<th>05-06</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-27.01</td>
<td>-14.00</td>
<td>0.25</td>
<td>10.21</td>
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<td>3.02</td>
<td>-3.71</td>
<td>2.40</td>
<td>-25.10</td>
<td>-4.32</td>
<td>0.86</td>
<td>11.44</td>
</tr>
<tr>
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<td>(-2.15)</td>
<td>(-2.02)</td>
<td>(0.05)</td>
<td>(1.27)</td>
<td>(1.57)</td>
<td>(0.63)</td>
<td>(-0.80)</td>
<td>(0.54)</td>
<td>(-1.84)</td>
<td>(-0.44)</td>
<td>(0.08)</td>
<td>(0.65)</td>
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<tr>
<td>DST</td>
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<td>-0.01</td>
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<td>-0.64</td>
<td>-0.63</td>
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<tr>
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<td>(-0.01)</td>
<td>(1.96)</td>
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<td>(0.30)</td>
<td>(0.34)</td>
<td>(-1.24)</td>
<td>(0.10)</td>
<td>(-0.70)</td>
<td>(-0.77)</td>
<td>(-0.35)</td>
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<td>RSV × DST</td>
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<td>-8.52</td>
<td>-3.65</td>
<td>-3.84</td>
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</tr>
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<td>(-0.53)</td>
<td>(-0.81)</td>
<td>(-1.89)</td>
<td>(0.62)</td>
<td>(-0.05)</td>
<td>(0.95)</td>
<td>(-0.53)</td>
</tr>
<tr>
<td>const</td>
<td>0.81</td>
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<td>-0.63</td>
<td>-0.68</td>
<td>-0.30</td>
<td>-0.01</td>
<td>0.34</td>
<td>0.62</td>
<td>1.67</td>
<td>0.35</td>
<td>0.57</td>
<td>0.55</td>
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<tr>
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<td>(0.09)</td>
<td>(-0.81)</td>
<td>(-1.49)</td>
<td>(-1.17)</td>
<td>(-0.05)</td>
<td>(1.40)</td>
<td>(2.09)</td>
<td>(10.08)</td>
<td>(0.40)</td>
<td>(0.93)</td>
<td>(0.72)</td>
</tr>
<tr>
<td>R² (%)</td>
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<td>0.64</td>
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<td>0.14</td>
<td>0.18</td>
<td>0.61</td>
<td>0.04</td>
<td>0.17</td>
<td>0.07</td>
</tr>
</tbody>
</table>

(b) 2010 – 2018

**Table VII. Daylight Saving Tests**

Hourly intraday returns are regressed on the relative signed volume leading up to the U.S. close period of the previous trading day and a dummy variable for daylight savings time:

\[ r_{t,n}^H = \mu_n + \beta_{RSV}^{RSV \times DST} RSV_{t-1,close} + \beta_{DST}^{DST} \mathbb{1}_{DST,t} + \beta_{RSV \times DST}^{RSV \times DST} RSV_{t-1,close} \times \mathbb{1}_{DST,t} + \varepsilon_{t,n} \quad n = 1, \ldots, 12, \]

where the dummy variable takes on a value of 0 in winter time (DST not active) and 1 in summer time (DST active) and daylight savings is seen from a U.S. perspective. The Tokyo Stock Exchange (TSE) opens at 19:00 (7 p.m.) ES when DST is not active and at 20:00 (8 p.m.) when DST is active. Estimates are in basis points. \( t \)-statistics reported in parenthesis are computed from robust standard errors clustered within months.
**Table VIII. Earnings Announcements**

We sort evening earnings announcements into negative, positive low/medium/high days, and non-announcement days. Within each sort we compute average returns for the close-to-close (CTC), close-to-open (CTO), open-to-close (OTC), overnight drift (OD) and opening return (OR) periods. We report t-tests of the difference against the null of zero in parenthesis.

<table>
<thead>
<tr>
<th></th>
<th>CTC</th>
<th>CTO</th>
<th>OTC</th>
<th>OD</th>
<th>OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEG</td>
<td>-6.71</td>
<td>-1.09</td>
<td>-5.77</td>
<td>1.49</td>
<td>-2.53</td>
</tr>
<tr>
<td>t-stat</td>
<td>(-1.20)</td>
<td>(-0.38)</td>
<td>(-1.29)</td>
<td>(2.08)</td>
<td>(-1.59)</td>
</tr>
<tr>
<td>POS-LOW</td>
<td>-1.02</td>
<td>-0.93</td>
<td>-0.09</td>
<td>1.54</td>
<td>-3.55</td>
</tr>
<tr>
<td>t-stat</td>
<td>(-0.24)</td>
<td>(-0.36)</td>
<td>-0.03</td>
<td>(3.33)</td>
<td>(-2.47)</td>
</tr>
<tr>
<td>POS-MEDIUM</td>
<td>2.27</td>
<td>-0.23</td>
<td>2.45</td>
<td>1.78</td>
<td>-0.16</td>
</tr>
<tr>
<td>t-stat</td>
<td>(0.52)</td>
<td>(-0.10)</td>
<td>(0.65)</td>
<td>(2.85)</td>
<td>(-0.10)</td>
</tr>
<tr>
<td>POS-HIGH</td>
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<td>3.80</td>
<td>-0.24</td>
<td>1.21</td>
<td>-1.74</td>
</tr>
<tr>
<td>t-stat</td>
<td>(0.89)</td>
<td>(1.78)</td>
<td>(-0.07)</td>
<td>(2.66)</td>
<td>(-1.32)</td>
</tr>
<tr>
<td>No Announcements</td>
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<td>2.25</td>
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<td>-1.26</td>
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<tr>
<td>t-stat</td>
<td>(1.83)</td>
<td>(1.71)</td>
<td>(1.07)</td>
<td>(4.89)</td>
<td>(-1.57)</td>
</tr>
</tbody>
</table>

**Table IX. Announcements**

We test the effect of announcements on the fixing return pattern in a bilateral regression framework with dummy variables which take a ‘1’ on days with an announcement and ‘0’ otherwise. Specifically, for each subinterval return we estimate the following regression

\[ r_{t,n}^H = \mu^n + b_1^n 1_{U.K} + b_2^n 1_{EU} + b_3^n 1_{JP} + b_4^n 1_{U.S.} + \varepsilon_t^n, \quad n = 1, \ldots, 15, \]

where for panel (a) \( 1_i \) is an employment, GDP or inflation announcement dummy for country \( i \). For panel (b) \( 1_i \) is a central bank announcement dummy for country \( i \). \( t\)-statistics are computed from HAC robust standard errors.
<table>
<thead>
<tr>
<th></th>
<th>18-19</th>
<th>19-20</th>
<th>20-21</th>
<th>21-22</th>
<th>22-22</th>
<th>23-24</th>
<th>24-01</th>
<th>01-02</th>
<th>02-03</th>
<th>03-04</th>
<th>04-05</th>
<th>05-06</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ESRSV</strong></td>
<td>-16.56</td>
<td>-16.02</td>
<td>-5.34</td>
<td>-7.79</td>
<td>-6.06</td>
<td>-6.24</td>
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<td>-19.51</td>
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<td>-5.73</td>
<td>14.15</td>
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<td>(-1.41)</td>
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<td>(-0.68)</td>
<td>(-1.06)</td>
<td>(-0.52)</td>
<td>(-1.03)</td>
<td>(-1.18)</td>
<td>(0.10)</td>
<td>(-2.67)</td>
<td>(0.89)</td>
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</tr>
<tr>
<td><strong>VXRSV</strong></td>
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<td></td>
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<td>(0.32)</td>
<td>(0.09)</td>
<td>(-0.88)</td>
<td>(0.48)</td>
<td>(-1.08)</td>
<td>(-1.12)</td>
<td>(0.79)</td>
<td>(1.23)</td>
</tr>
<tr>
<td><strong>const</strong></td>
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<td>0.31</td>
<td>-0.28</td>
<td>-0.32</td>
<td>-0.28</td>
<td>0.33</td>
<td>0.41</td>
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<td>-0.15</td>
<td>0.15</td>
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<td>(1.00)</td>
<td>(-0.53)</td>
<td>(-0.74)</td>
<td>(-0.68)</td>
<td>(1.12)</td>
<td>(1.33)</td>
<td>(0.88)</td>
<td>(4.49)</td>
<td>(-0.66)</td>
<td>(-0.30)</td>
<td>(0.37)</td>
</tr>
<tr>
<td><strong>R²(%)</strong></td>
<td>0.32</td>
<td>0.64</td>
<td>0.03</td>
<td>0.07</td>
<td>0.05</td>
<td>0.10</td>
<td>0.13</td>
<td>0.01</td>
<td>0.51</td>
<td>0.17</td>
<td>0.08</td>
<td>0.31</td>
</tr>
</tbody>
</table>

(a)

<table>
<thead>
<tr>
<th></th>
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<th>21-22</th>
<th>22-22</th>
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<th>02-03</th>
<th>03-04</th>
<th>04-05</th>
<th>05-06</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>VXRSV</strong></td>
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<td>36.40</td>
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<td>-4.99</td>
<td>10.86</td>
<td>41.07</td>
<td>-33.58</td>
<td>-25.64</td>
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<tr>
<td></td>
<td>(-0.73)</td>
<td>(1.35)</td>
<td>(0.17)</td>
<td>(0.18)</td>
<td>(0.79)</td>
<td>(-0.68)</td>
<td>(1.09)</td>
<td>(-0.56)</td>
<td>(1.02)</td>
<td>(1.91)</td>
<td>(-2.10)</td>
<td>(-2.02)</td>
</tr>
<tr>
<td><strong>ESRSV</strong></td>
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<td>167.47</td>
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<td>8.13</td>
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<td>99.53</td>
<td>19.55</td>
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<td>-73.64</td>
</tr>
<tr>
<td></td>
<td>(-1.13)</td>
<td>(2.07)</td>
<td>(0.65)</td>
<td>(1.78)</td>
<td>(0.04)</td>
<td>(1.43)</td>
<td>(1.04)</td>
<td>(-1.29)</td>
<td>(2.19)</td>
<td>(0.25)</td>
<td>(-0.05)</td>
<td>(-1.57)</td>
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<tr>
<td><strong>const</strong></td>
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<tr>
<td></td>
<td>(2.74)</td>
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<td>(0.27)</td>
<td>(2.52)</td>
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<td>(0.15)</td>
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<td>(-6.33)</td>
<td>(-2.02)</td>
<td>(1.17)</td>
<td>(0.23)</td>
</tr>
<tr>
<td><strong>R²(%)</strong></td>
<td>0.17</td>
<td>0.38</td>
<td>0.04</td>
<td>0.14</td>
<td>0.05</td>
<td>0.35</td>
<td>0.13</td>
<td>0.10</td>
<td>0.43</td>
<td>0.25</td>
<td>0.30</td>
<td>0.38</td>
</tr>
</tbody>
</table>

(b)

**Table X. Regression: overnight returns on closing signed volume: ES & VX**

Panel (a) displays regression estimates of hourly overnight ES returns regressed on ES and VX relative signed volume leading up to the U.S. close period of the previous trading day:

\[
ES r_{t,n}^H = \mu_n + \beta_n^{ESRSV} ES RSV_{t-1}^{close} + \beta_n^{VXRSV} VX RSV_{t-1}^{close} + \epsilon_{t,n}, \quad \text{for } n = 1, \ldots, 12,
\]

Panel (b) displays regression estimates of hourly overnight VX returns regressed on ES and VX relative signed volume leading up to the U.S. close period of the previous trading day:

\[
VX r_{t,n}^H = \mu_n + \beta_n^{VXRSV} VX RSV_{t-1}^{close} + \beta_n^{ESRSV} ES RSV_{t-1}^{close} + \epsilon_{t,n}, \quad \text{for } n = 1, \ldots, 12,
\]

Days where the time difference between London and New York is different from 5 hours are excluded. Estimates are in basis points. t-statistics reported in parenthesis are computed from robust standard errors clustered within each month.
Table XI. Trading Strategies

Summary statistics for returns of intraday trading strategies excluding (panel (a)) and including (panel (b)) transaction costs. CTC is continuously holding the E-mini contract. CTO is holding the contract from 16:15 (4:15 p.m.) to 8:30; OTC is from 9:30 to 16:15 (4:15 p.m.); OR is shortening the opening returns from 8:30 to 10:00; OD is the overnight drift from 02:00 to 03:00; OD+ is from 1:30 to 3:30. $RSV_{t-1}^{close} < 0$ is a buy the dip strategy that goes long from 1:30 to 3:30 only on days following a negative closing order flow. Means and standard deviations are in annualized percentages. The Sharpe ratios uses the 4 week U.S. Treasury bill as the risk-free rate. Betas are computed using the CTC return as the market return. Returns excluding transaction cost are computed from mid quotes and returns including transaction costs are computed from the best bid and ask prices quotes. The sample period is 2005.1 — 2018.12.
Figure 1. Overnight vs Intraday e-mini Volume Split
Panel (a) plots average daily trading volumes in the SP and ES contracts with the ES split by overnight versus intraday trading sessions. Panel (b) plots year-by-year average percentages of overnight volume relative to total volume for the ES contract. Volumes are measured as the total number of contracts traded.
Figure 2. Intraday Return Averages
Figure displays the average hourly log returns (bars) and average cumulative 5-minute log returns (solid black line) of the e-mini contract (first close-to-open and then open-to-close). Sample period is January 1998 — December 2018.
Figure 3. Calendar Effects
Panel (a) displays the cumulative 5-minute log returns of the e-mini across the trading day, for each day of the week, averaged across all trading days in our sample. Panel (b) displays the average cumulative 5-minute returns of the e-mini across the trading day, for the roll months March, June, September, and December Estimates are annualized and displayed in percentage points. Panel (c) plots yearly returns of the e-mini contract for the OD and OR periods and the p-values of t-tests for the OD/OR returns versus the null hypothesis.
**Figure 4. Intraday Equity Volumes**

Panel (a) plots the average 5 minute trading volume of the e-mini for the entire trading day, showing the full intraday pattern of volume. Panel (b) focuses only on volume outside U.S. open hours. All volumes are computed as averages of the 5 minute volume relative to the total daily volume.
Figure 5. Sorting on Order Flow

Panel (a) shows the distribution of closing order flow, defined as the relative signed volume during the last hour of trading (15:15 – 16:15). Panel (b) displays average cumulative intraday returns sorted on the closing relative signed volume of the preceding trading day. Days with negative closing RSV are defined as the bottom 25% of RSV, ~zero closing RSV is the middle 50% and positive closing RSV is the top 25%.
Figure 6. Market Depth
Figure displays the average market depth measured at a 5 minute frequency throughout the trading day. Market depth is measured as the number of contracts available and is reported for the first five levels on each side of the order book. The sample period is 2009 – 2019.

Figure 7. Ask Depth versus Bid Depth Sorted on Closing Order Flow
This figure displays the average difference in ask depth and bid depth for the first 5 levels of the order book. Trading days are sorted into groups based on the signed volume around U.S. close of the preceding trading day. The sample period is 2009 – 2019.
Figure 8. E-mini Trading Volume: Asian Hours

Figure displays average trading volume in the e-mini contract for the Asian trading hours. The sample period is split into 1997 – 2009 (a) and 2010 – 2019(b). Within each sub-sample, trading days are split into days where U.S. daylight savings time (DST) is active and where DST is not active, as the main Asian countries do not observe daylight savings time. Seen from a U.S. perspective, the Tokyo Stock Exchange (TSE) opens at 19:00 (7 p.m.) ET when U.S. DST is not active and at 20:00 (8 p.m.) when U.S. DST is active. TSE reopens at 22:30; 10:30 p.m. (23:30; 11:30 p.m.) after its lunch break when U.S. DST is not active (active). All volumes are computed as averages of the 5 minute volume relative to the total daily volume.
Figure 9. Volume Time

This figure displays the cumulative log returns and the cumulative signed volume in both clock time and volume time and sorted by closing order imbalance ($RSV_{t-1}^{close}$) on the previous trading day. Volume time is defined such that a one increment step on the x-axis advances each time a single contract is traded. The sample period is 2010 – 2018.
Figure 10. Realized Volatility
Figure displays the average intraday realized volatility of the E-mini computed from 1-minute data. Volatility is annualized and displayed in percentage points.
Figure 11. Liquidity Measures
Figure displays the intraday Amihud measure, Bid-Ask spread and Kyle’s lambda of the E-mini and time series of the 3 measures for the Asian, European and U.S. trading hours. The sample period is 2004 – 2018.
Figure 12. SUE score

Figure displays the time series of the SUE score for the S&P 500 index. The daily earnings surprise of the S&P 500 index is defined as the daily sum of all individual firm surprises, \( ES_{i,t} \). For each firm \( i \) and on day \( t \) we define the earnings surprise as

\[
ES_{i,t} = \frac{A_{i,t} - F_{i,t} - P_{i,t}}{P_{i,t}},
\]

where \( A \) is the the actual earnings per share (EPS) as reported by the firm, \( F \) is the most recent median forecast of the EPS and \( P \) is the stock price of the firm at the end of the quarter. The earnings data is obtained from I/B/E/S and Compustat.
Panel (a) displays the average hourly log returns (bars) and average cumulative 5-minute log returns (solid black line) of the VIX Futures contract (first close-to-open and then open-to-close). Panel (b) plots intraday 1-minute correlations between ES and VX futures returns ($r_t^{ES} \times r_t^{VX}$) for intervals where we observe quote updates and averaging these over all days in our sample. The sample period is June 23, 2014 to December 31, 2018.
Figure 14. Cumulative Returns with and without Transaction Costs

Figure displays time series of cumulative returns for a one dollar investment in various intraday trading strategies for the e-mini contract. The investment starts in 2005 when the overnight spread reached its effective minimum of one tick (0.25 index points). Panel a (b) is excluding (including) transaction costs. CTC is continuously holding the e-mini contract. OD is the strongest part of the overnight drift from 02:00 to 03:00, OD+ is from 1:30 to 3:30 and buy the dip goes long from 1:30 to 3:30 only on day following a negative closing order flow. The black line shows the cumulative risk-free return measured as the return of a 4 week U.S. Treasury bill. Returns excluding transaction cost are computed from the mid quotes and returns including transaction costs are computed from the best bid and best ask price.
IX. Internet Appendix

Not Intended for Publication

A. Global equity market opening hours

Table A.1 collects opening and closing times for 14 global equity markets, in the local time zone and in corresponding Eastern Time (ET). As U.S trading hours on GLOBEX close, New Zealand, Australia, Japan, Singapore and then China open between between 18:00 and 21:30. Day trading in these venues is closed by 3 a.m. Between 2 a.m and 3 a.m Dubai, Russia, London and Europe open. Therefore, the OD coincides with the opening of regular trading on Euronext, Eurex, and the Frankfurt Deutsche Börse, and pre-market trading on the London Stock Exchange, all occurring at 2:00 a.m. This observation highlights the geographical nature of 24-hour trading and points towards a potential explanation related to trade.

Figure A.1. Global Equity Market Trading Hours

Figure displays opening and closing times for 14 global equity markets in June 2019. Green bars indicate opening times and red bars indicate closing times. The abbreviations are NYSE=New York Stock Exchange, TSE=Tokyo Stock Exchange, LSE=London Stock Exchange, HKE=Hong Kong Stock Exchange, NSE=National Stock Exchange of India, BMF=Bovespa Bolsa de Valores Mercadorias & Futuros de Sao Paulo, ASX=Australian Securities Exchange, FWB=Frankfurt Stock Exchange Deutsche Borse, RTS=Russian Trading System, JSE=Johannesburg Stock Exchange, DIFX=NASDAQ Dubai, SSE=Shanghai Stock Exchange, NZSX=New Zealand Stock Exchange, TSX=Toronto Stock Exchange. Opening and closing times are collected from the public websites of the exchanges and reported in Eastern Standard Time (ES). Several of the opening times shift by one or two hours when U.S. DST is not active (see table A.1 for details).
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Name</th>
<th>Open</th>
<th>Close</th>
<th>Time difference</th>
<th>ET open</th>
<th>ET close</th>
</tr>
</thead>
<tbody>
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<td>17:00</td>
<td>16</td>
<td>18:00</td>
<td>01:00</td>
</tr>
<tr>
<td>TSE*</td>
<td>Tokyo</td>
<td>09:00</td>
<td>15:00</td>
<td>13</td>
<td>20:00</td>
<td>02:00</td>
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<td>02:00</td>
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<td>11:00</td>
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<td>16:00</td>
</tr>
</tbody>
</table>

Table A.1. Open and Closing Times of Global Equity Cash Indices

The table displays opening and closing times for 14 global equity markets, in the local time zone and in corresponding Eastern Time Zone (ET) for June, 2018. The abbreviations are NYSE=New York Stock Exchange, TSE=Tokyo Stock Exchange, LSE=London Stock Exchange, HKE=Hong Kong Stock Exchange, NSE=National Stock Exchange of India, BMF=Bovespa Bolsa de Valores Mercadorias & Futuros de Sao Paulo, ASX=Australian Securities Exchange, FWB=Frankfurt Stock Exchange Deutsche Börse, RTS=Russian Trading System, JSE=Johannesburg Stock Exchange, DIFX=NASDAQ Dubai, SSE=Shanghai Stock Exchange, SGX= Singapore Exchange, NZSX=New Zealand Stock Exchange, TSX=Toronto Stock Exchange. Opening and closing times are collected from the public website of each exchange. * Denotes locations that do not observe Daylight Savings Time (DST). Relative to the table, the time difference is plus 1 hour outside the U.S. DST period. ** Denotes locations south of equator that do observe DST. Relative to the table, the time difference is plus 2 hours when outside the U.S. DST period and in the DST period of the given region.

B. Granular Returns
Figure A.2. Intraday Return Averages
Figure plots average 5 minute returns for the hours 1.00-4.00 a.m. Estimates are annualized and displayed in percentage points.
C. Non-Parametric Tests

Table A.2 considers a non-parametric dissection of intraday returns. We report two sets of statistics: one using the daily sample and one using hourly returns aggregated within the calendar trading month. For each set, we report the percentage of positive and negative returns together with the \( p \)-value from a two-sided test of observing this many more returns in one direction than the other, under the null hypothesis of a driftless random walk (binomial test with a probability of success equal to \( \frac{1}{2} \)).

Panels (a) and (b) report the overnight returns statistics. Considering first returns computed from trades, for daily (monthly) sampling we reject the random walk hypothesis at the 5\% level or greater between the hours of 1 a.m. and 3 a.m. (12 a.m. and 3 a.m.). During the \( OD \) hour, at the monthly frequency, 65\% of the months in our sample are positive compared to 59\% for close-to-close returns (final column of panel (c)). Outside the hours of 24 (12 a.m.) and 3 a.m., we cannot reject the hypothesis that overnight returns follow a random walk. Computing returns from quotes gives consistent but stronger results \(^{28}\).

Panels (c) and (d) report the intraday returns statistics. At the daily sampling frequency, the \( OR \) has a roughly equal probability of being positive as negative for both trade-based and quote-based returns. At the monthly frequency, the \( OR \) is biased towards being negative but not in a significant sense.

D. Special Hours

To understand whether the \( OD \) and the \( OR \) are truly different from the other hourly returns, we plot a heat map of \( p \)-values from a two-sided \( t \)-test of equality of hourly returns in figure A.3. The \( t \)-test is computed from linear combinations of the dummy regression estimates. White values indicate a \( p \)-value of zero, i.e., a rejection that the average hourly return in two intervals is the same. Dark red values indicate \( p \)-values close to 1, indicating we cannot reject the null of equality. The axes labels indicate the hourly return intervals. Two regions stand out and intersect to form a white-cross of rejections: the \( OD \) and the \( OR \) are statistical different to all other hours of the day with high degrees of confidence. This result highlights the special nature of these periods and their contribution to close-to-close returns, consistent with figure 2 and table I discussed above.

\(^{28}\)For the hour 23–24 (11 p.m. – 12 a.m.), we observe a return of zero on more than 20\% of all days when using quotes. This is because the market was closed during this hour on Tuesday to Fridays from October 1998 to September 2003.
Table A.2. Non-Parametric Tests

Panels (a) and (c) compute returns from volume-weighted average prices. Panels (b) and (c) compute returns using mid quotes at the top of the order book. Returns are computed from log price changes in the most liquid contract maturity (either the front or the back month contract). “%POS” is the percentage of positive returns and “% NEG” is the percentage of negative returns. p-value reports the probability, from a two-sided test, of observing this many returns in one direction than the other, under the null hypothesis of a random walk.
Figure A.3. p-value heat map of hourly differences test
This figure displays a heat map visualising the p-values from a test of equality of hourly returns. White values indicate a p-value of zero, i.e., a rejection that the average hourly return in two intervals is the same. Dark red values indicate p-values close to 1, indicating we cannot reject the null of equality. x and y labels indicate the hourly return intervals.
Figure A.4. Announcements per Weekday

Figure displays the number of trading days, for each day of the week, where U.S macro, bank or earnings announcements are released.
### Table A.3. Trading Strategies

Summary statistics for returns of intraday trading strategies excluding (panels (a) and (c)) and including (panels (b) and (c)) transaction costs. Panels a and b consider the full sample period from 1998 to 2018 while panels c and d start in 2005 when the overnight b/a spread reached its effective minimum of one tick (0.25 index points). **CTC** is continuously holding the E-mini contract. **CTO** is holding the contract from 16:15 (4:15 p.m.) to 8:30; **OTC** is from 9:30 to 16:15 (4:15 p.m.); **−OR** is shortening the opening returns from 8:30 to 10:00; **OD** is the overnight drift from 02:00 to 03:00; **OD+** is from 1:30 to 3:30. **RSV\textsuperscript{close}_{t−1} < 0** is a buy the dip strategy that goes long on days following a negative closing order flow. Means and standard deviations are in annualized percentages. The Sharpe ratios uses the 4 week U.S. Treasury bill as the risk-free rate. Betas are computed using the CTC return as the market return. Returns excluding transaction cost are computed from mid quotes and returns including transaction costs are computed from the best bid and ask prices quotes. The sample period is 1998.1 — 2018.12.

<table>
<thead>
<tr>
<th></th>
<th><strong>CTC</strong></th>
<th><strong>CTO</strong></th>
<th><strong>OTC</strong></th>
<th><strong>OD</strong></th>
<th><strong>OD+</strong></th>
<th><strong>RSV\textsuperscript{close}_{t−1} &lt; 0</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>4.37</td>
<td>2.64</td>
<td>1.73</td>
<td>3.63</td>
<td>5.26</td>
<td>5.88</td>
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<tr>
<td><strong>Sdev</strong></td>
<td>19.18</td>
<td>10.20</td>
<td>16.07</td>
<td>2.32</td>
<td>3.62</td>
<td>2.67</td>
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<tr>
<td><strong>Sharpe ratio</strong></td>
<td>0.16</td>
<td>0.13</td>
<td>0.03</td>
<td>1.01</td>
<td>1.10</td>
<td>1.72</td>
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<tr>
<td><strong>beta</strong></td>
<td>1.00</td>
<td>0.29</td>
<td>0.71</td>
<td>0.02</td>
<td>0.04</td>
<td>0.02</td>
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<tr>
<td><strong>Skew</strong></td>
<td>-0.35</td>
<td>-0.56</td>
<td>-0.36</td>
<td>0.59</td>
<td>1.30</td>
<td>4.53</td>
</tr>
<tr>
<td><strong>Kurt</strong></td>
<td>10.84</td>
<td>12.89</td>
<td>11.03</td>
<td>33.26</td>
<td>38.78</td>
<td>104.60</td>
</tr>
</tbody>
</table>

(a) Without Transaction Costs

<table>
<thead>
<tr>
<th></th>
<th><strong>CTC</strong></th>
<th><strong>CTO</strong></th>
<th><strong>OTC</strong></th>
<th><strong>OD</strong></th>
<th><strong>OD+</strong></th>
<th><strong>RSV\textsuperscript{close}_{t−1} &lt; 0</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>4.37</td>
<td>-2.89</td>
<td>-3.88</td>
<td>-3.31</td>
<td>-1.50</td>
<td>2.57</td>
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<tr>
<td><strong>Sdev</strong></td>
<td>19.18</td>
<td>10.22</td>
<td>16.08</td>
<td>2.35</td>
<td>3.64</td>
<td>2.65</td>
</tr>
<tr>
<td><strong>Sharpe ratio</strong></td>
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<td>-0.41</td>
<td>-0.32</td>
<td>-1.95</td>
<td>-0.77</td>
<td>0.48</td>
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<tr>
<td><strong>beta</strong></td>
<td>1.00</td>
<td>0.29</td>
<td>0.71</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
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<tr>
<td><strong>Skew</strong></td>
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<td>-0.61</td>
<td>-0.38</td>
<td>0.33</td>
<td>1.19</td>
<td>4.16</td>
</tr>
<tr>
<td><strong>Kurt</strong></td>
<td>10.84</td>
<td>12.90</td>
<td>11.02</td>
<td>31.01</td>
<td>38.03</td>
<td>105.33</td>
</tr>
</tbody>
</table>

(b) With Transaction Costs