This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the authors.
Abstract

We show that nearly 100 percent of the U.S. equity premium is earned over a window around the opening hours of European markets when U.S. cash markets are closed. We explore two potential complementary explanations. First, consistent with predictions from dealer inventory risk models, we find (1) a strong negative link to end-of-day order imbalance; (2) reversals are amplified in periods of high volatility; and (3) in recent years dealers have increasingly offloaded inventory during Asian trading hours. Second, shocks to end-of-day quantities of risk lead to increases in overnight expected returns.

Key words: overnight returns, immediacy, inventory risk, volatility risk
Since the advent of electronic trading in the late 1990’s, U.S. equity futures have traded (close to) 24 hours a day. In this paper, we study the round-the-clock market for U.S. equities, decomposing trading activity by Asian, European and U.S. local hours and study intraday return patterns.

We begin by documenting that overnight (ON) trading in U.S. equity futures has accounted for at least 15% of total volume since 2009 (>15 billion daily). Considering return patterns, for the sample 1998 – 2019, close-to-close returns averaged 4.4% p.a., close-to-open returns (overnight) averaged 2.7% p.a., and open-to-close (intraday) returns averaged 1.7% p.a.\(^1\) Zooming in, we show that almost 100% of the U.S. equity premium is earned during a narrow window preceding the opening of regular European trading hours. Specifically, we show that returns between 2:00 a.m. and 3:00 a.m. (ET) averaged 3.6% p.a. We dub this hour the ‘overnight drift’ (OD) as the large average return in this hour is not driven by higher order moments or tail events but instead the distribution of returns seems shifted to the right, i.e. it appears to have an increased drift. In addition, we show that the return during the U.S. opening hours between 8:30 a.m. and 10:00 a.m. averaged −3.9% p.a.

The overnight drift is present on every trading day of the week, every month of the year, and every year in our sample. The negative opening return, instead, is only observed during recessions and is largest on Thursdays and Fridays, suggesting that the opening return is primarily related to macroeconomic events and earnings announcements. Importantly, the opening return has only a weak positive correlation with the overnight drift, so that the opening return is not a reversal of the overnight trading patterns but rather a distinct phenomenon. In this paper, we focus on understanding the economics of the overnight drift as the most salient empirical fact arising from our 24-hour decomposition.

What can explain these findings? Summarizing, we reject explanations based on contemporaneous liquidity and volatility effects, as well as the arrival of overnight news. Instead, we argue the overnight drift can be understood within 1) the context of market makers’ inventory management in a global market for equity risk and 2) end-of-day shocks to the quantity of risk that lead to higher expected overnight returns.

In a Grossman and Miller (1988)-style inventory risk model, risk-averse market makers profit by providing immediacy to investors who arrive asynchronously to the market, generating mean

\(^1\)The CTO sharpe ratio is 0.13 and the OTC Sharpe ratio is 0.03.
reversion in prices as market makers absorb shocks to their inventories. We test predictions from this framework along four dimensions: (i) a link between intraday price predictability (reversals) and order imbalance; (ii) a link between the quantity of inventory risk and the magnitude of reversals; (iii) the depth of the aggregate limit order book and order imbalance; and (iv) we exploit exogenous variation due to daylight savings time in the arrival time of Asia-based clients to test geographical shifts in liquidity provision.

We first show that overnight returns are negatively related to the closing order imbalance of the preceding day. Estimating intraday regressions of returns on closing order flow, we find statistically and economically significant loadings on the hours when London and Frankfurt financial markets open. This provides evidence of high frequency return predictability, arising when market makers take on large positions at the end of the U.S. trading day, which they then trade away in subsequent periods as new liquidity traders arrive to the market.

Repeating this test non-parametrically, we sort intraday returns on ex-ante closing order imbalance, and show that positive overnight drifts occur only on days following market sell-offs (negative order imbalances). When order imbalances are in the bottom quartile (most negative order imbalances), subsequent returns during the OD hour average 7% p.a while returns throughout the full European trading session are equal to 13.45% p.a. However, more importantly for an inventory risk explanation, during Asian trading hours we also observe significant and economically large positive returns equal to 9.8% p.a. Thus, even in our full sample, conditional on large market sell-offs, we observe two geographically distinct locations of liquidity provision: liquidity providers offload imbalances to Asian traders during Asian hours and later to European traders in European hours.

Furthermore, for the sample period 2009-2019, we obtain intraday quotes for the aggregate S&P 500 futures limit order book and can therefore trace the dynamics of market depth. Consistent with the idea that market makers set their price schedules to induce mean reverting inventory dynamics, sorting on day \( t - 1 \) closing order imbalance, we show the limit order book is deeper on the ask (bid) side when closing order imbalance was negative (positive).

We also investigate a prediction that price reversals should be amplified in states of high volatility since in these states risk averse liquidity providers bear larger quantities of risk. We test this by interacting order imbalance with the level of the VIX index prevailing at the close of day \( t - 1 \), and find volatility has a strong amplification effect on the relationship between order
imbalance and the overnight drift.

Our extended sample period (20-years) allow us to conduct two experiments. First, we show e-mini trading increased during Asian trading hours post-2010. This implies that, in the second half of our sample, dealers could offload their inventory at an earlier point in time during the overnight sessions. Consistent with this idea, post-2010, we provide strong evidence of high-frequency return predictability precisely when the Tokyo financial market opens. This stands in contrast to pre-2010 when there was virtually no trade during these hours and, indeed, we observe 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 Japanese markets open at 7 p.m. in winter and 8 p.m. in summer. 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.

While we argue that inventory risk can explain our main result, we provide an alternative explanation based on ‘risk sentiment’. Dating as far back as French, Schwert, and Stambaugh (1987), academics have documented a strong positive link between shocks to volatility and expected returns. We test for this relationship by computing volatility shocks from changes in the VIX index, and find that date $t - 2$ to $t - 1$ VIX changes contain strong predictive power for the overnight drift. Positive volatility shocks are ‘risk-off’ states of the world associated with unexpectedly bad news about the economic outlook, political uncertainty, natural disasters or periods of financial distress. A risk-off sentiment is frequently cited in the financial press as a period when investors sell risky positions and move into safe haven assets, and which subsequently are followed by market rebounds. However, while order imbalance and volatility shocks are highly correlated, we show they contain independent forecasting power for subsequent returns. We argue that volatility shocks provide an alternative to inventory risk, which is linked to overnight returns through a risk sentiment channel.

Finally, we explore whether news released after U.S. cash market close can explain overnight

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2 The Tokyo Stock Exchange trades from 9.00 a.m. to 3.00 p.m. in Japanese Standard Time.
3 For a recent examination across asset classes see Smales (2016).
4 For example, “the Cboe Volatility Index, also known as the VIX, closed at the fourth-highest level ever recorded [March 12th 2020]. The gauge has never hit such an extreme point without the S&P 500 immediately and sharply bouncing by more than 10% over the next day or two”, Nicholas Colas. Source: https://www.bloomberg.com/news/articles/2020-03-13/vix-shocks-like-this-have-perfect-record-of-signaling-a-bounce
returns. Indeed, a large fraction of U.S. corporate earnings announcements are released after U.S. market close, as are non-U.S. macro announcements. Studying this conjecture we examine hour-by-hour returns conditional on announcement dates and fail to detect a relationship between overnight news and the overnight drift.

The paper concludes 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. Accounting for bid-ask spreads reduces strategy returns to −0.8% p.a. implying that the overnight drift does not represent market inefficiency and instead is a phenomenon that arises due to inventory management by liquidity providers. 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 profitable with returns of 1.3% p.a. and a Sharpe ratio of 0.1. 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, a number of authors have documented that equities earn a substantial proportion of their returns during the overnight period compared to the regular U.S. trading-hours Cliff, Cooper, and Gulen (2008); Kelly and Clark (2011); Berkman, Koch, Tuttle, and Zhang (2012). In work subsequent to ours, Bondarenko and Muravyev (2020) confirm that the lion’s share of the U.S. equity premium is earned around the opening hours of European markets. By focusing on the full sample results only, Bondarenko and Muravyev (2020) miss the increasing time trend in trading volume during Asian market hours, thereby misinterpreting the weak return predictability around Asian opening hours in the first half of the sample as evidence against an inventory risk management channel. Instead, we show that, as trading becomes more prevalent during Asian market hours in the second half of our sample, dealers do in fact off-load their excess exposure at Asian open as would be predicted by standard inventory risk management
models.

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

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For a textbook treatment of the predictions studied here we refer the reader to Foucault, Pagano, Roell, and Röell (2013).
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 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).

Finally, we speak to the general property of equilibrium models which link conditional variances of state variables (quantities of risk) to expected returns (see, for example, Merton (1980); French, Schwert, and Stambaugh (1987); Le and Singleton (2013)). A well established puzzle in the asset pricing literature is that this link is difficult to detect in the data (see Duffee (2002) in the context of bond markets or more recently Eraker (2019) in the context of equity markets). This has motivated a significant discussion challenging the ability of structural models to explain risk premium dynamics. We contribute to this debate by documenting a strong link between shocks to volatility and expected returns, that is born out in high-frequency, as opposed to low frequency which has been the focus on extant literature.

The rest of the paper is organized as follows. We describe the high-frequency futures data in Section I. We present the baseline results in Section II. Section III describes a motivating framework and tests predictions arising from inventory risk models linking order imbalances to returns. Section IV studies the relationship between closing U.S order imbalances, and subsequent Asian trading patterns. Section V considers volatility risk. Section VI tests alternative explanations for the overnight drift based on the arrival of overnight news. We examine the profitability of a trading strategy based on the overnight drift in Section VII. Section VIII 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.\footnote{Regular trading hours are defined by the open outcry or pit session which trades between 9:30-16:15 (ET)} 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.\footnote{The 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.} 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) 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.). Given the continuous nature of trading
in U.S. equity futures, it is natural to study return dynamics over the 24-hour trading day. 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

A. Main result

We use log returns to measure intraday returns. The \( n \)-th log return on day \( t \) is defined as

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 r_{t,n}^{N} = \frac{p_{t,n}}{p_{t,n-1}} 
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8 Between 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.
for \( n = 1, \ldots, N \), where \( p_{t,n} \) 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.

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 \( \sim 4.5\% \), which equals the average yearly return on the S&P 500 index cash over this sample period.\(^9\) However, the majority of this return is generated during the \( ON \) session: between 6 p.m. and 8 a.m. equity returns average 3.1% p.a.\(^1\) 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’ (\( OD \)). Thereafter, between the hours of 8:30 a.m. and 10:00 a.m., we observe a sequence of negative returns averaging \(-3.9\% \) p.a., and we dub this sequence ‘opening returns’ (\( OR \)). Figure A.3 in the online appendix (OA) displays a more granularly 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.

\[^9\]Our 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.

\[^10\]The monthly correlation between S&P 500 value weighted cash index returns obtained from CRSP and our close-to-close returns is \( > 98\% \).

\[^11\]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.
B. **Summary statistics**

Stacking hourly returns in the vector $\vec{r}$ 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 $\vec{r} = D\mu^\top + \varepsilon$. 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 $\{0.53, 1.48\}$ basis points per hour per day, respectively, with corresponding $t$-statistics equal to $\{3.18, 7.10\}$. Using quotes, these returns are similar in magnitude. These are the only overnight hours statistically significant at conventional levels.

Median returns computed from VWAPs are also positive for the hours $\{01-02, 02-03\}$ and equal to $\{0.40, 0.85\}$ 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 $OD$ hour is large and positive equal to 0.89 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 $OD$ hour equal to 0.21 from VWAPS and 0.62 from quotes, which compares to daily $CTC$ return skewness of $-0.27$ and $-0.16$, respectively.

Consider now panels (c) and (d), which collect $ID$ 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 $t$-statistic of 3.50 (2.54). The remaining $ID$ 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 $OD$ hours but not for the $OR$, while table A.4 (OA) confirms $OD$ returns are special, in the sense that they are statistically different than all other hourly returns.

[ Insert table I here ]
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.

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, \( r_{\text{THU}}^{\text{CTC}} > r_{\text{TUE}}^{\text{CTC}} \sim r_{\text{WED}}^{\text{CTC}} > r_{\text{FRI}}^{\text{CTC}} > r_{\text{MON}}^{\text{CTC}} \); however, the differences in weekday CTC returns are not statistically different from each other. Considering the OD, it is clearly visible in each day of the week, and displays far less dispersion than close-to-close returns, i.e., it is systematic. 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 \( r_{\text{WED}}^{\text{OD}} > r_{\text{MON}}^{\text{OD}} > r_{\text{FRI}}^{\text{OD}} > r_{\text{TUE}}^{\text{OD}} > r_{\text{THU}}^{\text{OD}} \).

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 \(-2.87\) and \(-2.00\) basis points per hour per day, with \( t\)-statistics equal to \(-2.79\) and \(-2.94\), respectively. Figure 4 reports three 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 systematically 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 $OD$.

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 $-3.55\%$ with a $t$-stat of $-1.99$), 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 statically different than zero in 5 years. Moreover, the negative $OR$ 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 risk

In this section, we explore a set of potential explanations for the overnight drift returns based on standard predictions that arise from market microstructure theory.

A. 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 5 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 the illiquidity is highest during Asian hours when the trading activity is at its lowest (see figure 6). 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 6). 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.

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 measured 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 10 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 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.

\[
\text{[ Insert figure 5, figure 6 and 7 here ]}
\]

B. Inventory Models 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.\(^{12}\) Motivated by this literature, consider the following stylized example:

A large sell order arrives which transacts at the best available bid and, subsequently, executes at successively lower prices down the order book. As the sell-off shock is realized, prices drop below fundamental values and risk averse dealers bear inventory risk.\(^{13}\) The extra risk dealers hold drives down their marginal valuations as they anticipate offloading their portfolio to new customers entering the market. The distribution of demand shocks in subsequent periods depends on the endogenous probability of arrival of noise traders versus price-sensitive clients. Expected execution prices climb over time as new investors arrive and infer the likely motivation for the original trade. Conditional on the original shock, prices will revert due to a pure inventory effect but are not expected to fully recover because the original sell order may have been transacted by an investor with private information.

Models of this type provide an intuitive link between liquidity provision and price formation and a wealth of empirical evidence exists on return reversals that arise as a result of order imbalance.\(^{14}\)

---

\(^{12}\)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).

\(^{13}\)Micro-foundations for dealer risk aversion can arise from a multitude of sources, including regulatory limits on position size, constraints on dealer leverage, and margin requirements. Intuitively, the more binding these constraints are, the larger would be the effective risk aversion of the dealer.

\(^{14}\)See Hendershott and Menkveld (2014) and the references therein.
Following this literature, we now study an explanation for the overnight drift by testing predictions that relate price reversals to inventory risk.

B.1. Equity Order Imbalance

We test whether order imbalance affects expected returns by regressing future intraday realized returns on the closing order imbalance of the preceding trading day. Order imbalance is measured as relative signed volume during the last hour of the preceding trading day

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

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.). Panel (a) of Table IV 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

\[ r_{t,n}^{H} = \mu_{n} + \beta_{n}^{RSV} RSV_{t-1}^{\text{close}} + \epsilon_{t,n}, \text{ for } n = 1, ..., 12, \]

together with \(t\)-statistics computed from robust standard errors clustered within each month. Figure 8 repeats the regressions in equation 4 in finer granularity, visualizing the estimates at 15-minute intervals for the full trading day. In section IV we study in greater depth the link between end of day order imbalance and return dynamics in Asian hours.

As predicted by models of dealer 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 6). The estimates are both economically and statistically significant, with a 10 percentage point decrease (a sell-off) in closing relative signed volume corresponds to a 1.68 (1.99) basis point

\(^{15}\)Buy (sell) orders deplete the offered best ask (bid) quotes and thus increase (decrease) mid prices, conditional on no new quotes being submitted to the order book. Thus, there is a mechanical relation between order flow and returns. In reality, dealers constantly update their quotes however in high frequency, in liquid markets, it is well known that the strong positive relationship between order flow and returns remains. We choose to use order imbalance as a direct measure of inventory imbalance but note our findings quantitatively similar using returns as an explanatory variable.
increase in returns between 2 a.m – 3 a.m (3 a.m – 4 a.m). Figure 8 shows that the relationship is particularly strong in the first 15 minutes following the openings at 2 a.m and at 3 a.m., coinciding with trading volume spikes.

Figure 9 (a) provides a non-parametric illustration of these results by sorting trading days based on the closing RSV from the preceding trading day. The distribution of closing RSV that we sort on is shown in figure 9 (b). Table V reports summary statistics relating to the sorts.

We see that the positive OD returns occur only on days when the closing RSV was negative. Sorting on the lower quartile, OD returns are equal to 7% p.a. and returns through the European trading session are equal to 13.45% p.a. However, more importantly for an inventory risk explanation, during Asian trading hours we also observe significant and economically large positive returns equal to 9.8% p.a. These results are consistent with the basic prediction of Grossman and Miller (1988)-style models, which imply that, conditional on a shock, prices revert as new participants enter the market and dealers offload. In this case, there are two geographically distinct participants: dealers first offload to Asian traders as Asian markets opens and next to European traders as European markets opens.

Considering RSV within the top quartile, we observe the mean of the sorting variable equal -8.30% and, remarkably, this is associated with a -93% p.a sell off return in the last hour of trading, which accounts for the bulk of the -122% negative close-to-close return on that day. The subsequent day close-to-close return rebounds positively equal to 25.52% p.a, and importantly for an inventory risk explanation the reversal is almost completed during overnight hours, with returns in Asian hours equal to 9.7% p.a. and returns in European hours equal to 12.5%. We also note that large negative market sell offs have a residual permanent effect of 93% - 25% = 68% p.a.

As conjectured in the stylized example above, conditional on the original shock, prices revert but do not fully recover. Thus, we identify a transient and permanent component to large market sell-offs and argue that the transient component (the return that reverts) is an inventory effect, while the permanent component (the residual), reflects news about fundamentals and impacts prices through an asymmetric information channel.\footnote{The benchmark model of asymmetric information, Glosten and Milgrom (1985), has been extended in many directions, including Easley and O’Hara (1987) who consider trading multiple trade sizes while Easley, O’Hara, and Srinivas (1998) introduce learning from order flow and trading volume.}
Finally, we investigate the additional inventory risk prediction that price reversals should be amplified in states of high volatility. We test this prediction by interacting $RSV$ with the level of the VIX index at the close of the previous day

$$r_{t,n}^H = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{VIX} VIX_{t-1}^{close} + \beta_n^{RSV \times VIX} RSV_{t-1}^{close} \times VIX_{t-1}^{close} + \epsilon_{t,n} \quad (5)$$

for $n = 1, ..., 12$. Panel (b) of Table IV 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 $22.80 \cdot (-0.1) - 2.01 \cdot (0.1) \cdot 20 = 1.74$ 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 3.75 basis points.

### B.2. Asymmetry

Figure 9 (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 shows an unconditionally positive drift. This raises a question: why are overnight returns asymmetric?

One possible statistical explanation is that closing $RSV$ is negatively-skewed, but the bottom panel of figure 9 and table V show this is not the case. However, table V does show that moderate imbalances can generate large negative return realizations that would likely impact risk management and margin requirements; thus, making market makers even more unwilling to hold large inventories, leading to more aggressive inventory management during the following trading session. In the theory of Brunnermeier and Pedersen (2009), which builds on Grossman and Miller (1988), market liquidity and funding liquidity interact in such flight-to-quality episodes. In that model, capital required for trading evaporates when the market suffers negative shocks, which could explain why we observe large price reversals after negative but not positive demand shocks.
B.3. Market Depth

We can also trace the dynamics of the limit order book in response to large closing order imbalances. Figure 10 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 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.\footnote{Negative closing RSV from the clients’ side implies positive market maker inventory.} 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.

IV. Asian Trading

The previous section documents that trading days with large negative closing order imbalances (clients selling to market makers) are followed by large positive order flows and returns during the subsequent U.S overnight trading session which overlaps with the opening of Europe. In this section, we study the relationship between closing U.S order imbalances, and subsequent Asian trading patterns.

We do so by exploiting 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 the 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 (b) of figure 11 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. Panel (a) of figure 11 shows that these effects are indeed due to Asian-based clients entering the market: prior to 2010, when the total volume traded during Asian open hours is negligible, we do not observe the same increases in volume around Tokyo opening and post-lunch re-opening, regardless of whether the U.S. is observing DST.

We now formally test whether this exogenous change in the arrival time of Asia-based clients translates into a change in the timing of returns overnight. Table VI reports the estimated coefficients from a regression of hourly overnight returns (18:00 – 6:00 am), 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

\[
H_{t,n} = \mu_n + \beta_{RSV}^n RSV_{t-1,close} + \beta_{DST}^n I_{DST,t} + \beta_{RSV \times DST}^n RSV_{t-1,close} \times I_{DST,t} + \varepsilon_{t,n} \tag{6}
\]

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 \( \beta_{n}^{RSV} = \{-26.30; -13.95; 0.61\} \) for the hours 18-19, 19-20 and

\[^{18}\text{For an in-depth discussion of the TSE lunch break and its effects on trading on the NIKKEI, see Lucca and Shachar (2014).}\]

\[^{19}\text{The spike at 18:30 (6:30 p.m.) ET occurs because the futures market used to open at 18:30 on Mondays from 1998 to 2012. The drop in trading volume from 23:00 (11:00 p.m.) ET to 00:00 (12:00 a.m.) ET appears because futures trading was closed in this hour from 1998 to 2003 on Tuesdays to Fridays.}\]

[ Insert figure 11 here ]
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{20} Now, we find the effect of $RSV$ by summing $\beta_n^{RSV} + \beta_n^{RSV \times DST} = \{-2.38; -13.09; -10.26\}$ and, indeed, we see that the effect of $RSV$ shifts in accordance with DST.

Comparing panels (a) and (b) of table VI 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.

We can likewise exploit the fact that DST is observed both in Europe and the U.S.\textsuperscript{21} 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.

Summarising, 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 slightly weaker after 2010.

[ Insert table VI here ]

\section*{V. Volatility Risk}

Figure 12 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 U.S. trading hours where volatility is high at the beginning at the end of the trading period (see Andersen, Bondarenko, Kyle, and Obizhaeva, 2018). The level of volatility is lowest during Asian trading hours and highest during U.S. trading hours. This is in correspondence to the trading volume during the 3 periods. As with our intraday liquidity

\textsuperscript{20}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.

\textsuperscript{21}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 at London open switches by 1 hour according to the time difference.
estimates, we do not observe an obvious link between realised quantities of risk and returns. Running the regression

$$r_{OD}^t = -0.29 + 0.19 \text{vol}_{OD}^t + \varepsilon_t$$

(7)

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

Next, we consider changes in volatility which are known to have a strong negative contemporaneous relationship to equity returns: the ‘leverage effect’. Panel (a) of figure 13 displays the leverage effect in intraday data by computing the intraday 1-minute correlation between ES and VX futures returns only for intervals where we observe quote updates. Given the large correlation between ES returns and VX returns, it is natural to examine volatility dynamics around the European opening. Panel (b) of figure 13 displays the average hourly log returns (bars) and average cumulative 5-minute log returns (solid black line) for the front month VX contract. At the opening of European markets we see a decline in volatility (negative VX returns). This result highlights that overnight inventory effects can have spillover effects in correlated markets.

Finally, consider an alternative channel through which volatility may affect overnight returns which has been documented as far back as French, Schwert, and Stambaugh (1987): if priced volatility increases, investors should demand higher expected returns going forward as the quantity of risk has increased. This raises a question about an inventory risk interpretation: are OD drift returns driven by equity order imbalance (market sells offs) or shocks to risk sentiment which require higher expected returns for holding the e-mini overnight?

22A common explanation for this phenomenon 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).

23Investors 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.
To answer this question, Table VII estimates a multivariate regression of overnight returns on the change in the VIX level of the preceding trading day \((\Delta VIX_{t-1,close})\) relative signed volume \((RSV_{t-1,close})\) as defined above:

\[
r_{t, n}^{H} = \mu_n + \beta_{\Delta VIX} \Delta VIX_{t-1,close} + \beta_{RSV} RSV_{t-1,close} + \varepsilon_{t,n} \quad , \quad n = 1, \ldots, 12
\]

Including VIX shocks, the strength of the relationship between \(RSV\) and the \(OD\) is halved but remains economically and statistically significant. Conditional on \(\Delta VIX_{t-1,close}\), a 1-standard deviation (-7%) negative closing relative signed volume corresponds to a 0.80 (1.0) b.p return earned between 2:00 – 3:00 (3:00 – 4:00) a.m. A 1-standard deviation increase in the \(VIX\) (1.7%), on the other hand, corresponds to 1.9 (2.6) b.p positive return between 2:00 – 3:00 (3:00 – 4:00) a.m.

Table VIII reports average returns conditional on sorting trading days into three sets based on the \(CTC \Delta VIX_{t-1,close}\) of the preceding trading day. Average annualized returns of each group are reported for the contemporaneous \(CTC\) returns, closing returns, for returns during Asian trading hours (18:00 - 02:00), for returns at the opening of EU markets (02:00-04:00), for returns during the overnight drift hour (02:00-03:00) and for the subsequent close-to-close return.

Considering the upper quartile (increases in uncertainty), we observe that a mean 1.4 p.p. change in the VIX is followed by a 10.6% average annualized positive return in Asian trading hours, followed by a 9.5% positive returns in European trading hours, of which 7.1% is earned during the \(OD\) hour. The 1.4% average VIX change is associated with a \(-23.2\)% closing return, and a \(-168.44\)% close-to-close return from the day. The final column of Table VIII reports the close-to-close returns of the subsequent day. In the upper quartile, shocks to uncertainty that contemporaneously depress prices are followed by a 12.7% return in the 24-hours that follow the shock. However, returns in Asian hours plus returns in European hours are equal to 9.5% + 7.1% = 16.6% which implies that returns in regular trading hours are equal to 12.7% - 16.6% = \(-3.9\)%.

Volatility shocks, \(\Delta VIX_{t-1,close}\), are usually positive on the same days where \(RSV\) is negative. Still, we find that both \(CTC\) changes in VIX and \(RSV\) contain independent information about future \(OD\) returns. Thus, while price reversals arising from inventory risk provide one explanation, we document a link to volatility shocks that provides an additional explanation, potentially linked

\[^{24}\text{The results that follow are quantitively similar if we use open-to-close VIX changes from the preceding day.}\]
through a risk premium channel.

[Insert table VII and table VIII here]

VI. News

We now consider a final alternative explanation for the OD: news released after U.S. cash market close may not be immediately incorporated into prices during Asian hours but instead accumulate and are resolved at European open when 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. Explanations for the overnight drift along these lines are related to a literature that shows conditional risk premia are higher on days prior to and on days of macroeconomic announcements.

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.

A. 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 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

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

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

\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.}

\footnote{In the context of stock returns, Savor and Wilson (2014) show that equity risk premia are consistently larger on U.S. inflation, GDP and non-farm announcements days. Lucca and Moench (2015), on the other hand, document a drift in the U.S. stock market which precedes FOMC announcements.}
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\textsuperscript{27}. We define the daily earnings surprise of the S&P 500 index, $ES_t$, as the daily sum of all $ES_t$.\textsuperscript{28}

Figure 14 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 shock 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 IX 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). We see a strong positive relation between the earnings shocks and CTC returns. Interestingly, 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, we do not detect a post close information effect: the OD is not driven by earnings announcements as it is positive and significantly different from zero for all 5 set of days.

[Insert figure 14 and table IX here]

B. 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.

\textsuperscript{27}EPS is earnings per share outstanding, implying that EPS/P is earnings per market cap.
\textsuperscript{28}We also test specifications of $ES_{500}$ where firms are value weighted and result are similar.
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

\[ r_{t,n}^{H} = a^n + b_1^n \mathbb{1}_{\text{U.K.}} + b_2^n \mathbb{1}_{\text{EU}} + b_3^n \mathbb{1}_{\text{JP}} + b_4^n \mathbb{1}_{\text{U.S.}} + \varepsilon_{t}^{n}, \]

where \( \mathbb{1}_{i} \) is a macro or central bank announcement dummy for country \( i \).

Panel (a) of table X 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 affect in any of the overnight hours. U.S. announcements occur at 8:30 and indeed we see a large positive return of 3.66 bps with a t-statistics of 2.25.

Panel (b) of table X 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 6.11. 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). In unreported results, we find that on mornings before the FOMC announcements, between 9 a.m and 2 p.m, the average return is 18 basis points.

[Insert table X here]

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. This suggests that the uncertainty resolution at European market open postulated by Bondarenko and Muravyev (2020) cannot be related to either macroeconomic, central bank or firm earnings announcements.

VII. Trading Price Reversals

We conclude by studying a set of trading strategies 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

$$r_{j,[t_1,t_2]}^L = \frac{P_{j,t_2} - P_{j,t_1}}{P_{j,t_1}},$$

where $P$ denotes price of the ES contract. The analogous short position earns $r_{j,[t_1,t_2]}^S = -r_{j,[t_1,t_2]}^L$. Mid quotes are used to compute returns excluding transaction costs. Including transaction costs, returns are computed from quotes as

$$r_{j,[t_1,t_2]}^L = \frac{P_{j,t_2}^{bid} - P_{j,t_1}^{ask}}{P_{j,t_1}^{ask}}, \quad r_{j,[t_1,t_2]}^S = -1 \times \frac{P_{j,t_2}^{ask} - P_{j,t_1}^{bid}}{P_{j,t_1}^{ask}}.$$  

We consider the following simple 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: $t_1 = 9:30 \rightarrow t_2 = 16:15$;  
- short OR: $t_1 = 08:30 \rightarrow t_2 = 10:00$;  
- long OD: $t_1 = 02:00 \rightarrow t_2 = 03:00$;  
- long OD+: $t_1 = 01:30 \rightarrow t_2 = 03:30$.

Finally, we consider three conditional trading strategies: 1) a buy-the-dip strategy, denoted $RSV_{t-1}^{close} < 0$, which holds the ES during the $OD+$ period but only on trading days following a
negative order flow at market close. This implies we only hold the contract on ~ 50% of trading days. 2) $\Delta VIX_{t-1} > 0$, where we go long during the OD+ period following days where the VIX index increased. 3) Going long during the OD+ period following days where $RSV_{t-1}^{close} < \Delta VIX_{t-1}$ which captures trading days where both closing order flow was negative and the VIX index went up.

Table XI (a) reports summary statistics of the trading strategies when transaction costs are excluded. Holding the ES contract continuously (the CTC strategy) since 1998 has yielded an average yearly log return of 4.34% with a Sharpe ratio of 0.16. 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 2.64%, which implies that OTC returns averaged 1.70%. 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 3.63%. The OD strategy has a Sharpe ratio close to one, which outperforms the overall market Sharpe ratio of 0.16. The high Sharpe ratio arises from the combination of high excess returns and low volatility during the overnight drift period.

The best performing strategies are the conditional versions of OD+. All three conditional trading strategies perform similarly. This is because the ES order flow and VIX index are positively correlated and therefore often trade on the same days. This is also why we do not see a huge improvement when conditioning on both order flow and $\Delta VIX$. Focusing on order flow, when $RSV_{t-1}^{close} > 0$, the BtD strategy does not go long and it thus has a return of zero on half of all trading days. Returns from trading the BtD strategy are larger than OD+ returns, which should be interpreted as additional evidence in support of the inventory risk prediction that past $RSV$ should predict subsequent returns as price sensitive agents arrive to market. The large amount of zero returns entails that the variance of BtD is significantly lower and thereby the Sharpe ratio higher. Specifically, $RSV_{t-1}^{close} < 0$ has a Sharpe ratio of 1.72 compared to 1.10 of OD+.

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

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29 Sharpe ratios are computed from daily risk free rates implied by 4 week U.S. Treasury bills.

30 The large number of zero returns is also what causes the large kurtosis. The positive skewness of BtD occurs because the $RSV < 0$ signal filters a significant fraction of the negative returns.
on half of the trading days. Adding transaction costs have a limited effect on betas, volatility and higher order moments. The performance of the BtD strategy is even better in recent years. This is because the bid-ask spread during the overnight period dropped significantly in the early 2000s and reached its effective minimum of one tick size (=0.25 index points) around 2005. In panels (c) and (d) of table XI we report the performance of all trading strategies when starting in 2005. Compared to the full sample period, $OD$, $OD+$ and the conditional strategies perform significantly better because of the lower spreads.

While these numbers can be inferred from figure 2, it is important to highlight that they have long run effects: small yet persistent daily seasonalities in return profiles within the day can have large low frequency effects. To illustrate this point, figure 15 depicts the cumulative returns of the $CTC$, $OD$, $OD+$ and BtD strategies for a one dollar investment in January 2005. The overnight strategies has 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 $OD$ ($OD+$), 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 15 displays cumulative returns including transaction costs. The $CTC$ 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 $OD$ 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 15 here ]
VIII. 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, a larger fraction of the overnight drift accrues during London opening hours. Thus, as the market for U.S. equity futures becomes more global, market makers are able to offset closing-time order imbalances more quickly, suggesting a positive role for market globalization. Finally, while the evidence in favour of an inventory risk explanation is compelling, we study an alternative channel based on volatility risk. We show that shocks to end-of-day quantities of risk, as proxied by positive changes to the VIX index, lead to increases in overnight expected returns, and argue that volatility shocks operate through a complementary ‘risk sentiment’ channel.
References


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IX. Tables

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(a) Overnight hourly returns: Trades

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(c) Intraday hourly returns: Trades

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(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 (b) and (c)). 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). 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.

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<td>1.65</td>
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<td>(-2.30)</td>
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<td>(-0.15)</td>
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<td>(2.07)</td>
<td>(2.83)</td>
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<td>(1.06)</td>
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#### (b) Intraday hourly returns

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<th>17-18</th>
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<td>(1.41)</td>
<td>(-0.16)</td>
<td>(1.69)</td>
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<td>(-0.70)</td>
<td>(-0.32)</td>
<td>(2.18)</td>
<td>(0.86)</td>
<td>(-2.04)</td>
</tr>
</tbody>
</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

<table>
<thead>
<tr>
<th>Month</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>
<th>16-17</th>
<th>17-18</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>-1.67</td>
<td>-3.17</td>
<td>-1.09</td>
<td>0.54</td>
<td>1.72</td>
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<td>(1.10)</td>
<td>(0.44)</td>
<td>(0.67)</td>
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<td>(-1.39)</td>
</tr>
<tr>
<td>February</td>
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<td>-1.19</td>
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<td>0.58</td>
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<td>0.92</td>
<td>-0.97</td>
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<td>(0.51)</td>
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<td>(0.06)</td>
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<td>(-1.10)</td>
</tr>
<tr>
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<td>1.77</td>
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<td>(1.07)</td>
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<td>0.75</td>
<td>2.38</td>
<td>-0.12</td>
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<td>(2.34)</td>
<td>(-0.36)</td>
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<tr>
<td>May</td>
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<td>-0.93</td>
<td>-0.49</td>
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<td>(0.22)</td>
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<td>(0.51)</td>
<td>(-1.41)</td>
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<tr>
<td>June</td>
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<td>-2.37</td>
<td>0.36</td>
<td>-0.50</td>
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<tr>
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<td>2.44</td>
<td>-0.92</td>
<td>-0.38</td>
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<tr>
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<td>(-1.11)</td>
<td>(-0.00)</td>
<td>(0.85)</td>
<td>(2.36)</td>
<td>(-0.90)</td>
<td>(1.19)</td>
<td>(-1.07)</td>
<td>(-0.83)</td>
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<tr>
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<td>-1.39</td>
<td>-0.85</td>
<td>0.75</td>
<td>-0.54</td>
</tr>
<tr>
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<td>(-0.15)</td>
<td>(-0.85)</td>
<td>(0.59)</td>
<td>(0.86)</td>
<td>(-0.93)</td>
<td>(0.39)</td>
<td>(1.02)</td>
<td>(-1.34)</td>
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<tr>
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<td>0.75</td>
<td>-0.77</td>
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<td>1.62</td>
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<td>(0.59)</td>
<td>(0.86)</td>
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<td>-0.38</td>
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<td>(-0.91)</td>
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<td>(-0.61)</td>
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#### (b) Intraday hourly returns
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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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<td>-6.58</td>
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<td>0.75</td>
<td>-1.82</td>
<td>-5.96</td>
<td>-16.79</td>
<td>-19.92</td>
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<td>(-3.56)</td>
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<td>(0.49)</td>
<td>(-1.89)</td>
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<td>(-6.77)</td>
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<td>-0.04</td>
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<td>(0.47)</td>
<td>(2.27)</td>
<td>(2.83)</td>
<td>(5.59)</td>
<td>(1.06)</td>
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<td>0.42</td>
<td>0.03</td>
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</table>

(a)

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<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>
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<td>-6.61</td>
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<td>(0.35)</td>
<td>(0.16)</td>
<td>(1.58)</td>
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<td>-0.01</td>
<td>0.02</td>
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<td>0.03</td>
<td>0.04</td>
<td>-0.07</td>
<td>-0.09</td>
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<td>(0.54)</td>
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<td>(-0.37)</td>
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<td>0.35</td>
<td>-0.19</td>
<td>-0.41</td>
<td>-2.01</td>
<td>-2.12</td>
<td>0.36</td>
<td>0.92</td>
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<td>(1.03)</td>
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<td>-0.71</td>
<td>0.57</td>
<td>0.66</td>
<td>-0.53</td>
<td>1.40</td>
<td>1.83</td>
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<tr>
<td></td>
<td>(0.38)</td>
<td>(1.11)</td>
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<td>(-0.53)</td>
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<td>(0.46)</td>
<td>(-0.48)</td>
<td>(0.95)</td>
<td>(0.89)</td>
</tr>
<tr>
<td>$R^2(%)$</td>
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<td>0.45</td>
<td>0.07</td>
<td>0.05</td>
<td>0.07</td>
<td>0.17</td>
<td>0.20</td>
<td>1.13</td>
<td>0.68</td>
<td>0.14</td>
<td>0.28</td>
</tr>
</tbody>
</table>

(b)

Table IV. 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:

$$r_{t,n}^H = \mu_n + \beta_{RSV}^n RSV_{close}^{t-1} + \varepsilon_{t,n}, \quad n = 1, \ldots, 12.$$ 

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

$$r_{t,n}^H = \mu_n + \beta_{RSV}^n RSV_{close}^{t-1} + \beta_{VIX}^n VIX_{close}^{t-1} + \beta_{RSV \times VIX}^n RSV_{close}^{t-1} \times VIX_{close}^{t-1} + \varepsilon_{t,n}, \quad \text{for} \ n = 1, \ldots, 12.$$ 

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 V. Average Returns Sorted on Closing Orderflow
We sort trading days into three groups based on the closing order flow of the preceding trading day. 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 at the opening of EU markets (02:00-04:00), for returns during the overnight drift hour (02:00-03:00) and for the subsequent close-to-close return.

<table>
<thead>
<tr>
<th>$RSV_{t-1}^{close}$</th>
<th>obs</th>
<th>min (%)</th>
<th>max (%)</th>
<th>mean (%)</th>
<th>$r_{t-1}^{CTC}$ (%)</th>
<th>$r_{t}^{close}$ (%)</th>
<th>$r_{t}^{Asia}$ (%)</th>
<th>$r_{t}^{EU}$ (%)</th>
<th>$r_{t}^{OD}$ (%)</th>
<th>$r_{t}^{CTC}$ (%)</th>
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<td>−8.29</td>
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<td>−93.19</td>
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<td>7.11</td>
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</tr>
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<td>4.01</td>
<td>4.00</td>
<td>0.23</td>
</tr>
<tr>
<td>$(Q_3, 1]$,</td>
<td>1,296.00</td>
<td>4.48</td>
<td>34.62</td>
<td>8.71</td>
<td>139.27</td>
<td>90.25</td>
<td>−1.43</td>
<td>−3.24</td>
<td>−0.79</td>
<td>7.50</td>
</tr>
</tbody>
</table>
Table VI. 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:

\[ r^H_{t,n} = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{DST} 1_{DST,t} + \beta_n^{RSV \times DST} RSV_{t-1,close} \times 1_{DST,t} + \epsilon_{t,n}, \quad n = 1, \ldots, 12, \]

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 VII. Regression: overnight returns on ∆VIX and Order Flow

Hourly intraday returns are regressed on closing order flow from day \(t-1\) (\(RSV_{t-1}^{close}\)) and the \(t-2\) to \(t-1\) change in the VIX level from the preceding trading day (\(\Delta VIX_{t-1,close}\)): 

\[
r^{H}_{t,n} = \mu_n + \beta^{RSV} RSV_{t-1}^{close} + \beta^{\Delta VIX} \Delta VIX_{t-1}^{close} + \varepsilon_{t,n}, \quad n = 1, \ldots, 12.
\]

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 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>(RSV)</td>
<td>-1.89</td>
<td>-4.32</td>
<td>-3.57</td>
<td>-1.95</td>
<td>4.82</td>
<td>-0.51</td>
<td>1.02</td>
<td>-7.62</td>
<td>-10.22</td>
<td>-10.70</td>
<td>0.52</td>
<td>-2.28</td>
</tr>
<tr>
<td></td>
<td>(-0.55)</td>
<td>(-1.24)</td>
<td>(-1.71)</td>
<td>(-0.80)</td>
<td>(2.76)</td>
<td>(-0.28)</td>
<td>(0.70)</td>
<td>(-6.32)</td>
<td>(-5.02)</td>
<td>(-3.85)</td>
<td>(0.12)</td>
<td>(-0.80)</td>
</tr>
<tr>
<td>(\Delta VIX)</td>
<td>-0.15</td>
<td>0.35</td>
<td>0.49</td>
<td>-0.09</td>
<td>0.44</td>
<td>-0.17</td>
<td>0.49</td>
<td>-0.19</td>
<td>1.14</td>
<td>1.50</td>
<td>-0.54</td>
<td>-0.83</td>
</tr>
<tr>
<td></td>
<td>(-0.52)</td>
<td>(2.14)</td>
<td>(0.99)</td>
<td>(-0.49)</td>
<td>(3.24)</td>
<td>(-1.14)</td>
<td>(1.69)</td>
<td>(-0.94)</td>
<td>(6.14)</td>
<td>(4.07)</td>
<td>(-1.69)</td>
<td>(-1.81)</td>
</tr>
<tr>
<td>const</td>
<td>-0.19</td>
<td>0.26</td>
<td>0.01</td>
<td>-0.07</td>
<td>0.03</td>
<td>0.04</td>
<td>0.33</td>
<td>0.41</td>
<td>1.43</td>
<td>0.26</td>
<td>-0.07</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(-0.52)</td>
<td>(1.72)</td>
<td>(0.07)</td>
<td>(-0.53)</td>
<td>(0.23)</td>
<td>(0.30)</td>
<td>(2.17)</td>
<td>(2.88)</td>
<td>(5.34)</td>
<td>(0.95)</td>
<td>(-0.19)</td>
<td>(-0.09)</td>
</tr>
<tr>
<td>(R^2(%))</td>
<td>0.01</td>
<td>0.33</td>
<td>0.36</td>
<td>0.02</td>
<td>0.38</td>
<td>0.09</td>
<td>0.58</td>
<td>0.27</td>
<td>2.28</td>
<td>1.75</td>
<td>0.25</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Table VIII. Average Returns Sorted on \(\Delta VIX\)

We sort trading days into three groups based on the \(CTC\) \(\Delta VIX\) of the preceding trading day. 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 at the opening of EU markets (02:00-04:00), for returns during the overnight drift hour (02:00-03:00) and for the subsequent close-to-close return.
Table IX. 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>-5.76</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>2.19</td>
<td>-0.31</td>
<td>2.45</td>
<td>1.78</td>
<td>-0.16</td>
</tr>
<tr>
<td>t-stat</td>
<td>(0.50)</td>
<td>(-0.13)</td>
<td>(0.65)</td>
<td>(2.85)</td>
<td>(-0.10)</td>
</tr>
<tr>
<td>POS-HIGH</td>
<td>3.56</td>
<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>
<td>4.54</td>
<td>2.27</td>
<td>2.14</td>
<td>1.38</td>
<td>-1.26</td>
</tr>
<tr>
<td>t-stat</td>
<td>(1.84)</td>
<td>(1.73)</td>
<td>(1.07)</td>
<td>(4.90)</td>
<td>(-1.58)</td>
</tr>
</tbody>
</table>

Table X. 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

\[ r_{i,t,n}^H = a^n + b_{1i}^n I_{U.K.} + b_{2i}^n I_{EU} + b_{3i}^n I_{JP} + b_{4i}^n I_{U.S.} + \epsilon_{i,t,n}^n, \quad n = 1, \ldots, 15, \]

where for panel (a) \( I_i \) is an employment, GDP or inflation announcement dummy for country \( i \). For panel (b) \( I_i \) is a central bank announcement dummy for country \( i \).
Table XI. 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_{close}^{t-1} < 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. **ΔVIX_{t-1} > 0** goes long from 1:30 to 3:30 only on days following an increase in the VIX index. **RSV_{close}^{t-1} < ΔVIX_{t-1}** goes long when the change in the VIX index is larger than the closing order flow measured in percentage points. 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.
X. Figures

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).
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. 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.
Figure 5. 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 6. Intraday Equity Volumes
Panel (a) plots the average 5 minute trading volume of the e-mini for the entire trading day in order to show the 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. This assures that the early part of the sample period which is characterized by a lower total trading volume, carries the same weight as the later part of the sample period.

Figure 7. 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.
Regression coefficients and adjusted $R^2$ of 15-by-15 minute returns regressed on closing relative signed volume of the preceding trading day.

Panel (a) 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%. Panel (b) shows the distribution of closing order flow, defined as the relative signed volume during the last hour of trading (15:15 - 16:15).
Figure 10. 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 11. E-mini Trading Volume: Asian Trading 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 12. Realised 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 13. VIX
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 the average trading volume of the VIX futures for the entire trading day in order to show the intraday pattern of volume. The normalized volume spikes at 16:15 with a value of 25. The sample period is June 23, 2014 to December 31, 2018.
Figure 14. 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 $ES_{i,t} = A_{i,t} - F_{i,t} - P_{i,t}$, where $A$ is 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.

Figure 15. 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.
XI. Internet Appendix
Not Intended for Publication

A. Close-to-open versus open-to-close returns

Figure A.1 displays cumulative close-to-close ($CTC$) log returns on S&P 500 futures: $1$ invested at the beginning of 1983 becomes $17$ dollars at the beginning of 2019, translating into an annual return of $8\%$. Decomposing into open-to-close ($OTC$) and close-to-open ($CTO$) returns (red and yellow lines), one finds that the returns are split approximately equally between intraday and overnight sessions, $4.2\%$ and $3.7\%$, respectively. This result is not surprising, in itself, but provides a strong motivation for studying the mechanics of overnight markets.

![Figure A.1. Time series of Returns for the S&P 500 futures contract](image)

Figure plots the time series of close-to-close, open-to-close and close-to-open log returns for the S&P 500 futures contract.
### B. Opening Times

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Name</th>
<th>Open</th>
<th>Close</th>
<th>Time difference</th>
<th>ES open</th>
<th>ES close</th>
</tr>
</thead>
<tbody>
<tr>
<td>NZSX**</td>
<td>New Zealand</td>
<td>10:00</td>
<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>
</tr>
<tr>
<td>ASX**</td>
<td>Australia</td>
<td>10:00</td>
<td>16:00</td>
<td>14</td>
<td>20:00</td>
<td>02:00</td>
</tr>
<tr>
<td>SGX*</td>
<td>Singapore</td>
<td>09:00</td>
<td>17:00</td>
<td>12</td>
<td>21:00</td>
<td>05:00</td>
</tr>
<tr>
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<td>12</td>
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<td>03:00</td>
</tr>
<tr>
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<td>12</td>
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<td>04:00</td>
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<td>10</td>
<td>23:00</td>
<td>05:30</td>
</tr>
<tr>
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<td>14:00</td>
<td>8</td>
<td>02:00</td>
<td>06:00</td>
</tr>
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<td>19:00</td>
<td>7</td>
<td>02:30</td>
<td>14:00</td>
</tr>
<tr>
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<td>20:00</td>
<td>6</td>
<td>02:00</td>
<td>14:00</td>
</tr>
<tr>
<td>JSE*</td>
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<td>08:30</td>
<td>17:00</td>
<td>6</td>
<td>02:30</td>
<td>11:00</td>
</tr>
<tr>
<td>LSE</td>
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<td>16:30</td>
<td>5</td>
<td>03:00</td>
<td>11:30</td>
</tr>
<tr>
<td>BMF**</td>
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<td>17:00</td>
<td>1</td>
<td>09:00</td>
<td>16:00</td>
</tr>
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<td>09:30</td>
<td>16:00</td>
</tr>
<tr>
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<td>Toronto</td>
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<td>16:00</td>
<td>0</td>
<td>09:30</td>
<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 Borse, 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.
Figure A.2. 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).

C. Granular Returns
Figure A.3. 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.
D. 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.

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.

E. 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.4. 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.

\[31\] 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.
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.4. 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.