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THE OVERNIGHT DRIFT

Abstract

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JEL Classification: G13, G14, G15

Keywords: Equity Risk, Overnight Returns, Intraday Immediacy, Inventory management

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The Overnight Drift

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ABSTRACT

Since the advent of electronic trading in the mid 1990's, U.S. equities have traded (almost) 24 hours a day through equity index futures. This allows new information to be incorporated continuously into asset prices, yet, we show that almost 100% of the U.S equity premium is earned during a 1-hour window between 2:00 a.m. and 3:00 a.m. (ET) which we dub the 'overnight drift'. We study explanations for this finding within a framework a là Grossman and Miller (1988) and derive testable predictions linking dealer inventory shocks to high-frequency return predictability. Consistent with the predictions of the model, we document a strong negative relationship between end of day order imbalance, arising from market sell offs, and the overnight drift occurring at the opening of European financial markets. Further, we show that in recent years dealers have increasingly offloaded inventory shocks at the opening of Asian markets and exploit a natural experiment based on daylight savings time to show that Asian offloading shifts by one hour between summer and winter.

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In recent decades, financial markets across the world have grown increasingly integrated. While much of the literature on globalization has focused on funding markets and cross-border flows, the effect of globalization on trading activity has received relatively little attention. In this paper, we study the round-the-clock market for U.S. equities, decomposing the close-to-close return on S&P 500 futures into returns earned during trading hours across the world.

As a prelude to our main result, figure 1 updates the findings of Cliff, Cooper, and Gulen (2008) and Kelly and Clark (2011), who study intraday versus overnight return patterns on contracts linked to U.S. equity. The blue line plots cumulative close-to-close (CTC) log returns on S&P 500 futures: $1 invested invested at the beginning of 1983 becomes $20 dollars at the beginning of 2019, translating into an annual return of 8%. However, 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 in itself is not surprising. It is roughly what one would expect if returns were earned in a continuous linear fashion throughout the trading day. However, it provides a strong motive for studying the mechanics of overnight markets and the returns earned during these hours.

With this in mind, the central contribution of this paper is to dissect the intraday and overnight return components into higher frequency intervals throughout the trading day, which is possible since the advent of electronic trading as indicated by the dotted lines in the plot. Indeed, overnight trading the U.S. equity futures represents a substantial proportion of total trade, representing 15% of total trade in 2019 averaging $15 billion daily. For the sample in which equities trade 24-hours a day (1998 – 2019), close-to-close returns averaged 4.5% p.a., close-to-open returns (overnight) averaged 3.1% p.a., and open-to-close (intraday) returns averaged 1.4% p.a. Zooming in to returns earned hourly through the 24-hour trading day, we document that almost 100% of the U.S. equity premium is earned during a 1-hour window which precedes 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' 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.

We document that the overnight drift is observed for every trading of the week, every month of the year, and every year in our sample. The opening return, instead, is largest on Thursdays and Fridays, suggesting that the opening return is primarily related to macroeconomic and earnings announcements. Importantly, the opening return only has 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? We argue the overnight drift can be understood within the context of market makers' inventory management practices in a global market for equity risk. In a Grossman and Miller (1988)-style motivating framework, we show that risk-averse market makers profit by providing immediacy to investors who arrive asynchronously into the market, generating mean reversion in both prices and market makers' aggregate inventory. We test predictions from this framework along three dimensions: (*i*) inventory risk, order flow and price predictability; (*ii*) a natural experiment test of intraday liquidity provision; (*iii*) trading price reversals.

First, we show that, as predicted by the model, intraday returns are negatively related to the closing order imbalance of the preceding day. Estimating intraday regressions of high frequency returns in day t on closing order imbalance observed on day $t-1$, we obtain highly statistically and economically significant loadings on exactly the hours when London and Frankfurt financial markets open. This provides evidence of high frequency return predictability arising because market makers have large long (short) positions at the end of the trading day, which they then trade away in subsequent periods as new liquidity traders arrive asynchronously to the market. Next, 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 e-mini limit order book is deeper on the ask (bid) side when closing order imbalance was negative (positive). In a similar vein, sorting again on closing order imbalance, we show the overnight drift only arises on days following market sell-offs (negative order imbalance).

Second, the extended sample period (20-years) and 24-hour nature of our data allow us to conduct two natural experiments. First, splitting the sample in two, we show e-mini trading increased during Asian trading hour 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 find 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 which shifts by one hour with daylight savings time (DST) which is not observed in Japan. Remarkably, when the U.S. shifts from winter to summer time, the strong return predictability around Tokyo open moves forward by one hour as seen from the perspective of a U.S. investor. In summary, as volumes during the Japanese trading hours have increased and the market for S&P 500 futures became more global, market makers became able to off-set shocks to their inventories faster.

Finally, we show that, pre-transaction costs, the trading strategy that goes long the e-mini during the overnight drift hour between 2:00 a.m. and 3:00 a.m. earns large positive returns equal to 3.6% p.a. with a Sharpe ratio of 1.00. Accounting for bid-ask spreads reduces strategy returns to −3.3% p.a. implying that the overnight drift does not represent market inefficiency and instead is a phenomenon priced by dealers when providing intraday liquidity.

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 that shows the theoretical relationship between order flow and returns. We test the predictions of the model in Sections IV and V. We examine the profitability of a trading strategy based on the overnight drift in Section VI. Section VII concludes.

Related Literature: Since the seminal work of Harris (1986) on the intraday equity return patterns, various studies have documented 'high frequency' patterns in asset markets, including patterns in volatility (Andersen, Bollerslev, et al., 1997; Andersen and Bollerslev, 1998), liquidity (McInish and Wood, 1992), and volumes (Jain and Joh, 1988; Foster and Viswanathan, 1993).

In the foreign exchange market, an early contribution is Cornett, Schwarz, and Szakmary (1995), who exploit hourly data for the sample period 1977 – 1991 and argue that local currencies tend to depreciate during local trading hours. Ranaldo (2009) and Breedon and Ranaldo (2013) confirm this result for the sample period 1997-2007 and link this return pattern to order flow dynamics. In the context of return predictability, Lyons and Rose (1995) and more recently Chaboud and Wright (2005) re-visit the classic (close-to-close) study of Fama (1984) and show that the expectation hypothesis largely holds overnight, and that differences between forward rates and expected future spot rates are generated during intraday U.S. hours.

Time-of-day effects in equity returns have received more attention in the literature. The early literature did not find consistent intraday patterns (Smirlock and Starks 1986 and Yadav and Pope 1992) but more recently Cliff, Cooper, and Gulen (2008) documented that individual stocks, stock indices and stock index futures yield higher returns during the overnight non-trading period compared to the regular U.S. trading-hours. They examine potential causes for the large overnight return and find that neither volatility nor liquidity premia can explain this finding. Kelly and Clark (2011) also study overnight returns in the context of ETFs and shows that risk adjusted returns of stocks held overnight vastly exceeds the returns during regular trading hours. They argue that under-diversified semi-professional/noise traders could possibly explain their finding if they liquidate their positions before market close.

Exploring the cross-sectional implications of time-of-day effects, Lou, Polk, and Skouras (2017) document a diverging return pattern between intraday and overnight returns for equities and they provide evidence for strong reversal patterns between intraday and overnight returns. Bogousslavsky (2018) reports large variations in intraday and overnight stock returns for various portfolio compositions: Portfolios based on size and illiquidity earn their return just before the market close while others accrue their return gradually throughout the day. The author argues some of these patterns can be explained by information asymmetry around market closures. Related, Della Corte, Kosowski, and Wang (2015) assess the impact of market openings and closures on returns of international stocks and futures across various asset classes. They show that a overnight-intraday strategy that forms intraday portfolios based on overnight signals outperforms conventional short-term reversal strategies, while Hendershott, Livdan, and Rösch (2018) discuss the implications of the intraday return pattern for the capital asset pricing model (CAPM) and present strong evidence that the CAPM holds in overnight U.S. hours.

In contrast to these prior studies, we focus on higher-frequency movements in returns to U.S. equities, allowing us to uncover the overnight drift, which we argue arises due to rational inventory management by risk-averse market makers. Moreover, using the higher-frequency data enables us to directly test the implications of the inventory management model, 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 mainly focus on the information asymmetry in the Kyle-sense (Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990). Hong and Wang (2000) model a stock market with open and closures, which can generate several of the empirically observed trading patterns. However, their model does not explain the large opening drift returns. Chordia and Subrahmanyam (2004) study the relationship between order imbalances and returns on individual stocks and show that price pressures caused by autocorrelated imbalances cause a positive relation between lagged imbalances and returns, which reverses sign after controlling for the current imbalance. In our motivating framework, future high frequency returns are negatively related to past order imbalances; coupled with slow arrival of price-sensitive clients overnight and negative skewness of order imbalances, this negative relationship is sufficient to generate the large, positive ON returns observed in the data.

Our results on the immediacy provision by market makers in equity futures is complementary to earlier research on the investors' demand for liquidity (see e.g. Chordia and Subrahmanyam, 2004; Avramov, Chordia, and Goyal, 2006), the return to liquidity-providing trading strategies (e.g. Khandani and Lo, 2007, 2011; Nagel, 2012), liquidity demand by mutual funds (e.g. Coval and Stafford, 2007; Da, Gao, and Jagannathan, 2011; Hau and Lai, 2013; Bhattacharya, Lee, and Pool, 2013; Rinne and Suominen, 2016) and by hedge funds (e.g. Jylhä, Rinne, and Suominen, 2014; Choi, Shachar, and Shin, 2019). The high frequency nature of our data allows us to construct *exogenous* variation in the timing of client arrival, alleviating some of the endogeneity concerns usually faced in the trading immediacy literature.

This paper is also related to the literature on market globalization. While much of the recent literature has focused on the determinants of cross-border funding flows (see e.g. Rose and Wieladek, 2014; Van Rijckeghem and Weder, 2001, 2014; Giannetti and Laeven, 2012a,b, 2016; Cetorelli and Goldberg, 2012a,b; Bruno and Shin, 2015a,b), an earlier literature studied the interrelationship between country development and the integration of the country's financial markets into the global economy (see e.g. King and Levine, 1993; Jayaratne and Strahan, 1996; Bekaert and Harvey, 1995, 1997; Henry, 2000; Rajan and Zingales, 2003; Bekaert, Harvey, and Lundblad, 2007; Bekaert, Harvey, Lundblad, and Siegel, 2007; Bekaert and Mehl, 2019). Closer in spirit to our exercise, the literature on cross-market stock listings (see e.g. Tinic and West, 1974; Domowitz, Glen, and Madhavan, 1998; Foerster and Karolyi, 1999; Sarkissian and Schill, 2004, 2016) has argued that, not only does a country's own level of financial development affect global market intergration, but also the level relative to the level of financial development in the rest of the world. Unlike this prior literature on market globalization, we focus on a product traded on a single exchange (CME) in a developed country (U.S.) by market participants around the world generally but in other developed economies (Japan, U.K., Western Europe) in particular.

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.[1] This 'big' futures (henceforth SP) contract 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 big contract is \$250,000. As the index level rose over time, the big contract became expensive to trade at this multiplier so the contract multiplier was cut to \$250 times the index on November 3, 1997.[2] In September 1993 the big contract began trading electronically outside regular hours via the CME GLOBEX electronic trading platform. The S&P 500 e-mini futures (henceforth ES) contract 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.

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). We convert the UT timestamps to U.S. Eastern Time (ET), so that we can define the intraday and overnight trading sessions relative to when the cash equity market is open in the U.S. We identify the direction of the trade

[1] Regular trading hours are defined by the open outcry or pit session which trades between 9:30-16:15 (ET)

[2] 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.

by comparing the trade price to the most recent top level of the limit order book as buy (sell) orders must trade at the best available ask (bid) price. Our sample period with 24 hour trading starts in 1997 and ends in 2018. Our full sample period starts in 1982, with limited overnight trading beginning in 1993.

Panel (a) of figure 2 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.[3] We measure volume as the total number of contracts traded in both the front and the next-to-delivery contracts, multiplying the volume for the SP contract by 5 (10 prior to 1997) to make the trades comparable to the e-mini. The figure shows that, since the advent of electronic trading, volume in the SP has been trending down over time. Instead, the trading volume in the ES (plotted in dark blue for ON and light blue for ID) was growing through the financial crisis but has since stabilized at around 1 million contracts per day during the intraday session and a further 0.15 million contracts traded during the overnight session. In 2019, 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. 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 be around 15% in 2010 and has remained flat at that level since then.

[Insert figure 2]

II. Overnight Drift and Opening Returns

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 maintenance break between 16:15 – 16:30 (4:15 p.m. – 4:30 p.m.).[4] Given the continuous nature of trading in U.S.

[3] CME exchanges have 'spotters' in open outcry sessions who try to punch prices as fast as possible with hand-held devices. The exchange does not record intra-day trade volumes for this session. Since the vast majority of volumes for the SP contract are executed during the physical outcry/pit sessions, we cannot compute ID vs ON volume for the SP.

[4] 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

equity futures, it is natural to study return dynamics over the 24-hour trading day. This section studies intraday returns computed from returns to 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 from best bid-offers.

A. Returns Around the Clock

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

$$r^N_{t,n} = p_{t,\frac{n}{N}} - p_{t,\frac{n-1}{N}} \tag{1}$$

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

The grey bars in panel (a) figure 3 display hour-by-hour returns averaged across all trading days in our sample (January 5, 1998 – December 31, 2018). Estimates are annualized and displayed in percentage points. Over the last 20 years, ON returns have been large and positive between the hours of 24 (12 a.m.; midnight) and 3. 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 15:00 (3:00 p.m.) followed by a sequence of large positive returns until the closing bell (16:15; 4:15 p.m.).

This return pattern is surprising. The red line in panel (a) figure 3 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.[5] However, the majority of this return is generated during the ON session: between 18:00

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.

[5]The monthly correlation between S&P 500 value weighted cash index returns obtained from CRSP and our

(6 p.m.) and 8:00 (8 a.m.) equity returns average 3.1% p.a.[6] More striking than this, a significant proportion of this return, averaging 3.6% p.a., occurs in 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). Panel (b) of figure 3 zooms in around the OD hours by plotting average 5-minute returns between 1 a.m.and 4 a.m. Viewing granularly, 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.

$\left[\text{Insert figure 3 here}\right]$

B. *Summary Statistics*

We measure the statistical significance by projecting hourly returns on a set of dummy variables. Stacking hourly returns in the vector $\vec{r}$ and denoting D as a dummy matrix containing appropriately located 0 and 1's, then μ is a 1×24 vector of mean returns which we estimate via the projection

$$\vec{r} = D\mu^\top + \varepsilon. \tag{2}$$

Table I reports estimates for μ 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 {24-01, 01-02, 02-03} is equal to {0.35, 0.45, 1.36} basis points per hour per day, respectively, with corresponding t-statistics equal to {1.79, 2.41, 5.67}. Using quotes, these returns are similar in magnitude albeit with larger statistical significance. These are the only overnight hours statistically significant at conventional levels.

Median returns computed from VWAPs are also positive for the hours {24-01, 01-02, 02-03}

close-to-close returns is > 98%.

[6] 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.

and equal to $\{0.20\ , \ 0.40\ , \ 0.85\ \}$ basis points per day. Due to the minimum tick size, median returns computed from quotes are always always zero during the night. Indeed, table II below shows that, for the hours {24-01, 01-02, 02-03}, approximately {13%, 13%, 9% } of days produce zero returns computed from quotes. However, even median quote returns for the OD are large and positive equal to 0.78 basis points per day. Thus, median returns are lower than mean returns, implying that the return distribution in these hours is positively skewed. We find return skewness estimates equal to {0.12, -0.19, 0.19 } from VWAPS and {1.98, -0.62, 0.64 } from quotes, which compares to daily return skewness of -0.09 and -0.18, 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 -1.33 (-1.21) basis points per hour per day with a t-statistic of 2.87 (2.54). The remaining ID returns are flat and statistically indistinguishable from zero.

[Insert table I here]

C. Non-Parametric Tests

Table II 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 [7].

[7] 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

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.

[Insert table II here]

D. *Special Hours*

To understand whether the OD and the OR are truly different from the other hourly returns, we plot a heat map of p-values from a two-sided t-test of equality of hourly returns in figure 4. The t-test is computed from linear combinations of the dummy regression parameters estimated in equation 2. 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 3 and table I discussed above.

[Insert figure 4 here]

E. *Calendar Effects*

We now investigate the findings above by dissecting intraday returns within calendar time and study time-variation in the overnight drift across years in our sample.

E.1. *Day of the Week*

Panel (a) of figure 5 plots cumulative 5-minute returns sampled for each trading day of the week. In terms of close-to-close returns, $r^{THU} > r^{TUE} \sim r^{WED} > r^{FRI} > r^{MON}$; however, the differences in weekday CTC returns are not statistically different from each other. Considering the OD, it is

using quotes. This is because the market was closed during this hour on Tuesday to Fridays from October 1998 to September 2003.

clearly visible in each day of the week, and displays far less dispersion than close-to-close returns, again suggesting its systematic nature. Table III tests this claim formally using a regression dummy framework as above. Remarkably, in all days of the week, the 2 a.m. – 3 a.m. return is positive and significant at the 1% level, except for Thursday, which is significant at the 5% level. Excluding Thursdays, the magnitude of the returns is also quite close and ordered $r^{WED} > r^{MON} > r^{FRI} > r^{TUE} > r^{THU}$.

Panel (b) 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 day, with t-statistics equal to -2.79 and -2.94, respectively. In the online appendix we conduct further investigations to why the OR occurs only on Thursdays and Fridays. Suggestive evidence as to the origins of this result are threefold: 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 (see 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:

$$OR_t = \underbrace{-0.00}_{(-3.17)} + \underbrace{0.12}_{(1.48)} OD_t + \underbrace{-0.01}_{(-0.28)} OR_{t-1} \tag{3}$$

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.

[Insert figure 5 and table III]

E.2. Month of the Year

Figure 6 plots average cumulative 5-minute returns across the trading day, for January each year versus February-December. In our sample, we observe the opposite of the 'January effect', that is, close-to-close returns are negative, consistent with existing evidence that positive January returns are concentrated in small stocks. However, the *OD* is clearly visible and the overall negative January return is driven by very large negative returns at U.S. open. Table IV confirms this finding statistically by sampling monthly and testing each of the day separately via the dummy regression above: the *ON* drift is positive in all months of the year and statistically significant at conventional levels in 9/12 months.

[Insert figure IV and table 6]

E.3. Year-by-Year

Figure 7 examines the economic and statistical importance of returns year by year for *OD* versus *OR* return. The *OD* drift is positive in 18 out of 20 years in our sample. Moreover, the *OD* is only negative in the recessionary years of 2002 and 2008. The bottom panel of figure 7 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 22 years in our sample. In contrast, the *OR* return is only statically different than zero in 5 years. 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 3.

[Insert figure 7 here]

III. Intraday Immediacy

Empirical studies linking liquidity provision to asset prices follow naturally from inventory models. In this section, we discuss a textbook example that serves to make clear the role of dealer inventory shocks and high frequency return predictability in overnight markets. We then discuss predictions which provide guidance for the empirical work that follows.

A. Framework

Assume the existence of a risk averse representative dealer supplying liquidity to two type of clients in the form of price-sensitive asset managers and noise traders. The timing of the model is a two-period repeated sequence spaced evenly on a grid $t = \{t = 1, \ldots, T\}$ representing the intraday time. The dealer holds an inventory consisting of cash (c_t) and θ_t e-mini futures contracts. Denote by s_t the quantity of futures the dealer is willing to supply at price p_t. When $s_t > 0$ the dealer is buying at the bid and when $s_t < 0$ the dealer is selling at the ask. Let w_t denote the value of the dealer's portfolio. We have that

$$c_{t+1} = c_t - p_t s_t \tag{4}$$

$$\theta_{t+1} = \theta_t + s_t \tag{5}$$

$$w_{t+1} = p_{t+1}\theta_{t+1} + c_{t+1}, \tag{6}$$

The dealer is myopic in the sense that when evaluating its supply he only takes into account the mark-to-market value of its position in the subsequent period $t + 1$ and not later. Endowing the dealer with mean-standard deviation preferences over next period's wealth (w_{t+1}), the dealer maximizes its post trade mean-standard deviation utility

$$\begin{aligned} U(s_t) &= \mathrm{E}_t(w_{t+1}) - \alpha\sigma(w_{t+1}) \\ &= \mathrm{E}_t(p_{t+1})(\theta_t + s_t) + c_t - p_t s_t - \alpha\sigma_t(p_{t+1})\left|\theta_t + s_t\right|, \end{aligned} \tag{7}$$

where α is the dealer risk aversion and $\sigma(\cdot)$ is the standard deviation. While we do not micro-found dealer risk aversion, in a more complex model, α could 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. The first order condition with respect to supply implies equilibrium prices depend on inventory

$$p_t|_{s_t>0} = \mathrm{E}_t(p_{t+1}) - \alpha\sigma_t(p_{t+1}) \tag{8}$$

$$p_t|_{s_t=0} = \mathrm{E}_t(p_{t+1}) = \mu_t \tag{9}$$

$$p_t|_{s_t<0} = \mathrm{E}_t(p_{t+1}) + \alpha\sigma_t(p_{t+1}), \tag{10}$$

where $\mu_t = \mu_{t-1} + \varepsilon_t$ is the expected fundamental value which follows a random walk with shock volatility σ_ε. A dealer with a long e-mini position offers a discount relative to the security's expected price because a new sell order increases its inventory risk; similarly, a dealer who is short the e-mini is willing to pay a premium relative to expected prices. Unconditionally, prices are equal to fundamentals and dealers have a zero position in futures.

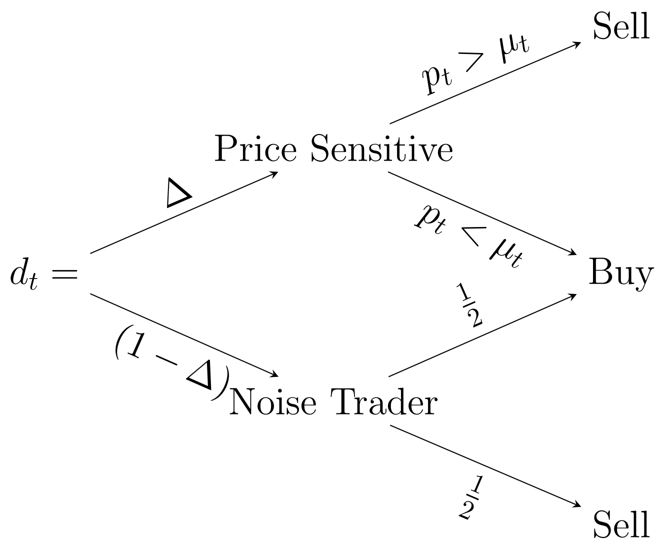
Dealers provide liquidity to clients to clear the market such that supply equals demand ($s_t = -d_t$) in equilibrium. We conjecture equilibrium prices are linear in the dealer's post-trade inventory

$$p_t = \mu_t - \beta\theta_{t+1} = \mu_t - \beta(\theta_t + s_t). \tag{11}$$

For positive β, the conjecture implies that, after filling a sell order, dealers mark down the current price. The magnitude of the drop is determined by β, which sets in motion a feedback effect such that dealers' inventories revert to neutral: lower prices are more attractive to buyside customers who enter in the next period, lowering future inventory levels.

To close the model, we specify a simple trading rule depicted in the figure below. With probability $1 - \Delta$, a noise trader arrives and places a buy or sell order with equal probabilities; with probability Δ, a price-sensitive client who evaluates prices relative to their fundamental value arrives. Thus, when the market price is below the fundamental value of the security, the probability of observing a buy order is $\frac{1}{2}(1 + \Delta)$, while the probability of a sell order is $\frac{1}{2}(1 - \Delta)$. In this case, buys are more likely than sells; the probabilities of buy and sell orders are similarly evaluated when the price is above the fundamental value.

The parameter Δ captures the responsiveness of the order flow to the difference between the fundamental value of the security and the price schedule of the dealer: if $p_t < \mu_t$, the dealer expects to receive a net order flow Δ at the next point in time, whereas if $p_t > \mu_t$ he expects a



Order Flow Response to Prices

net order flow $-\Delta$. If $\Delta < 1$, order flow responds sluggishly to prices, so that it takes dealers multiple periods to bring their inventory back to neutral. Moreover, when $\Delta < 1$, noise traders arrive with positive probability, generating order flow risk for the dealers. Computing expected prices and variances and substituting into the dealers first order conditions, we obtain

$$p_{t,\theta_{t+1}>0} = \mu_t - \beta\theta_{t+1} + \beta\,\Delta - \alpha\sqrt{\beta^2\left(1-\Delta^2\right)+\sigma_\varepsilon^2} \tag{12}$$

$$p_{t,\theta_{t+1}=0} = \mu_t \tag{13}$$

$$p_{t,\theta_{t+1}<0} = \mu_t - \beta\theta_{t+1} - \beta\Delta + \alpha\sqrt{\beta^2\left(1-\Delta^2\right)+\sigma_\varepsilon^2}. \tag{14}$$

Finally, imposing the conjectured equilibrium pricing function we establish

$$\beta = \frac{\alpha\sigma_\varepsilon}{\sqrt{\Delta^2-\alpha^2\left(1-\Delta^2\right)}}, \tag{15}$$

which measures how much dealers adjust p_t in response to inventory imbalance. Intuitively, β is increasing in dealer risk aversion α and in fundamental risk σ_ε, but decreasing in order flow sensitivity Δ since this determines how quickly inventories revert.

Dealers quote prices at a spread around the mid quote: ask prices for buy orders ($d_t > 0$) and bid prices for sell orders ($d_t < 0$). Consider unit buy and sell orders, so that

$$ask_t = p|_{s_t=-1} = \mu_t - \beta\theta_t + \beta \quad \text{and} \quad bid_t = p|_{s_t=+1} = \mu_t - \beta\theta_t - \beta, \tag{16}$$

and equilibrium mid quotes and bid-ask spreads are equal to

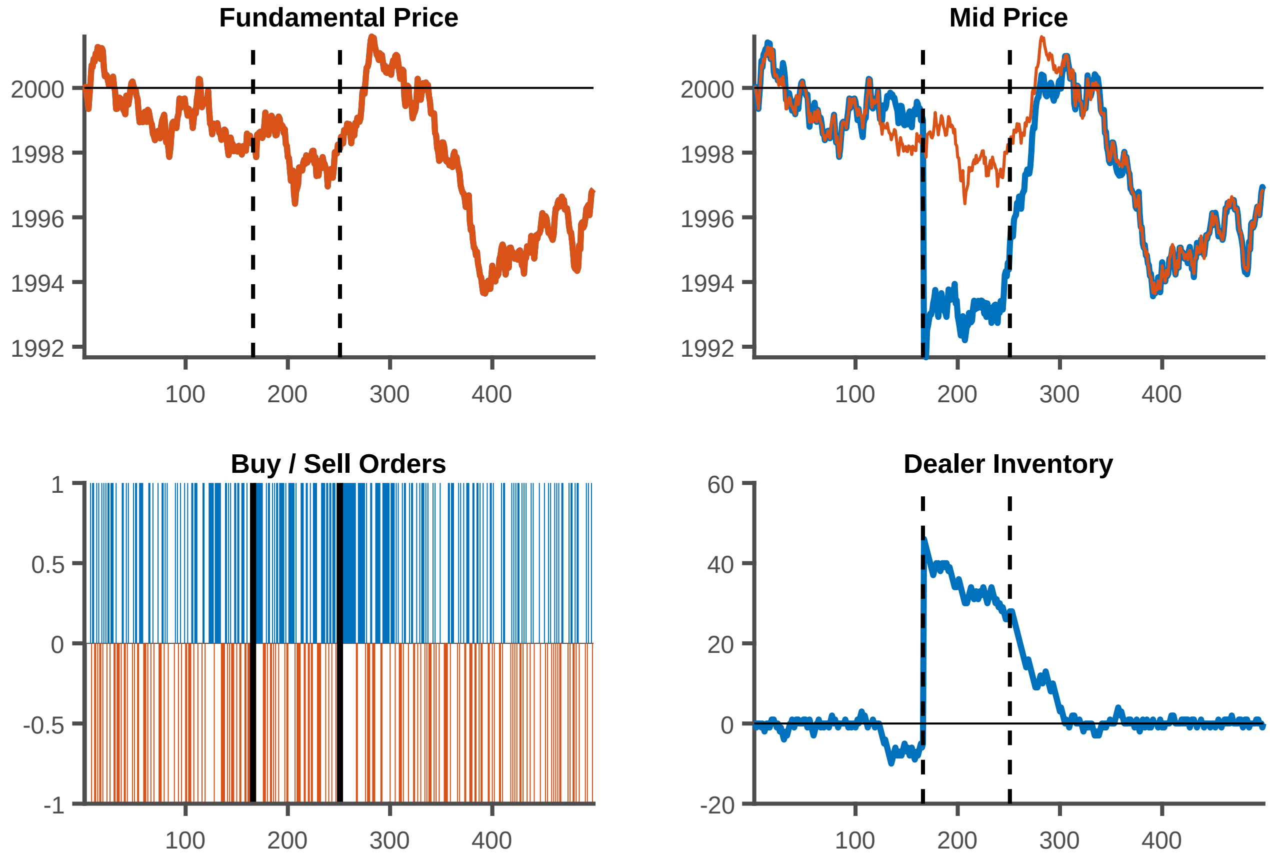
$$m_t = \mu_t - \beta\theta_t \quad \text{and} \quad bas_t = 2\beta = \frac{2\alpha\sigma_\varepsilon}{\sqrt{\Delta^2 - \alpha^2(1-\Delta^2)}}, \tag{17}$$

respectively. The mid price is interpreted as the dealer's marginal valuation, given its prevailing inventory. When a dealer has a short (long) position, selling (buying) additional units increases its inventory risk while buying (selling) additional units reduces its exposure. As a result, the dealer sets prices at a premium (discount) relative to the fundamental values.

B. Simulated Price and Inventory Dynamics

The figure below illustrates a typical simulated sample path for fundamental values, mid quotes, order imbalance, and inventory levels. The fundamental value μ_t of the contract is assumed to start at 2000 and evolve as a random walk, with innovations ε_t that are normally distributed with mean zero and standard deviation $\sigma_\varepsilon = 0.25$; the dealers' risk aversion is fixed at $\alpha = 0.2$ and their initial aggregate inventory is set to zero $\theta_0 = 0$. We shock dealers with a sell order at t_1, which implies that they agree to absorb a large supply of futures contracts. To capture new clients arriving to trade at a market open, we assume that the arrival rate of price-sensitive clients increases at t_2 from 0.4 to 0.5, and remains at this elevated level for the rest of the simulated path.

This provides a stylized interpretation of the role of dealers in matching intraday supply and demand. When a shock is realized, prices drop below the fundamental value as dealer inventories rise. The extra risk they hold drives down their marginal valuations as they anticipate offloading their portfolio to new customers entering the market. The distribution of demand in subsequent periods is driven by the realized arrival of noise traders and price-sensitive clients. In subsequent periods, prices drift upwards as, on average, agents buy (top left panel). At t_2, the speed of the price reversal increases, reflecting the higher arrival rate of price-sensitive clients. In periods subsequent to t_2, the price reversal slows down as dealers offload their inventory shock until they are back to equilibrium inventory levels (bottom right panel).



Sampled Equilibrium Dynamics

Simulation of the inventory model. $T = 500$, $\mu_1 = 2000$, $\sigma_\varepsilon = 0.25$, $\alpha = 0.2$ and $z_1 = 0$. The system is shocked at $t_1 = 500/3 = 166$ (first dashed line) with a sell order of 50 contracts. $\delta = 0.4$ for $t_2 < 250$ and $\delta = 0.5$ for $t_2 \geq 250$ (second dashed line), implying the fraction of price-sensitive clients increases.

C. Model Predictions

The simulation above highlights that intermediaries take time to move investors' capital between investment opportunities and bear risk in doing so. This point is also emphasised by Grossman and Miller (1988): Dealers and specialists offer immediacy to investors who arrive asynchronously and intermediaries profit by absorbing order imbalances and subsequently trading them away. Inventory models of this type generate a number of testable predictions.

Prediction 1: Price Predictability and Order Flow. The dynamics of the mid price are driven by changes in dealers' inventories, which ultimately depend on order flow:

$$r_t = m_t - m_{t-1} = \mu_t - \mu_{t-1} - \beta(\underbrace{\theta_t - \theta_{t-1}}_{s_{t-1}}) = \beta d_{t-1} + \varepsilon_t, \tag{18}$$

which shows that, contemporaneously, one-period returns (r_t) and order flow (d_{t-1}) are positively correlated: sell orders drive prices down and vice-versa. Considering the lead-lag relationship between returns and order flow

$$r_t = m_t - m_{t-1} = m_t - (m_{t-2} + r_{t-1}) = m_t - (m_{t-3} + r_{t-2}) - r_{t-1} \tag{19}$$

$$= \ldots m_t - m_{t-1-n} - \sum_{i=1}^{n} r_{t-i} \tag{20}$$

$$= m_t - m_{t-1-n} - \beta \sum_{i=1}^{n} d_{t-1-i} - \sum_{i=1}^{n} \varepsilon_{t-i}, \tag{21}$$

shows that returns depend negatively on the sum of all *past* order flows. This implies prices are mean-reverting – we expect to observe price reversals – and dealers' aggregate inventory is mean-reverting as well. Empirically, a projection of future returns on past inventory shocks should generate a negative regression coefficient. This relationship is stronger when more price-sensitive agents are present in the market.

Prediction 2: Trading Price Reversals. Quoted mid prices and associated bid-ask spreads compensate dealers for two types of independent risk: (i) fundamental risk measured by σ_ε, i.e., the risk due to news about fundamental values; and (ii) order flow risk measured by $1 - \Delta$, i.e., the risk that liquidity provision generates an unfavourable inventory imbalance for the dealers at e.g. the close of trade. As these risks are priced by dealers through their inventory position and the spread (see equations 16 - 17), agents trading price reversals of the type discussed above will on average not profit from such strategies. An agent going long immediately following a price drop caused by a major sell-off cannot easily profit from subsequent price predictability since they must trade at bid-ask spreads which dealers set to manage their inventory risk.

IV. Price Predictability and Order Flow

We test if order imbalance predict future returns by regressing intraday returns on the closing order imbalance of the preceding trading day. We use returns sampled at a 15 minute frequency. The 15 minute frequency is chosen as it is low enough to capture trends in trading but still sufficiently high to provide a detailed view of the trading day. Order imbalance is measured as relative signed volume over the last hour of the preceding trading day

$$RSV_{t,close} = \frac{\text{Signed Volume}_{t,close}}{\text{Total Volume}_{t,close}} \in [-1, 1], \tag{22}$$

where Signed $\text{Volume}_{t,close} = \#buys - \#sells$ and Total $\text{Volume}_{t,close} = \#buys + \#sells$ sampled during the closing hour between 15:15 – 16:15 (3:15 p.m. – 4:15 p.m). Using 15 minute returns, we have $N = 96$ return observations per trading day. Table V reports the estimated coefficients from the regression of returns (measured in basis points) on order flow imbalance at the end of the preceding trading day

$$r^{96}_{t,n} = \mu_n + \beta_n RSV_{t-1,close} + \epsilon_{t,n}, \qquad \text{for } n = 1, ..., 96, \tag{23}$$

together with t-statistics computed based on HAC-robust standard errors, for the trading hours around EU open. As predicted by our inventory model, we observe a strong negative relation between the closing order imbalance and returns. The relation is strongest at 2 a.m. and 3 a.m., when new traders enter the market (see figure 8). The estimates are both economically and statistically significant, with a 10 percentage point increase in closing relative signed volume corresponding to a 1.471 basis point drop in the return earned between 3:00 and 3:15 a.m.

Figure 9 illustrates these regression results by sorting trading days based on the closing RSV of the preceding trading day. We see that the positive OD is driven by days where the closing RSV was negative. Returns from 2-3 a.m. are negative when RSV was positive but the relationship is asymmetric in that the reaction following negative RSV days is stronger. We also observe positive but not statistically significant returns at U.S. close following days with negative closing RSV, potentially driven by end-of-day portfolio management by U.S. asset managers.

Since we observe the aggregate limit order book for the market, we can trace directly how the limit order book responds to closing order imbalances of the preceding trading day, as plotted in figure 10. 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.[8] 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. More formally, table VI reports the estimated coefficients from the regression of 15 minute relative signed volume on the closing relative signed volume at the end of the preceding trading day

$$RSV_{t,n}^{96} = \mu_n + \beta_n RSV_{t-1,close} + \epsilon_{t,n}, \qquad \text{for } n = 1, ..., 96, \tag{24}$$

together with t-statistics computed based on HAC-robust standard errors, for the trading hours around EU open. As with the realized returns in table V, the negative relationship between overnight relative signed volume and order flow imbalance at the end of the preceding trading day is strongest at 2:00 a.m. and 3:00 a.m., with a 10 percentage point increase in closing relative signed volume corresponding to a 4.4 percentage point decrease in relative signed volume between 3:00 and 3:15 a.m. the following day.

We do not observe a significant relationship between closing order imbalance and returns in the hours after 6 a.m. ET, i.e. the closing signed volume does not predict returns during the U.S. open hours. We argue this is because dealers are fully able to revert their closing positions from the preceding trading day during the London open period. In the later part of the sample period, we see a strong relation between closing order imbalance and returns around the opening of the Tokyo stock exchange, as we discuss in greater detail in the following section. Figure 11 plots the regression betas and adjusted R^2s for the full trading day.

[Insert tables V and VI here]

[Insert figures 8, 9, 11 and 10 here]

Given the negative relationship between order imbalance at the close of the previous trading day and overnight returns, why is the OD on average positive? From a purely mechanical perspective,

[8] Negative closing RSV from the clients' side implies positive market maker inventory.

in our sample, closing hour relative signed volume is negatively-skewed, so that we observe more extreme positive than negative inventory imbalances for the market makers: fire sales are much more common than 'fire buys'. If, in addition, large closing hour sell-offs coincide with large negative return realizations, risk management considerations and margin requirements could make market makers even more unwilling to hold large inventories, leading to more aggressive inventory management during the following trading session.

Finally, we highlight the contemporaneous relation between order flow and returns for the e-mini contract. The e-mini trades on the GLOBEX platform which is a centralized market with a centralized order book. Assuming the order book to be fixed, returns and order flow are therefore related mechanically one-to-one as e.g. a buy order will use up the ask side of the order book and thereby increase the ask price if all available contracts at the best ask price are bought. However, dealers constantly update their quotes, and the order book is updated much more often due to dealers than buy/sell orders from asset managers. Thus, it is possible to have e.g. a positive order flow and negative returns at the same time if dealers supply new bid/ask quotes at lower price. In practice, this will not happen in a high frequency setting, as dealers use the buy/sell orders as signals and increase prices when they receive buy orders and decrease prices when they receive sell orders. Therefore, the correlation between order flow and returns is close to 1 when the time span goes to zero. Running contemporaneous regressions of 5 minute returns on 5 minute signed volumes, we find R^2 to be in the region of 50% for all times during the trading day. However, the relationship between returns and order flow becomes weaker when we consider longer time periods. In fact, the average daily order flow of the E-mini contract is negative while returns on average are positive. This is because the e-mini is often used as a hedging instrument for long equity positions while the long run returns are driven by the performance of the underlying stocks in the S&P 500 index which is positive on average.

V. Natural Experiments

The previous section documents that trading days that close with a large negative order imbalance (clients selling to market makers) are followed by large positive order flow and return during the immediately proximate overnight trading session. One possible criticism of those results is that, in practice, the arrival of price-sensitive agents into the market is an endogenous choice by economic agents, so that the empirical relationship between closing hour order imbalance and overnight returns the following day is driven by an omitted variable. In this section, we exploit the high frequency nature of our data to construct exogenous variation, from the perspective of U.S.-based market makers, in the arrival time of Asia-based clients.

More 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 thus arrive 1 hour earlier (at 19:00 or 7 p.m. ET) when DST is not active in the U.S., which represents *exogenous* variation in the arrival time of Japan-based clients. Indeed, panel (b) of figure 12 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 the 19:00 (7 p.m.) ET Tokyo open when DST is not active in the U.S. (red line). When DST is active, the increase in volume occurs instead at 20:00 (8 p.m.) ET, corresponding once again to the Tokyo open. Notice that there is also a corresponding secondary spike in trading volume around 22:30 (10:30 p.m.) ET when the TSE re-opens after the lunch break during the summer months and around 23:30 (11:30 p.m.) ET when the TSE re-opens after the lunch break during the winter months.[9] Panel (a) of figure 12 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.[10]

We now test formally whether this exogenous change in the timing of arrival of Asia-based clients translates into a change in the timing of returns overnight. Table VII reports the estimated coefficients from the regression of returns (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

$$r^{96}_{t,n} = \mu_n + \beta^{RSV}_n RSV_{t-1,close} + \beta^{DST}_n \mathbb{1}_{DST,t} + \beta^{RSV\times DST}_n RSV_{t-1,close} \times \mathbb{1}_{DST,t} + \varepsilon_{t,n} \quad n = 1, \ldots, 24 \tag{25}$$

[9] For an in-depth discussion of the TSE lunch break and its effects on trading on the NIKKEI, see Lucca and Shachar (2014).

[10] The spike at 18:30 (6:30 p.m.) ET occurs because the futures market used to open at 18:30 on Mondays from 1997 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.

where the dummy variable takes on a value of 0 in summer time (DST not active) and 1 in winter time (DST active) and daylight savings is seen from a U.S. perspective. 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 timing of arrival of Asia-based clients, the coefficient on the interaction term $\beta_n^{RSV \times DST}$ is negative and significant around 20:00 (8 p.m.) ET, with a one percentage point increase in closing relative signed volume corresponding to a 9.05 basis point drop in returns between 19:00 – 19:15 (7 p.m. – 7:15 p.m.) ET when the DST is not active, and a 8.51 basis point in returns between 20:00 – 20:15 (8:00 – 8:15 p.m.) ET when the DST is active. Panel (a) of table VII shows that these results are exclusive to the post-2010 sample, confirming once again that the DST difference is only relevant when there is a significant volume of trade during the Asian open hours.

We can also use the fact that DST is observed both in Europe and the U.S.[11] to construct a placebo test. Table A.5 repeats regression (25) for European opening hours. Consistent with DST being (almost) synchronized between Europe and the U.S., the coefficients on the DST dummy and the interaction between closing order imbalance and the DST dummy are not significant for any of the trading time intervals.

Finally, the increase in trading activity during Asian open hours starting in 2010 suggests that, post-2010, U.S.-based market makers are able to (partially) offload their inventory at TSE open instead of waiting for the London open. Consistent with this hypothesis, in unreported results, we find that the relationship between closing order flow and returns at London open are indeed slightly weaker after 2010.

[Insert table VII and A.5 here]

[Insert figure 12 here]

[11] 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. In unreported results, we also see that the beta coefficients from the regressions in Section IV move by 1 hour, although the estimated coefficients are not statistically different from zero due to the low number of observations.

VI. Trading Price Reversals

We investigate the performance of various trading strategies characterized by holding the ES contract for a pre-defined sub-period of each trading day and compare these strategies to holding the ES contract continuously. Returns on trading day j earned on a strategy that goes long the ES contract each day in the sub-period $[t_1, t_2]$ are computed as

$$r^L_{j,[t_1,t_2]} = \frac{P_{j,t_2} - P_{j,t_1}}{P_{j,t_1}}, \tag{26}$$

where P denotes price of the ES contract. The analogous short position earns $r^S = -r^L$. Mid quotes are used to compute returns excluding transaction costs. Including transaction costs, returns are computed from quotes as

$$r^L_{j,[t_1,t_2]} = \frac{P^{\text{bid}}_{j,t_2} - P^{\text{ask}}_{j,t_1}}{P^{\text{ask}}_{j,t_1}} \quad , \quad r^S_{j,[t_1,t_2]} = -1 \times \frac{P^{\text{ask}}_{j,t_2} - P^{\text{bid}}_{j,t_1}}{P^{\text{bid}}_{j,t_1}}. \tag{27}$$

We consider the following strategies: (i) long CTC: t_1=16:15, t_2 = 16:15; (ii) long CTO: t_1 = 16:15,t_2 = 9:30; (iii) long OTC: t_1 = 9:30,t_2 = 16:15; (iv) long OD: t_1 = 02:00,t_2 = 03:00; (v) short OR: t_1 = 08:30 , t_2 = 10:00.

Table VIII (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 4.47% with a Sharpe ratio of 0.18. 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 3.09%, which implies that OTC returns averaged just 1.38%. As discussed above, a dissection of this magnitude may not be particularly surprising in itself. However, it is surprisingly that the CTO return is largely due to the OD component which averaged 3.63%. The OD strategy has a Sharpe ratio close to one, which far outperforms the overall market Sharpe ratio of 0.18. The high Sharpe ratio arises from the combination of high excess returns and low volatility during the overnight drift period. The beta of the OD strategy is close to zero, implying a low correlation with CTC returns. This is surprising as the OD return mechanically is a part of the CTC return. OR, is equally surprisingly, equal to −3.88%. While these numbers are easily inferred from figure 3, 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. Investing \$1 in the e-mini at its introduction in September, 1997 and holding the position continuously to December, 2019 would have yielded a portfolio value of \$2.80. A hypothetical investor who can trade without transaction costs would have a portfolio value of \$2.06 by only holding the e-mini in the CTO period. In comparison, the investor would have \$1.28 by only holding the e-mini in the OTC period, \$2.17 by only holding the contract in the OD period and \$2.33 by shorting the market on open (the OR period).

Panel (a) of figure 13 depicts the cumulative returns to the CTC, OD and short OR strategies throughout the sample period. The OD strategy has performed exceptionally well in the sense that it never experience large negative returns. While shorting the OR would have also been profitable, returns have been more volatile and in general moved opposite the business cycle, which is not surprising given the strategy is shorting the S&P 500 index.

Table VIII (b) reports summary statistics of the trading strategies when transaction costs are included. We first note that transaction costs do not affect either the betas or volatility of any of the sub period returns. Instead, after accounting for transaction costs, all sub-period intraday returns have significantly negative mean returns. Thus, the returns on all strategies are significantly lowered due to transaction costs and none of the trading strategies are profitable over the full sample period. Panel (b) of figure 13 visualizes the cumulative returns when transaction costs are included. 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 1998 and final sell in 2018). With transaction costs, the OD is not profitable in practice. However, we see that the OD strategy primarily earned negative returns in the first part of the sample when the bid-ask spread was notably higher during the overnight period. Around 2004, bid-ask spreads sampled at 2 a.m. and 3 a.m. reached the minimum tick size of 0.25 index points[12], and interestingly, the OD strategy earned close to zero returns since 2004 and slightly positive returns since 2016. Notice finally that, although the documented high frequency return patterns are not directly profitable, the persistent presence of the overnight drift suggests that the intraday timing

[12]The bid-ask spreads during other parts of the overnight period have followed quantitatively similar patterns and reached the minimum tick size around 2004. Spreads during the U.S. open hours have historically, almost always, equalled the minimum tick size.

of portfolio adjustments should be an important consideration for money managers.

[Insert table VIII and figure 13 here]

VII. Conclusion

At the same time as the market for cash U.S. equity products has become increasingly fragmented across trading platforms, the market for U.S. equity futures has become more globally integrated. In this paper, we studied the 24 hour trading returns on U.S. equity futures, 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.

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VIII. Tables

Hour	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09
Mean	0.25	0.27	0.08	−0.03	−0.09	0.01	0.35	0.45	1.36	0.15	−0.15	0.17	0.35	0.12	−0.09
t-stat	0.69	1.65	0.37	−0.15	−0.50	0.03	2.25	2.63	6.27	0.56	−0.58	0.74	1.54	0.50	−0.27
Median	0.00	0.17	0.06	0.01	0.15	0.13	0.20	0.40	0.85	−0.04	0.24	0.22	0.34	0.53	−0.31
Sdev	11.79	10.55	12.92	11.82	11.09	10.27	9.81	10.33	13.77	19.80	17.87	15.77	15.78	16.85	25.40
Skew	0.08	−0.26	0.20	−0.21	−0.47	−0.27	0.12	−0.19	0.19	0.02	−0.23	−0.11	0.33	−0.23	0.06
Kurt	11.56	10.69	8.42	8.88	9.85	10.38	9.43	10.26	10.76	7.59	8.28	7.40	9.39	8.18	8.85

(a) Overnight hourly returns: Trades

Hour	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09
Mean	−0.25	0.32	0.14	0.08	−0.02	0.10	0.28	0.43	1.35	0.33	−0.06	0.09	0.57	0.07	0.08
t-stat	−0.84	1.78	0.66	0.47	−0.10	0.77	2.06	2.98	7.01	1.27	−0.22	0.40	2.47	0.27	0.23
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.78	0.00	0.00	0.00	0.00	0.00	0.00
Sdev	21.70	13.63	15.97	12.46	11.99	9.56	10.61	10.77	14.53	20.72	18.46	16.72	16.88	18.88	27.25
Skew	−1.54	0.89	−0.64	−0.89	−3.57	0.51	1.98	−0.62	0.64	−0.04	−0.69	−0.43	1.38	1.06	−0.34
Kurt	72.25	45.84	65.38	41.48	80.76	29.31	43.97	38.76	32.89	17.78	16.31	19.59	22.35	63.07	25.73

(b) Overnight hourly returns: Quotes

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	CTC
Mean	−0.99	0.35	−0.68	0.68	0.34	0.47	1.79	−2.16	−0.74	2.81
t-stat	−2.15	0.61	−1.48	1.85	0.86	1.01	3.00	−0.89	−1.58	1.86
Median	−0.45	1.38	0.94	0.93	1.29	0.96	1.93	0.78	−0.62	6.28
Sdev	33.77	41.70	33.48	27.41	29.15	35.44	45.36	21.90	12.44	115.18
Skew	−0.07	0.14	−0.49	−0.24	0.10	0.37	0.67	−2.92	0.30	−0.09
Kurt	7.66	7.20	7.00	9.70	9.50	9.30	12.79	17.63	6.88	8.37

(c) Intraday hourly returns: Trades

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	CTC
Mean	−1.12	−0.28	−0.38	0.29	0.11	−0.13	0.66	0.01	−0.49	2.17
t-stat	−2.43	−0.49	−0.88	0.76	0.29	−0.28	1.07	0.03	−4.15	1.38
Median	0.00	0.32	1.07	0.99	0.94	0.00	1.19	1.05	0.00	6.73
Sdev	34.76	41.42	32.19	27.95	29.99	36.37	49.38	20.14	8.84	122.18
Skew	−0.56	−0.11	−0.43	−0.85	0.74	0.40	1.26	−1.81	−0.99	−0.18
Kurt	13.66	11.33	9.97	23.69	22.15	14.63	31.68	19.81	65.20	13.10

(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.

Hour	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09
daily % POS	49.59	51.04	50.39	50.06	51.28	50.86	51.50	52.71	54.30	49.73	50.91	50.78	51.66	52.11	48.86
daily % NEG	47.95	48.42	49.14	49.59	48.38	48.43	47.80	46.69	45.41	50.21	49.01	49.07	48.24	47.84	51.09
daily p-val	0.60	0.10	0.44	0.78	0.07	0.15	0.03	0.00	0.00	0.75	0.20	0.25	0.02	0.00	0.10
monthly % POS	28.41	56.06	50.38	49.62	50.38	39.02	51.89	48.86	64.39	52.65	48.11	52.65	52.65	55.30	50.00
monthly % NEG	21.97	42.42	46.97	47.73	45.83	46.21	36.36	38.26	28.79	43.94	49.62	45.08	46.59	44.70	50.00
monthly p-val	0.17	0.03	0.62	0.80	0.49	0.23	0.01	0.07	0.00	0.17	0.85	0.24	0.35	0.10	1.00

(a) Overnight hourly returns: Trades

Hour	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09
daily % POS	47.08	45.16	44.29	44.88	45.80	39.69	45.06	46.00	50.09	47.54	47.88	47.96	47.78	49.24	46.85
daily % NEG	46.26	42.50	44.40	43.53	41.61	37.70	41.63	40.96	41.21	46.91	46.04	45.08	44.77	44.45	48.10
daily p-val	0.54	0.04	0.94	0.29	0.00	0.10	0.01	0.00	0.00	0.64	0.16	0.03	0.02	0.00	0.35
monthly % POS	52.27	54.92	53.41	54.92	54.55	50.38	57.95	59.47	70.45	54.17	53.03	54.17	54.92	57.20	52.27
monthly % NEG	47.73	45.08	46.59	45.08	45.45	49.62	42.05	40.53	29.55	45.83	46.97	45.83	45.08	42.80	47.73
monthly p-val	0.50	0.12	0.30	0.12	0.16	0.95	0.01	0.00	0.00	0.20	0.36	0.20	0.12	0.02	0.50

(b) Overnight hourly returns: Quotes

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	CTC
daily % POS	49.16	51.93	52.10	52.34	52.84	52.04	53.09	55.26	47.01	53.81
daily % NEG	50.84	48.07	47.90	47.66	47.16	47.96	46.91	44.74	52.70	46.19
daily p-val	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.42	0.15	0.00
monthly % POS	45.45	47.73	50.00	59.85	50.38	50.00	55.30	4.17	10.98	59.47
monthly % NEG	54.55	52.27	50.00	40.15	49.62	50.00	44.70	4.55	14.39	40.53
monthly p-val	0.16	0.50	1.00	0.00	0.95	1.00	0.10	0.00	0.33	0.00

(c) Intraday hourly returns: Trades

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	CTC
daily % POS	48.14	50.00	50.33	50.45	50.33	49.08	50.67	50.85	33.87	53.93
daily % NEG	49.17	47.36	45.99	44.94	45.68	46.35	45.26	42.78	43.04	45.60
daily p-val	0.45	0.05	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00
monthly % POS	45.83	51.52	52.27	55.68	50.00	49.62	53.41	53.03	37.12	61.74
monthly % NEG	54.17	48.48	47.73	44.32	50.00	50.38	46.59	46.97	62.88	38.26
monthly p-val	0.20	0.67	0.50	0.07	1.00	0.95	0.30	0.36	0.00	0.00

(d) Intraday hourly returns: Quotes

Table II. Non-Parametric Tests

Panels (a) and (c) compute returns from volume-weighted average prices. Panels (b) and (c) compute returns using mid quotes at the top of the order book. Returns are computed from log price changes in the most liquid contract maturity (either the front or the back month contract). " %POS" is the percentage of positive returns and "% NEG" is the percentage of negative returns. p-value reports the probability, from a two-sided test, of observing this many returns in one direction than the other, under the null hypothesis of a random walk.

Hour	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09
Monday	-1.78	0.41	0.27	-0.41	0.01	0.22	-0.42	0.08	1.46	1.51	0.13	-0.05	0.45	1.09	-0.47
t-stat	(-1.54)	(0.95)	(0.60)	(-0.99)	(0.04)	(0.70)	(-1.41)	(0.24)	(3.18)	(2.33)	(0.24)	(-0.11)	(1.01)	(2.12)	(-0.85)
Tuesday	0.26	0.40	0.08	0.88	-0.16	0.32	0.24	0.83	1.26	-0.27	-0.79	1.31	0.73	0.71	-0.35
t-stat	(0.41)	(1.18)	(0.19)	(2.62)	(-0.53)	(1.14)	(0.80)	(2.51)	(2.87)	(-0.50)	(-1.41)	(2.62)	(1.35)	(1.40)	(-0.49)
Wednesday	-0.01	0.47	-0.15	-0.54	-0.11	0.25	0.66	0.12	1.69	-0.37	0.25	0.36	0.38	-0.21	-1.17
t-stat	(-0.03)	(1.34)	(-0.34)	(-1.34)	(-0.33)	(0.98)	(2.30)	(0.42)	(4.10)	(-0.61)	(0.44)	(0.70)	(0.72)	(-0.33)	(-1.40)
Thursday	-0.33	1.64	1.67	0.26	0.26	-0.27	0.33	0.38	1.03	0.31	0.45	-0.95	0.68	-0.88	0.76
t-stat	(-0.98)	(3.55)	(3.01)	(0.63)	(0.75)	(-0.96)	(1.04)	(1.23)	(2.35)	(0.48)	(0.79)	(-1.66)	(1.36)	(-1.36)	(0.87)
Friday	0.53	-1.33	-1.14	0.16	-0.07	-0.04	0.57	0.72	1.32	0.60	-0.31	-0.25	0.58	-0.30	1.65
t-stat	(1.26)	(-3.00)	(-2.30)	(0.48)	(-0.15)	(-0.12)	(1.52)	(2.07)	(2.83)	(1.02)	(-0.55)	(-0.49)	(1.06)	(-0.57)	(1.54)

(a) Overnight hourly returns

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
Monday	-0.57	-0.00	-2.04	0.12	-0.12	-1.21	0.34	-0.21	-0.64
t-stat	(-0.48)	(-0.00)	(-2.11)	(0.16)	(-0.14)	(-1.24)	(0.22)	(-0.35)	(-3.32)
Tuesday	0.35	0.00	0.52	-0.73	-0.15	-0.91	0.19	0.09	-0.79
t-stat	(0.38)	(0.00)	(0.57)	(-0.87)	(-0.19)	(-0.81)	(0.13)	(0.14)	(-2.37)
Wednesday	0.04	-0.85	1.70	1.06	-0.16	1.95	-2.08	-0.70	-0.65
t-stat	(0.04)	(-0.70)	(1.82)	(1.41)	(-0.16)	(1.69)	(-1.35)	(-1.22)	(-1.00)
Thursday	-2.79	0.31	-0.08	0.21	1.57	-0.27	2.20	0.33	-0.26
t-stat	(-2.71)	(0.23)	(-0.08)	(0.23)	(1.60)	(-0.25)	(1.47)	(0.54)	(-0.98)
Friday	-2.67	-0.82	-2.20	0.76	-0.59	-0.31	2.69	0.54	-0.09
t-stat	(-2.40)	(-0.68)	(-2.16)	(0.87)	(-0.70)	(-0.32)	(2.18)	(0.86)	(-2.04)

(b) Intraday hourly returns

Table III. 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.

Hour	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09
January	-0.10	0.49	0.40	-0.04	-0.16	-0.50	-0.85	-0.06	1.38	-0.98	0.51	0.71	1.18	-0.20	-0.24
t-stat	(-0.09)	(0.78)	(0.64)	(-0.08)	(-0.29)	(-1.31)	(-1.74)	(-0.15)	(2.13)	(-1.05)	(0.61)	(0.79)	(1.48)	(-0.24)	(-0.19)
February	-0.12	1.28	-0.97	0.34	-0.45	-0.31	0.36	1.06	2.12	0.43	-0.60	-0.87	0.33	0.96	-1.79
t-stat	(-0.13)	(2.28)	(-1.17)	(0.82)	(-0.95)	(-0.90)	(0.67)	(2.82)	(2.77)	(0.51)	(-0.72)	(-1.33)	(0.42)	(1.23)	(-1.47)
March	-2.05	0.02	0.58	-1.06	0.09	0.67	0.31	0.25	1.01	1.45	-0.18	0.12	-0.17	1.21	1.21
t-stat	(-2.50)	(0.02)	(0.98)	(-1.90)	(0.17)	(1.48)	(0.77)	(0.61)	(1.75)	(1.77)	(-0.23)	(0.16)	(-0.26)	(1.61)	(1.06)
April	-0.35	-0.03	-0.12	0.38	-0.12	0.16	0.05	-0.01	1.92	0.36	0.25	1.12	0.20	1.96	0.06
t-stat	(-0.35)	(-0.09)	(-0.12)	(0.74)	(-0.24)	(0.50)	(0.12)	(-0.01)	(3.53)	(0.45)	(0.36)	(1.75)	(0.30)	(2.74)	(0.05)
May	-0.54	0.67	0.26	-0.46	0.41	-0.17	0.29	0.65	0.89	0.39	-0.56	-0.13	-0.27	0.53	-1.05
t-stat	(-0.72)	(1.28)	(0.49)	(-0.96)	(1.05)	(-0.50)	(0.81)	(1.63)	(1.74)	(0.54)	(-0.80)	(-0.22)	(-0.43)	(0.76)	(-0.99)
June	-0.48	0.70	0.49	0.44	-0.04	0.12	0.47	0.43	2.13	0.22	-1.15	0.39	-0.05	-0.16	0.18
t-stat	(-0.61)	(1.72)	(0.54)	(0.88)	(-0.06)	(0.33)	(1.00)	(1.04)	(3.53)	(0.28)	(-1.55)	(0.64)	(-0.08)	(-0.24)	(0.17)
July	-0.64	0.01	-0.33	-0.25	0.94	0.47	-0.26	0.48	1.28	-0.09	0.86	0.25	1.10	0.87	-0.50
t-stat	(-0.83)	(0.02)	(-0.74)	(-0.53)	(2.08)	(1.45)	(-0.80)	(1.36)	(2.38)	(-0.12)	(1.11)	(0.37)	(1.58)	(1.09)	(-0.44)
August	-2.18	-0.39	0.31	0.07	-0.20	-0.38	0.67	0.76	0.91	0.43	0.22	-1.17	0.71	0.12	-0.50
t-stat	(-2.34)	(-0.91)	(0.46)	(0.12)	(-0.41)	(-0.74)	(1.51)	(1.46)	(1.24)	(0.43)	(0.29)	(-1.61)	(1.10)	(0.13)	(-0.39)
September	0.23	-0.03	-0.33	0.34	-0.01	-0.35	0.19	0.48	3.09	-1.42	0.71	-0.07	-2.13	-0.66	-0.55
t-stat	(0.14)	(-0.04)	(-0.38)	(0.47)	(-0.02)	(-0.79)	(0.43)	(0.80)	(4.11)	(-1.27)	(0.72)	(-0.08)	(-2.41)	(-0.76)	(-0.42)
October	-2.18	-0.39	0.31	0.07	-0.20	-0.38	0.67	0.76	0.91	0.43	0.22	-1.17	0.71	0.12	-0.50
t-stat	(-2.34)	(-0.91)	(0.46)	(0.12)	(-0.41)	(-0.74)	(1.51)	(1.46)	(1.24)	(0.43)	(0.29)	(-1.61)	(1.10)	(0.13)	(-0.39)
November	2.17	0.81	-0.34	0.59	-0.24	0.50	1.17	0.16	0.55	1.03	-0.41	-0.16	1.03	-1.68	1.72
t-stat	(1.99)	(1.20)	(-0.44)	(0.82)	(-0.37)	(0.87)	(2.02)	(0.33)	(0.62)	(1.07)	(-0.40)	(-0.20)	(1.08)	(-1.72)	(1.31)
December	2.14	0.14	0.00	-0.16	-0.41	-0.23	0.80	1.22	0.00	1.48	2.00	1.11	0.09	-1.01	0.64
t-stat	(2.30)	(0.17)	(1.73)	(-0.41)	(-0.62)	(-0.50)	(1.37)	(2.46)	(2.05)	(1.92)	(2.74)	(1.73)	(0.13)	(-1.33)	(0.57)

(a) Overnight hourly returns

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
January	-1.67	-3.17	-1.09	0.54	1.72	0.70	1.22	-0.43	-0.74
t-stat	(-0.90)	(-1.52)	(-0.71)	(0.44)	(1.10)	(0.44)	(0.67)	(-0.45)	(-1.39)
February	-1.14	-1.19	0.82	0.58	-1.04	0.10	0.92	-0.97	-0.41
t-stat	(-0.71)	(-0.61)	(0.51)	(0.51)	(-0.67)	(0.06)	(0.46)	(-1.07)	(-1.10)
March	-1.12	2.77	0.38	1.98	-1.40	1.77	0.18	0.87	-0.80
t-stat	(-0.71)	(1.50)	(0.26)	(1.82)	(-1.19)	(1.07)	(0.09)	(1.14)	(-2.29)
April	-1.35	1.58	-0.62	0.94	0.27	-1.52	0.75	2.38	-0.12
t-stat	(-1.02)	(0.96)	(-0.40)	(0.81)	(0.22)	(-1.10)	(0.46)	(2.34)	(-0.36)
May	0.14	-0.84	0.28	0.30	-0.78	-0.55	0.83	-0.93	-0.49
t-stat	(0.11)	(-0.45)	(0.22)	(0.26)	(-0.71)	(-0.38)	(0.51)	(-1.41)	(-1.51)
June	0.17	0.71	0.36	-1.84	0.57	-1.50	-2.37	0.36	-0.50
t-stat	(0.12)	(0.45)	(0.29)	(-1.85)	(0.51)	(-1.05)	(-1.55)	(0.51)	(-1.81)
July	-0.62	-1.92	-1.68	-0.99	2.89	-1.30	2.44	-0.92	-0.38
t-stat	(-0.46)	(-1.11)	(-0.00)	(-0.85)	(2.36)	(-0.90)	(1.19)	(-1.07)	(-0.83)
August	-2.02	-0.27	-1.25	0.75	1.03	-1.39	-0.85	0.75	-0.54
t-stat	(-1.41)	(-0.15)	(-0.85)	(0.59)	(0.86)	(-0.93)	(-0.39)	(1.02)	(-1.34)
September	-3.55	0.36	0.75	-0.77	0.72	1.62	-0.63	-0.38	-0.03
t-stat	(-1.99)	(0.18)	(0.50)	(-0.59)	(0.49)	(0.92)	(-0.30)	(-0.36)	(-0.08)
October	-2.02	-0.27	-1.25	0.75	1.03	-1.39	-0.85	0.75	-0.54
t-stat	(-1.41)	(-0.15)	(-0.85)	(0.59)	(0.86)	(-0.93)	(-0.39)	(1.02)	(-1.34)
November	-1.23	0.71	-0.61	0.01	0.92	0.90	1.27	-0.11	-1.34
t-stat	(-0.71)	(0.39)	(-0.40)	(0.00)	(0.60)	(0.45)	(0.48)	(-0.12)	(-3.46)
December	-0.67	1.52	-1.36	-0.34	-2.55	-1.07	-0.37	-0.06	-0.38
t-stat	(-0.41)	(0.81)	(-0.90)	(-0.31)	(-1.88)	(-0.61)	(-0.19)	(-0.06)	(-1.23)

(b) Intraday hourly returns

Table IV. 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.

	00:00-15	00:15-30	00:30-45	00:45-00	01:00-15	01:15-30	01:30-45	01:45-00	02:00-15	02:15-30	02:30-45	02:45-00
μ	0.13	0.02	0.07	0.11	-0.02	0.05	0.12	0.24	0.50	0.33	0.26	0.37
	(1.39)	(0.29)	(1.03)	(1.71)	(-0.23)	(0.75)	(1.72)	(2.94)	(4.43)	(3.59)	(2.58)	(3.51)
β_{RSV}	0.68	-1.51	-0.51	-0.49	0.34	-0.75	-1.53	-4.03	-8.98	-2.97	-3.31	-1.50
	(0.50)	(-1.59)	(-0.62)	(-0.63)	(0.38)	(-0.84)	(-1.67)	(-4.03)	(-6.88)	(-2.59)	(-2.64)	(-1.10)
adj R^2 (%)	-0.01	0.02	-0.02	-0.01	-0.02	-0.01	0.02	0.21	0.58	0.08	0.08	-0.00

	03:00-15	03:15-30	03:30-45	03:45-00	04:00-15	04:15-30	04:30-45	04:45-00	05:00-15	05:15-30	05:30-45	05:45-00
μ	0.17	0.07	0.14	-0.12	-0.05	0.03	0.02	-0.02	0.03	0.03	-0.09	-0.02
	(1.07)	(0.51)	(0.99)	(-0.84)	(-0.36)	(0.22)	(0.14)	(-0.18)	(0.26)	(0.26)	(-0.70)	(-0.15)
β_{RSV}	-14.71	-1.26	-0.96	-3.01	1.95	-0.18	1.31	1.54	0.01	-0.47	1.94	-0.28
	(-7.77)	(-0.66)	(-0.51)	(-1.67)	(1.11)	(-0.11)	(0.80)	(1.03)	(0.01)	(-0.29)	(1.22)	(-0.19)
adj R^2 (%)	0.80	-0.01	-0.02	0.02	-0.00	-0.02	-0.01	-0.01	-0.02	-0.02	0.00	-0.02

Table V. Regression: overnight returns on closing signed volume

15-minute intraday returns are regressed on the relative signed volume leading up to the U.S. close period of the previous trading day: $r^{96}_{t,n} = \mu_n + \beta_n RSV_{t-1,close} + \varepsilon_{t,n}$, $n = 25, \ldots, 48$. 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.

	00:00-15	00:15-30	00:30-45	00:45-00	01:00-15	01:15-30	01:30-45	01:45-00	02:00-15	02:15-30	02:30-45	02:45-00
μ	0.01	0.00	-0.01	0.00	0.01	0.01	0.01	0.03	0.03	0.02	0.01	0.01
	(0.99)	(0.54)	(-1.34)	(0.53)	(1.36)	(1.21)	(1.66)	(4.27)	(6.45)	(4.44)	(2.19)	(2.01)
β_{RSV}	0.00	0.12	-0.31	-0.08	-0.02	-0.11	-0.19	-0.47	-0.63	-0.27	-0.40	-0.28
	(0.01)	(0.95)	(-2.50)	(-0.62)	(-0.13)	(-0.80)	(-1.52)	(-4.04)	(-6.50)	(-2.62)	(-4.09)	(-3.09)
adj R^2 (%)	-0.03	0.01	0.20	-0.01	-0.03	-0.00	0.06	0.61	1.65	0.24	0.63	0.34

	03:00-15	03:15-30	03:30-45	03:45-00	04:00-15	04:15-30	04:30-45	04:45-00	05:00-15	05:15-30	05:30-45	05:45-00
μ	0.01	0.00	-0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	-0.00
	(1.62)	(0.24)	(-0.12)	(0.04)	(0.92)	(0.45)	(1.61)	(0.30)	(0.57)	(3.06)	(0.38)	(-0.14)
β_{RSV}	-0.44	-0.20	-0.10	-0.12	-0.07	-0.10	-0.06	0.01	-0.08	-0.05	-0.03	-0.06
	(-6.98)	(-3.02)	(-1.47)	(-1.78)	(-0.98)	(-1.36)	(-0.90)	(0.09)	(-1.07)	(-0.70)	(-0.38)	(-0.74)
adj R^2 (%)	1.87	0.35	0.06	0.10	0.01	0.05	0.01	-0.03	0.02	-0.01	-0.02	-0.01

Table VI. Regression: overnight signed volume on closing signed volume

15-minute relative signed volumes are regressed on the relative signed volume leading up to the U.S. close period of the previous trading day: $RSV_{t,n}^{96} = \mu_n + \beta_n RSV_{t-1,close} + \varepsilon_{t,n}$, $n = 25, \ldots, 48$. Days where the time difference between London and New York is different from 5 hours are excluded. t-statistics reported in parenthesis are computed from HAC robust standard errors.

	18:00-15	18:15-30	18:30-45	18:45-00	19:00-15	19:15-30	19:30-45	19:45-00	20:00-15	20:15-30	20:30-45	20:45-00
$\beta_{signedVol}$	1.10	0.00	-6.17	-0.06	-9.19	-3.16	2.42	-2.55	-1.38	-1.48	-2.58	-1.99
	(0.31)	(0.00)	(-1.97)	(-0.04)	(-1.69)	(-2.11)	(1.59)	(-1.89)	(-0.83)	(-1.04)	(-1.83)	(-1.15)
β_{DST}	-0.37	0.02	-0.21	0.07	0.06	0.06	-0.50	0.10	0.40	0.04	0.24	0.01
	(-0.87)	(0.13)	(-0.99)	(0.51)	(0.42)	(0.37)	(-3.61)	(0.70)	(1.45)	(0.19)	(1.80)	(0.04)
$\beta_{RSV\times DST}$	2.16	2.85	7.15	-0.74	9.58	5.12	-0.98	1.10	-1.41	2.24	0.60	-0.21
	(0.36)	(1.26)	(1.83)	(-0.37)	(1.69)	(2.48)	(-0.48)	(0.55)	(-0.42)	(0.00)	(0.30)	(-0.10)
adj R^2 (%)	-0.04	-0.02	0.03	-0.07	0.09	0.03	0.32	-0.00	0.02	-0.06	0.02	-0.08

	21:00-15	21:15-30	21:30-45	21:45-00	22:00-15	22:15-30	22:30-45	22:45-00	23:00-15	23:15-30	23:30-45	23:45-00
$\beta_{signedVol}$	-0.53	-0.64	-3.07	-0.45	0.18	2.64	-0.03	1.23	-0.93	3.13	-0.63	-1.18
	(-0.35)	(-0.44)	(-1.62)	(-0.28)	(0.12)	(1.76)	(-0.02)	(0.82)	(-0.75)	(1.39)	(-0.60)	(-0.92)
β_{DST}	0.19	-0.10	-0.24	-0.12	-0.07	0.11	-0.08	0.12	-0.06	0.14	0.28	-0.09
	(1.01)	(-0.72)	(-1.80)	(-0.88)	(-0.47)	(0.92)	(-0.65)	(1.09)	(-0.66)	(1.30)	(2.09)	(-0.92)
$\beta_{RSV\times DST}$	2.25	-0.91	2.57	0.34	0.40	-4.41	0.08	-0.51	1.32	-1.10	-0.52	0.80
	(1.02)	(-0.44)	(1.05)	(0.15)	(0.19)	(-2.20)	(0.04)	(-0.27)	(0.83)	(-0.43)	(-0.31)	(0.47)
adj R^2 (%)	-0.02	-0.01	0.11	-0.05	-0.07	0.02	-0.06	-0.12	-0.05	0.09	-0.01	-0.05

(a) 1998 - 2010

	18:00-15	18:15-30	18:30-45	18:45-00	19:00-15	19:15-30	19:30-45	19:45-00	20:00-15	20:15-30	20:30-45	20:45-00
β_{RSV}	-24.60	-1.91	-3.67	0.34	-9.05	-2.82	-3.27	7.58	2.58	-4.66	-1.83	2.99
	(-2.58)	(-0.61)	(-1.19)	(0.12)	(-2.21)	(-0.83)	(-1.02)	(2.59)	(0.61)	(-1.20)	(-0.53)	(0.77)
β_{DST}	-0.65	-0.38	0.04	-0.21	0.14	0.02	0.03	0.60	-0.41	-0.16	-0.07	0.00
	(-1.29)	(-2.46)	(0.28)	(-1.41)	(1.20)	(0.13)	(0.23)	(4.01)	(-1.83)	(-0.98)	(-0.45)	(0.01)
$\beta_{RSV\times DST}$	27.68	3.36	2.59	-6.17	6.10	1.45	-0.66	-12.40	-11.09	4.73	2.50	-5.50
	(2.22)	(0.85)	(0.71)	(-1.71)	(1.35)	(0.37)	(-0.17)	(-3.21)	(-1.93)	(1.01)	(0.58)	(-1.21)
adj R^2 (%)	0.13	0.08	-0.07	0.07	0.23	-0.09	0.06	0.48	0.25	-0.06	-0.15	-0.04

	21:00-15	21:15-30	21:30-45	21:45-00	22:00-15	22:15-30	22:30-45	22:45-00	23:00-15	23:15-30	23:30-45	23:45-00
β_{RSV}	3.79	4.47	1.51	-1.82	3.97	1.62	4.01	-0.10	0.29	-3.56	2.04	1.81
	(1.29)	(1.29)	(0.48)	(-0.66)	(1.26)	(0.66)	(1.41)	(-0.04)	(0.11)	(-1.58)	(0.75)	(0.80)
β_{DST}	-0.02	0.20	0.19	-0.01	-0.01	-0.12	-0.02	0.02	-0.15	0.17	-0.10	0.16
	(-0.12)	(1.07)	(1.06)	(-0.03)	(-0.06)	(-0.88)	(-0.11)	(0.13)	(-1.08)	(1.37)	(-0.78)	(1.23)
$\beta_{RSV\times DST}$	-5.05	-2.92	-3.19	-3.90	-5.33	-0.77	-1.12	2.17	3.38	2.12	-1.05	-5.65
	(-0.00)	(-0.63)	(-0.71)	(-0.91)	(-1.26)	(-0.22)	(-0.23)	(0.67)	(0.99)	(0.67)	(-0.29)	(-1.66)
adj R^2 (%)	-0.07	-0.05	-0.04	0.06	-0.07	-0.04	-0.02	-0.05	-0.20	0.00	-0.03	0.01

(b) 2010 - 2020

Table VII. Natural Experiments.

15-minute 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:

$$r^{96}_{t,n} = \mu_n + \beta^{RSV}_n RSV_{t-1,close} + \beta^{DST}_n \mathbb{1}_{DST,t} + \beta^{RSV\times DST}_n RSV_{t-1,close} \times \mathbb{1}_{DST,t} + \varepsilon_{t,n} \quad n = 1,\ldots,24$$

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 HAC robust standard errors.

	CTC	CTO	OTC	OD	- OR
Mean	4.68	3.09	1.38	3.63	3.88
Sdev	19.15	10.32	15.72	2.32	6.18
Sharpe ratio	0.18	0.17	0.01	1.01	0.42
beta	1.00	0.31	0.69	0.02	−0.11
Skew	−0.35	−0.68	−0.41	0.59	0.01
Kurt	10.89	14.38	10.84	33.28	10.19

(a) Without Transaction Costs

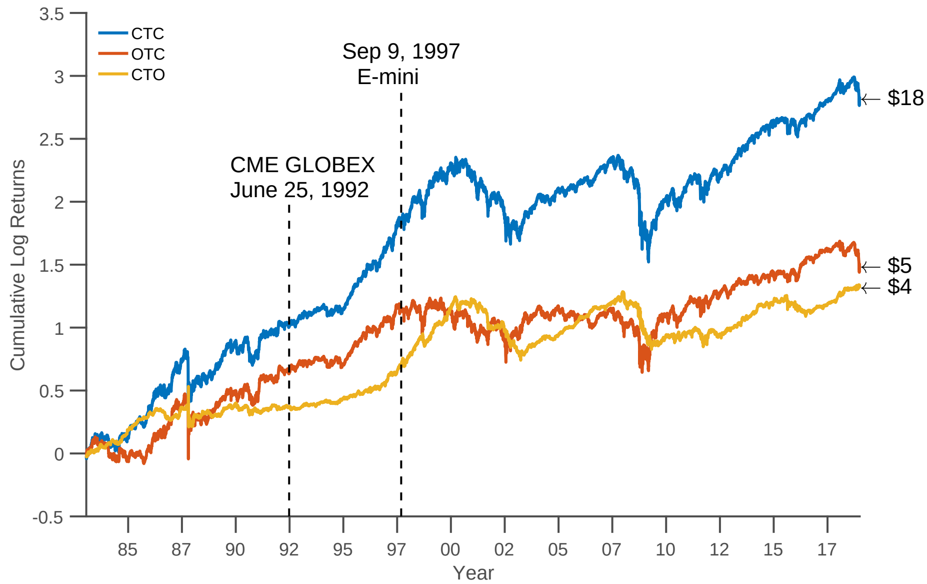
	CTO	OTC	OD	- OR
Mean	−2.87	−3.91	−3.32	−1.87
Sdev	10.22	16.07	2.35	6.18
Sharpe ratio	−0.41	−0.32	−1.96	−0.51
beta	0.29	0.71	0.02	−0.11
Skew	−0.61	−0.38	0.33	−0.05
Kurt	12.90	11.02	31.01	10.22

(b) With Transaction Costs

Table VIII. Trading Strategies

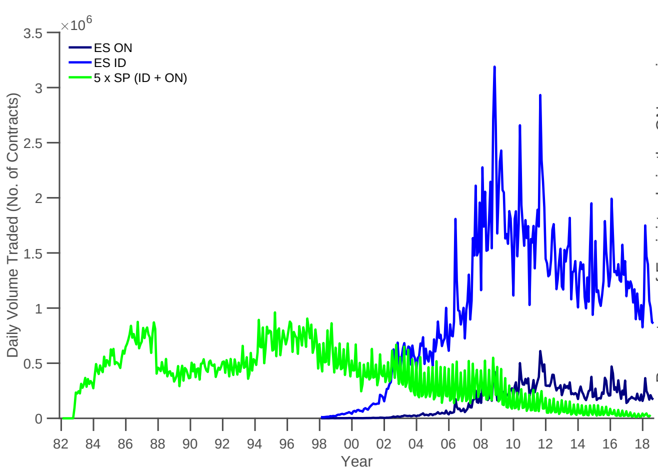
Summary statistics for various trading strategy returns excluding (panel a) and including (panel b) transaction costs. CTC is continuously holding the E-mini contract. CTO is holding the contract from 16:15 (4:15 p.m.) to 8:30, OTC is from 9:30 to 16:15 (4:15 p.m.), OD is the overnight drift from 02:00 to 03:00 and - OR is shortening the opening returns from 8:30 to 10:00. 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.

IX. Figures

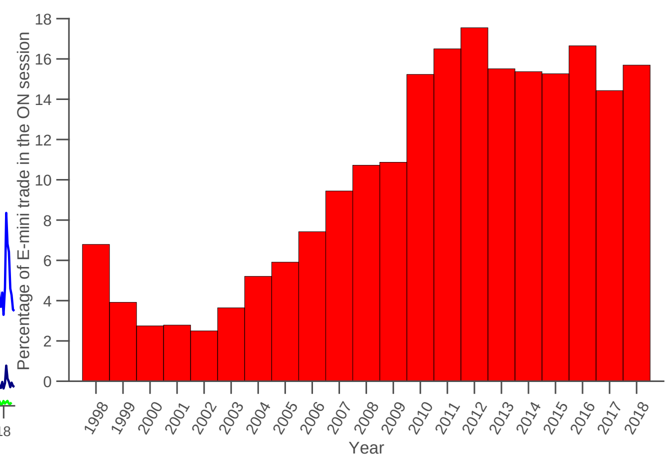


(a)

Figure 1. Time series of Returns for the S&P 500 futures contract
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.

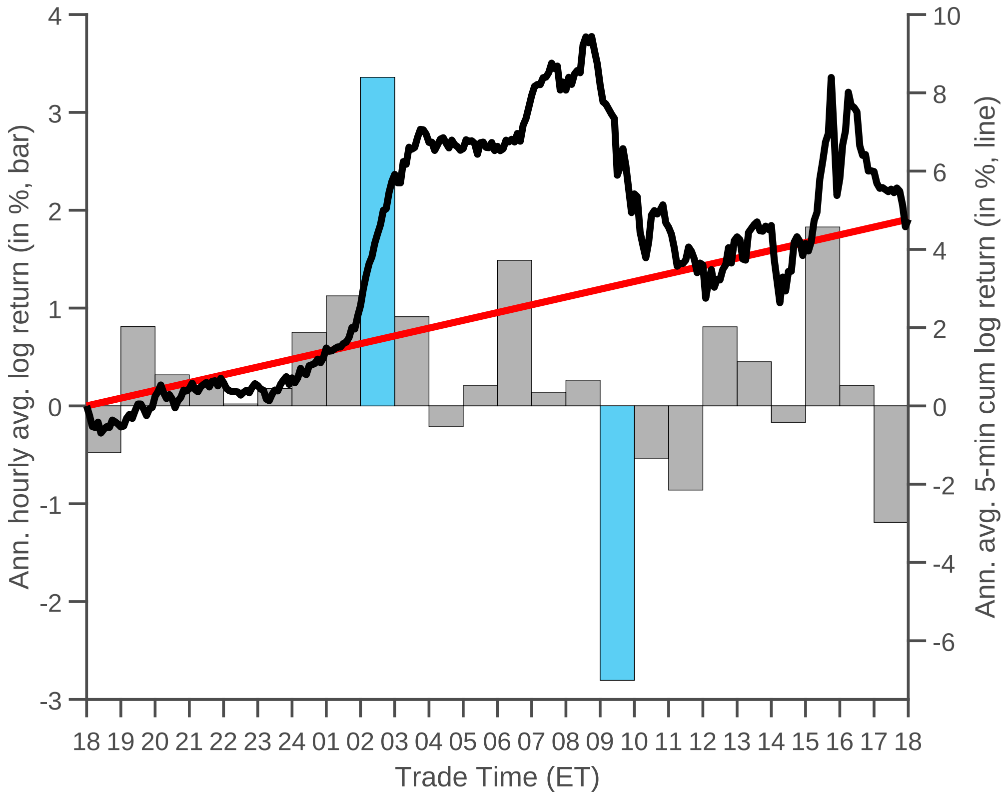


(a)

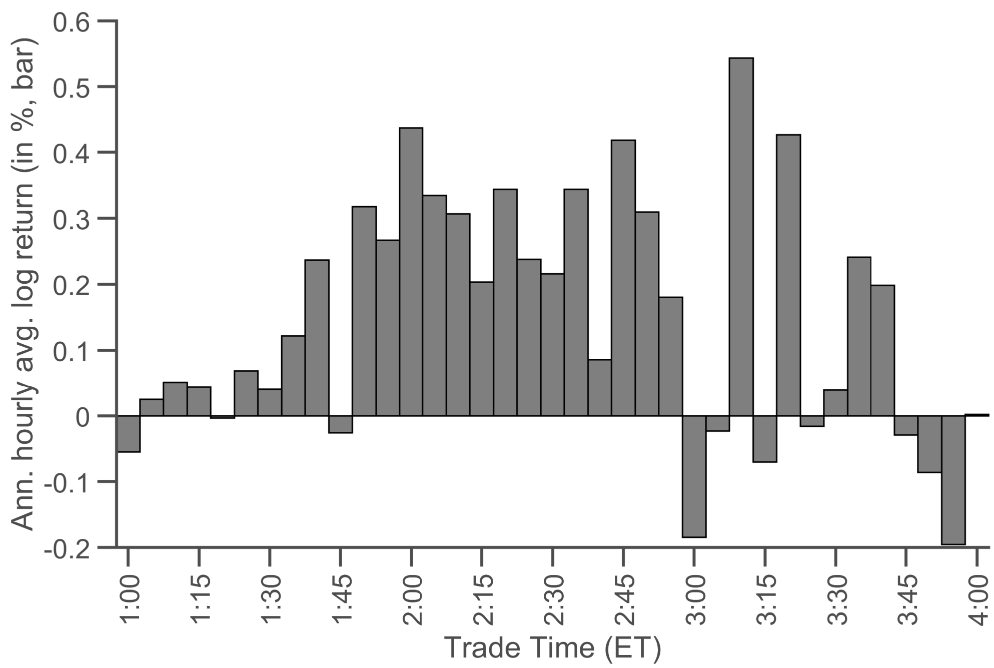


(b)

Figure 2. Overnight vs Intraday e-mini Volume Split
Panel (a) plots daily average 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.



(a)



(b)

Figure 3. Intraday Return Averages

Panel (a) 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 (b) plots average 5 minute returns for the hours 1.00-4.00 a.m. Estimates are annualized and displayed in percentage points.

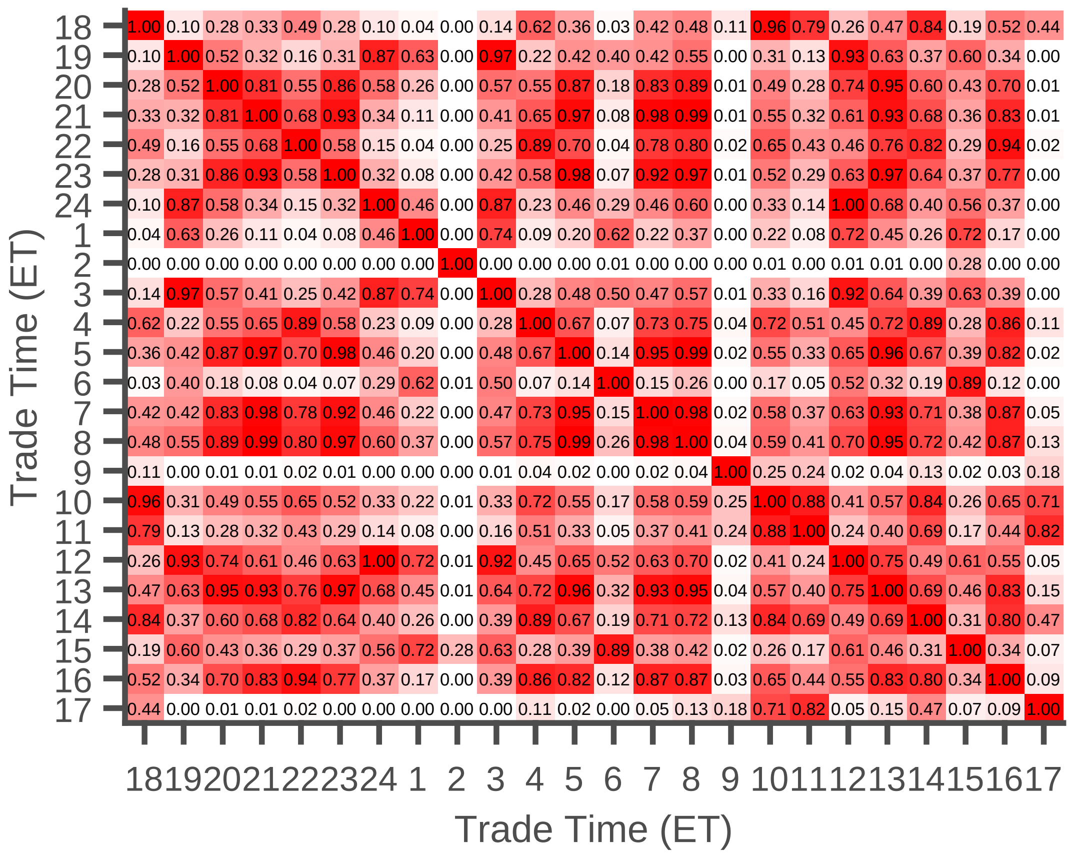


Figure 4. p-value heat map of hourly differences test

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 samee. Dark red values indicate p-values close to 1, indicating we cannot reject the null of equality. x and y labels indicate the hourly return intervals.

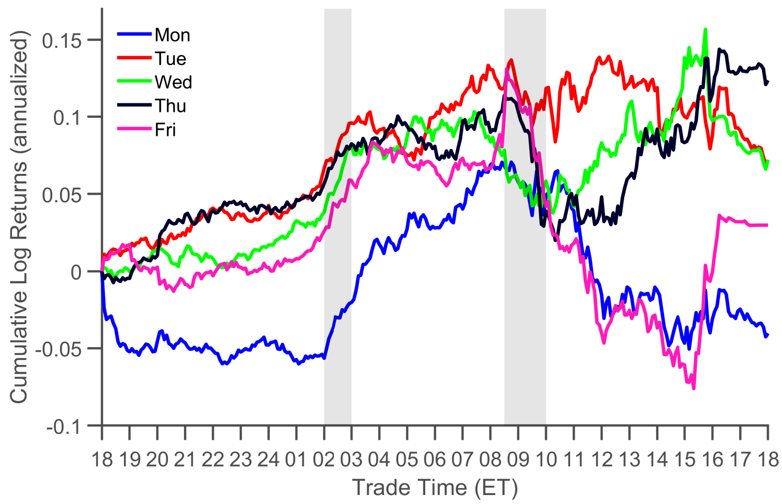


Figure 5. Day-of-Week Effects

Figure 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. Estimates are annualized and displayed in percentage points.

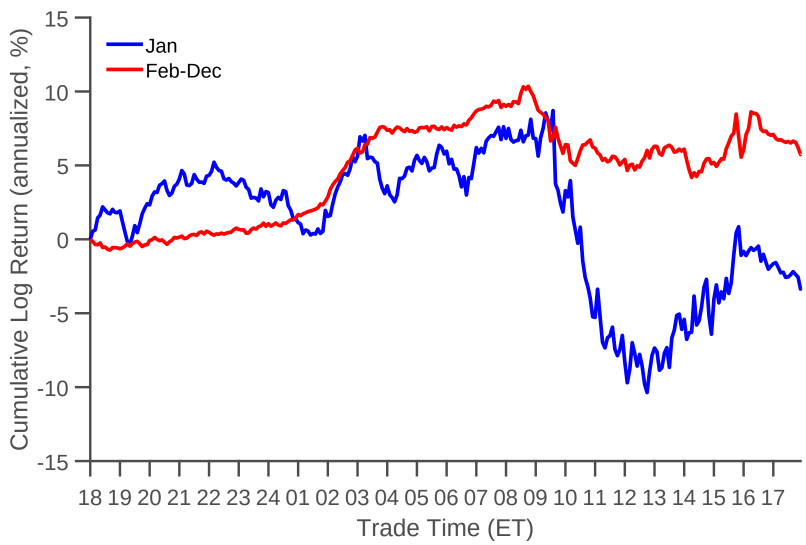


Figure 6. Monthly Effects

Figure displays the average cumulative 5-minute returns of the e-mini across the trading day, for January each year versus February-December each year. Estimates are annualized and displayed in percentage points.

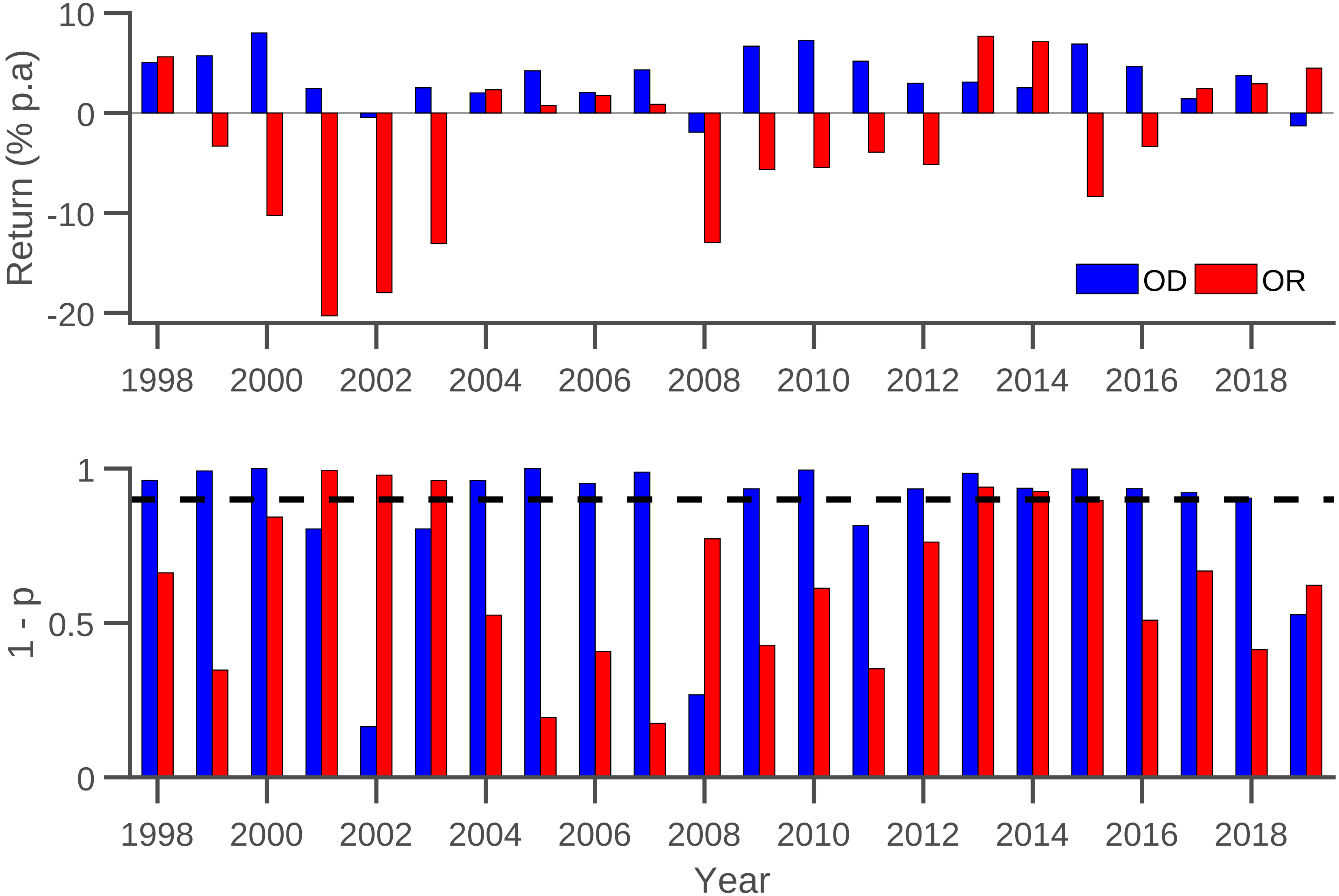
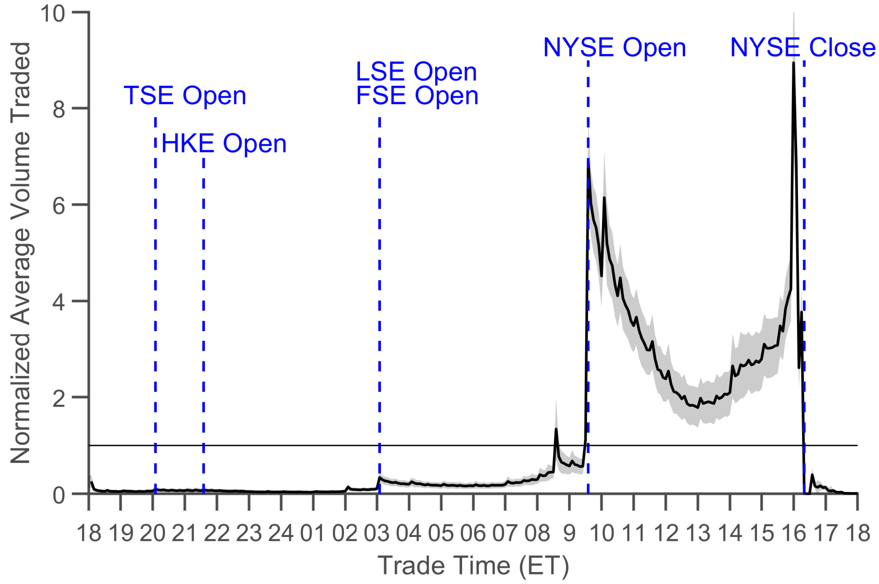
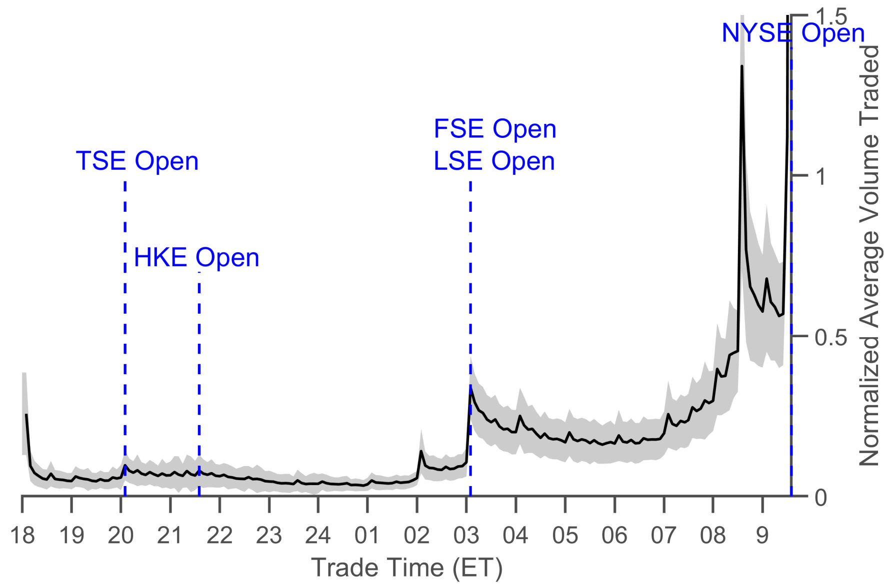


Figure 7. Subsample Analysis Effects

Panel (a) plots yearly returns of the e-mini contract for the OD and OR periods. Panel (b) plots the p-values of t-tests for the OD/OR returns versus the null hypothesis.



(a) Close-to-close



(b) Overnight

Figure 8. 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.

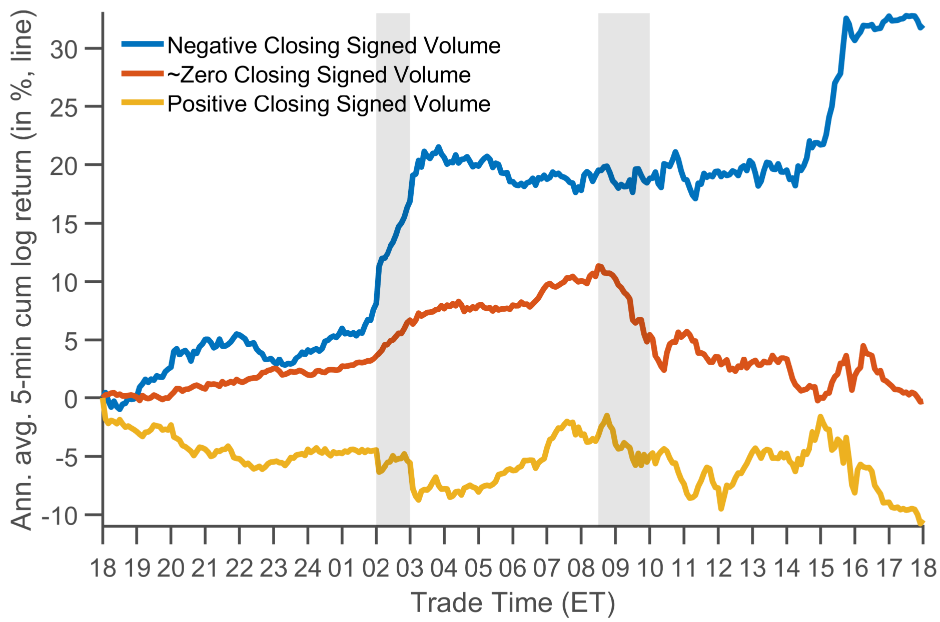


Figure 9. Sorting on Order Flow

Figure display average cumulative intraday returns sorted on the closing relative signed volume of the preceding trading day. Days with negative closing RSV are defined as the bottom 25% of RSV, ∼zero closing RSV is the middle 50% and positive closing RSV is the top 25%.

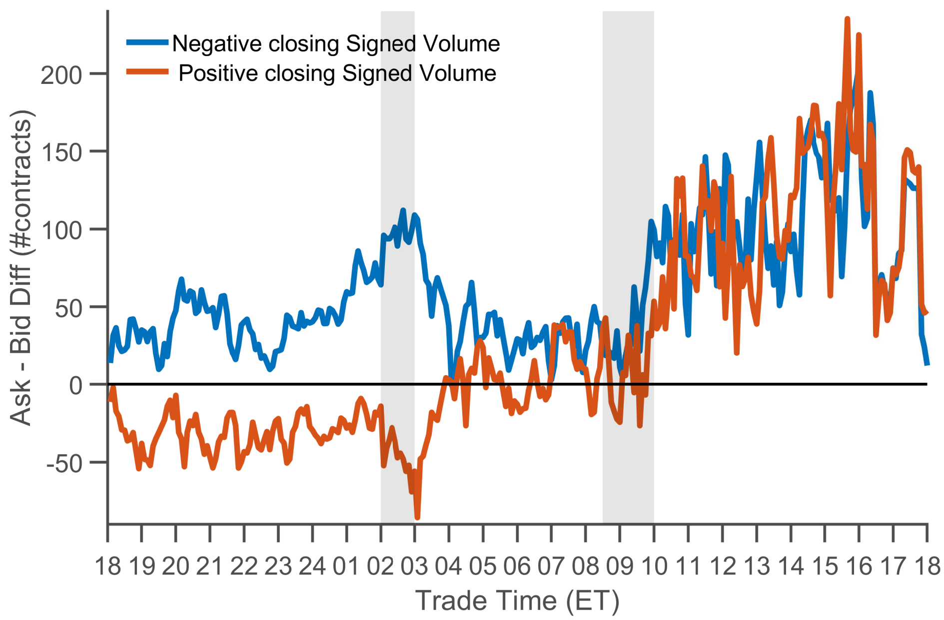
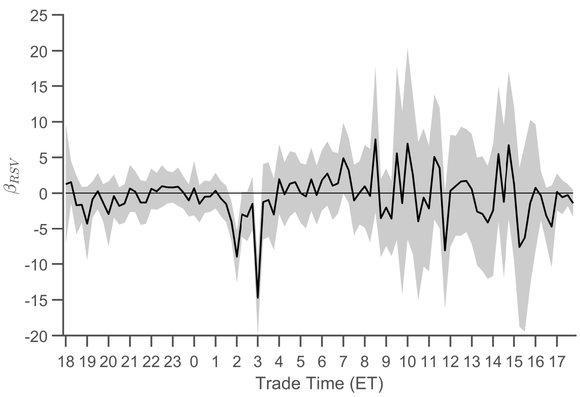
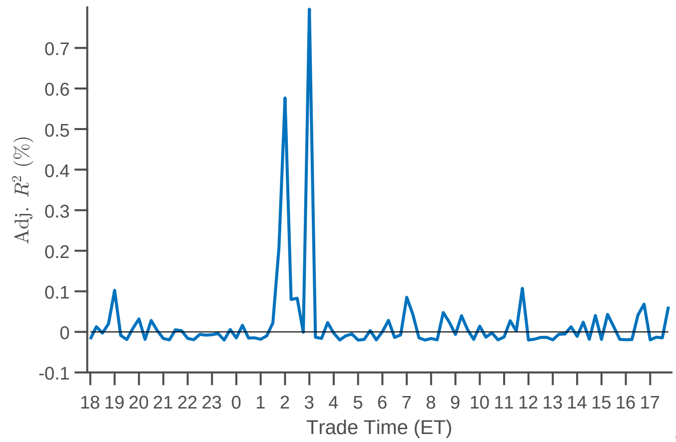


Figure 10. Ask Depth versus Bid Depth

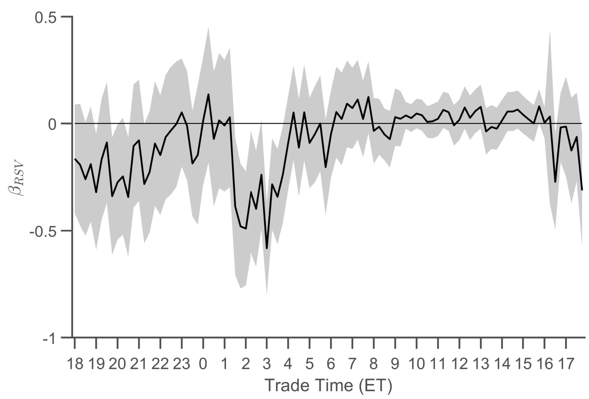
Figure displays the average difference in ask depth and bid depth for the first 4 levels of the order book. Trading days are sorted into groups based on the signed volume around U.S. close of the preceding trading day.



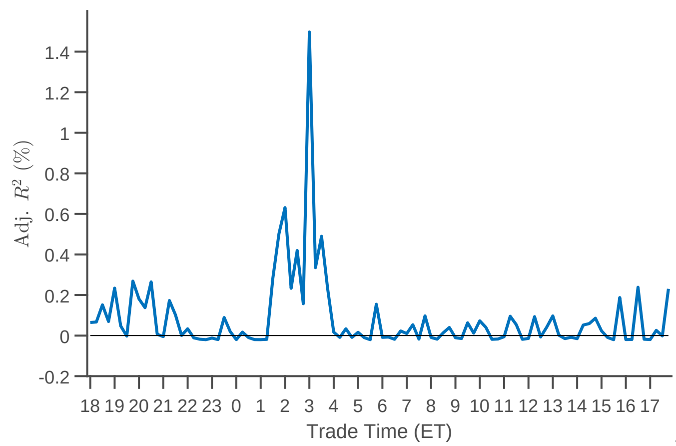
(a) β_n: $r^{96}_{t,n} = \mu_n + \beta_n RSV_{t-1,close} + \varepsilon_{t,n}$



(b) Adj. R^2: $r^{96}_{t,n} = \mu_n + \beta_n RSV_{t-1,close} + \varepsilon_{t,n}$



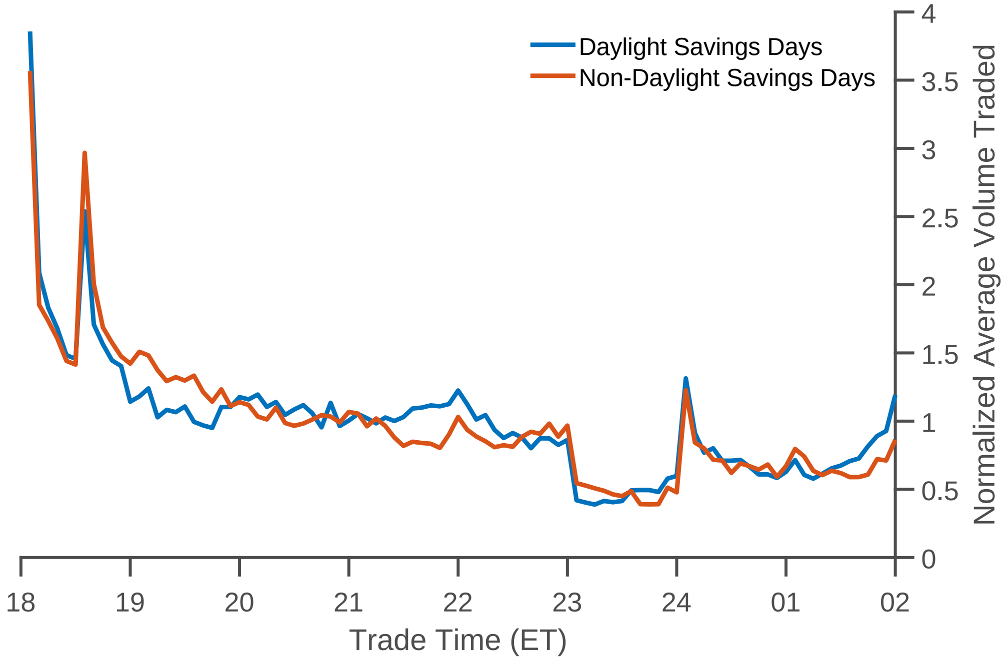
(c) β_n: $RSV^{96}_{t,n} = \mu_n + \beta_n RSV_{t-1,close} + \varepsilon_{t,n}$



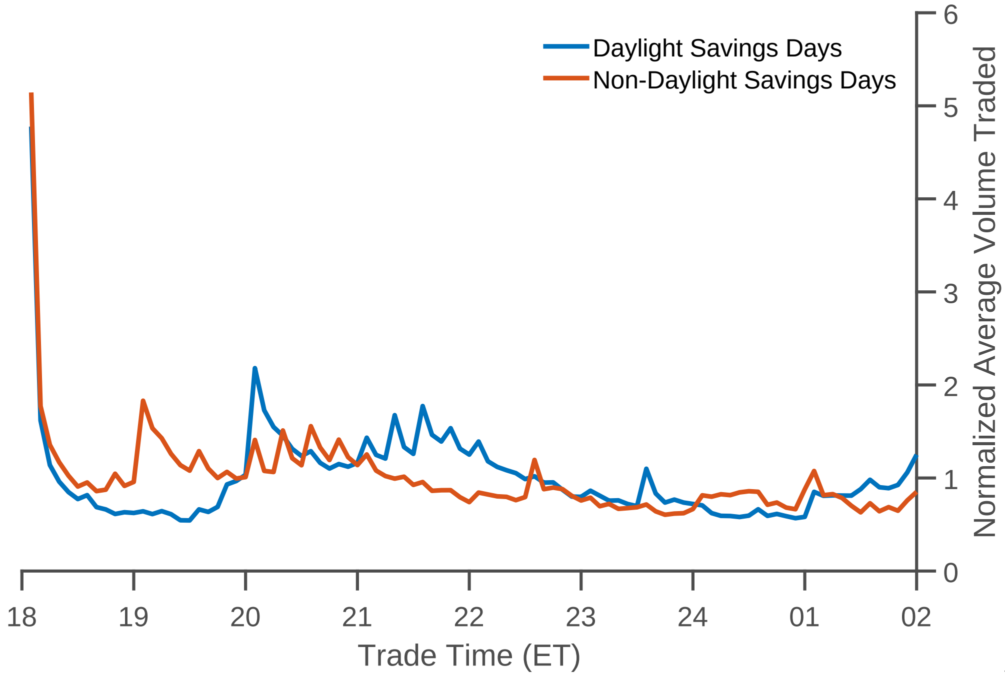
(d)
Adj. R^2: $RSV^{96}_{t,n} = \mu_n + \beta_n RSV_{t-1,close} + \varepsilon_{t,n}$

Figure 11. Regression Coefficients and Adj. R^2

Regression coefficients and adjusted R^2 of 15-by-15 minute returns(a)-(b) and 15-by-15 relative signed volume regressed on closing relative signed volume of the preceding trading day.



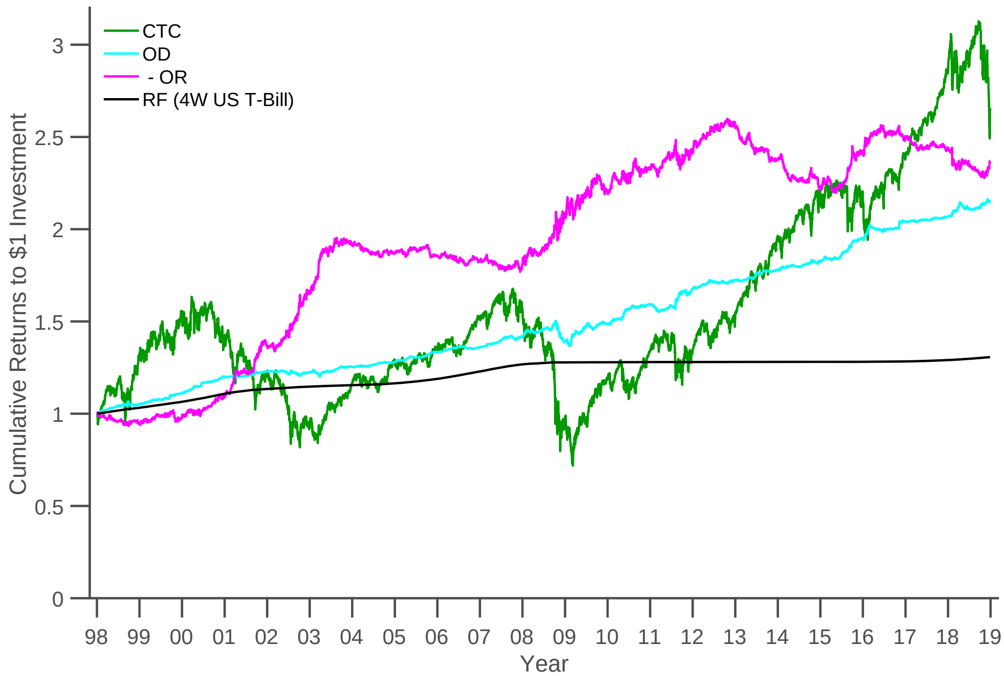
(a) 1997-2009



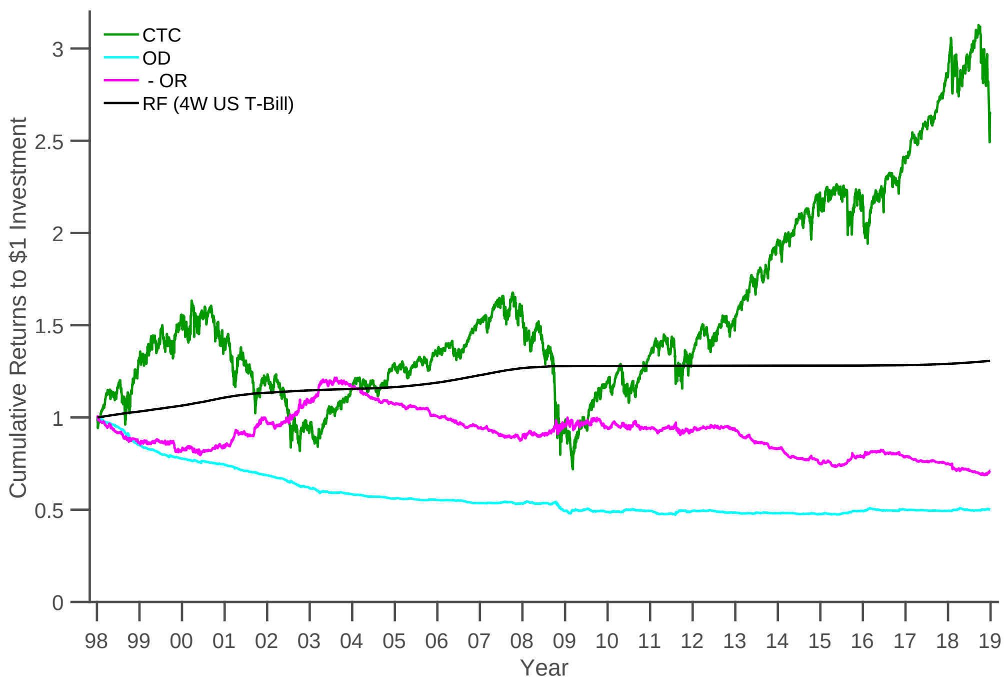
(b) 2010-2019

Figure 12. 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 active (not active). All volumes are computed as averages of the 5 minute volume relative to the total daily volume.



(a) Without Transaction Costs



(b) With Transaction Costs

Figure 13. Total Returns with and without Transaction Costs

Figure displays time series of cumulative returns for a one dollar investment without (panel a) and with (panel b) transaction costs of various trading strategies for the e-mini contract. CTC is continuously holding the e-mini contract. OD is the strongest part of the overnight drift from 02:00 to 03:00 and - OR is shortening the opening returns from 8:30 to 10:00. 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.

X. Online Appendix

Not Intended for Publication

A. *Opening Times*

Abbreviation	Name	Open	Close	Time difference	ES open	ES close
NZSX**	New Zealand	10:00	17:00	16	18:00	01:00
TSE*	Tokyo	09:00	15:00	13	20:00	02:00
ASX**	Australia	10:00	16:00	14	20:00	02:00
SGX*	Singapore	09:00	17:00	12	21:00	05:00
SSE*	Shanghai	09:15	15:00	12	21:15	03:00
HKE*	Hong Kong	09:30	16:00	12	21:30	04:00
NSE*	India	09:00	15:30	10	23:00	05:30
DIFX*	Dubai	10:00	14:00	8	02:00	06:00
RTS*	Russia	09:30	19:00	7	02:30	14:00
FWB	Frankfurt	08:00	20:00	6	02:00	14:00
JSE*	South Africa	08:30	17:00	6	02:30	11:00
LSE	London	08:00	16:30	5	03:00	11:30
BMF**	Sao Paulo	10:00	17:00	1	09:00	16:00
NYSE	New York	09:30	16:00	0	09:30	16:00
TSX	Toronto	09:30	16:00	0	09:30	16:00

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.

B. *Announcements*

A large literature has presented evidence that conditional risk premia are higher on days prior to and on days of macroeconomic announcements. The basic idea is that risk-averse investors who are exposed to scheduled news releases demand higher expected returns in equilibrium. This is because even though investors know information will be released, they do not know what the sign of the shock will be. In the context of stock returns, Savor and Wilson (2014) examine this prediction for U.S. inflation, GDP and non-farm payroll announcements, and document consistently larger risk premia on these announcement days for holding the U.S. stock market. Lucca and Moench

(2015), on the other hand, document a drift in the U.S. stock market which precedes FOMC announcements. Aside from the magnitude, this finding is surprising in that returns are earned in the 24 hours prior to the announcement, which is contrary to the prediction of time-separable expected utility theory. For a recent non-expected utility explanation, we refer the reader to Ai and Bansal (2018).

Motivated by the announcement literature, we examine both pre- and post-announcement returns for our intraday fixing splits for U.S., European, U.K. and Japanese macro- and central bank announcements.

MACRO ANNOUNCEMENTS: From Bloomberg's Economic Calendar we collect dates and times for

- U.S.: (*i*) Non-farm Payrolls; (*ii*) PPI; (*iii*) CPI Ex Food and Energy; (*iv*) GDP.
- Eurozone: (*i*) Employment; (*ii*) CPI Ex Food and Energy; (*iii*) GDP.
- U.K: (*i*) Employment; (*ii*) CPI Ex Food and Energy; (*iii*) GDP.
- Japan: (*i*) Jobless Rate; (*ii*) CPI Ex Food and Energy; (*iii*) GDP.

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.

CENTRAL BANK ANNOUNCEMENTS: 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.

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

$$ret_{t,n} = a^n + b_1^n \mathbb{1}_{\text{U.K.}} + b_2^n \mathbb{1}_{\text{EU}} + b_3^n \mathbb{1}_{\text{JP}} + b_4^n \mathbb{1}_{\text{U.S.}} + \varepsilon_t^n \qquad \text{(A.1)}$$

where $\mathbb{1}_i$ is a macro or central bank announcement dummy for country i. Table A.2 reports estimates for macro announcements and table A.3 reports estimates for central bank announcements.

[Insert table A.2 and table A.3 here]

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 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[13]. We define the daily earnings surprice of the S&P 500 index, $ES_t^{S\&P500}$, as the sum of all ES_i on day t[14].

Figure A.3 plots the time series of $ES_t^{S\&P500}$. 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. Given the periodicity of the shocks and that they are generally positive, we would have picked up a potential earnings effect when sorting returns by month of the year (see tableIV).

To test if shocks in earnings announcements predict intraday returns, we sort all trading days based on $ES_t^{S\&P500}$. We choose to only consider announcements that are published after U.S. close (16:00, 4 p.m. ET). This is because the effect of announcements published early in the day is incorporated into the price on that day (and these announcements occur after the CTO hours of trading so they only affect OTC hours). Table A.4 reports the average returns for day $t+1$ after sorting on $ES_t^{S\&P500}$. We have 5 sets of days. In the first, $ES_t^{S\&P500} < 0$. $ES_t^{S\&P500} > 0$ and increasing for the next 3 sets. The fifth is for days where $ES_t^{S\&P500}$ 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. The overnight drift is not driven by earnings announcements as it is positive and significantly different from zero for all 5 set of days.

[Insert figure A.3 and table A.4 here]

[13] EPS is earnings per share outstanding, implying that EPS/P is earnings per market cap.

[14] We also test specifications of $ES_t^{S\&P500}$ where firms are value weighted and result are similar.

XI. OA: Tables

	18	19	20	21	22	23	24	01	02	03	04	05	06	07	08
μ	-1.02	1.43	0.53	0.18	0.21	0.17	0.73	0.82	3.71	1.09	-0.66	0.13	1.83	0.18	-0.96
	(-1.06)	(2.67)	(0.84)	(0.35)	(0.44)	(0.44)	(1.66)	(1.88)	(6.19)	(1.27)	(-0.86)	(0.19)	(2.63)	(0.23)	(-0.97)
$\mathbf{1}_{UK}$	0.95	1.63	-2.90	-1.77	-1.54	0.14	-0.48	-0.98	-2.02	-6.35	2.04	2.70	-1.98	1.60	1.62
	(0.54)	(0.00)	(-1.58)	(-1.28)	(-1.18)	(0.13)	(-0.46)	(-0.67)	(-1.01)	(-2.74)	(0.88)	(1.53)	(-0.99)	(0.81)	(0.58)
$\mathbf{1}_{EU}$	-1.65	-3.31	1.02	-3.37	-3.89	2.06	-0.81	2.92	-0.34	1.99	2.92	-3.56	-0.70	-3.05	-0.76
	(-0.64)	(-1.18)	(0.26)	(-1.97)	(-1.75)	(1.03)	(-0.49)	(1.73)	(-0.15)	(0.53)	(1.09)	(-1.21)	(-0.26)	(-1.01)	(-0.17)
$\mathbf{1}_{JP}$	-0.80	-2.93	5.06	-0.15	1.12	-0.29	0.70	-0.23	-0.36	-0.23	-1.77	1.36	-4.26	0.68	-2.06
	(-0.28)	(-1.98)	(2.15)	(-0.09)	(0.54)	(-0.16)	(0.41)	(-0.13)	(-0.16)	(-0.08)	(-0.69)	(0.58)	(-1.77)	(0.25)	(-0.47)
$\mathbf{1}_{US}$	2.77	-2.45	-1.46	0.56	-0.65	0.16	0.65	1.02	0.82	1.02	0.80	-0.66	0.46	-0.55	6.40
	(2.24)	(-1.85)	(-1.00)	(0.53)	(-0.53)	(0.19)	(0.65)	(1.03)	(0.68)	(0.53)	(0.51)	(-0.44)	(0.29)	(-0.33)	(1.78)

(a) Overnight hourly returns

	09	10	11	12	13	14	15	16	17
μ	-3.39	-0.09	-3.13	0.48	-0.29	-0.80	1.33	-0.42	-1.25
	(-2.44)	(-0.05)	(-2.38)	(0.42)	(-0.23)	(-0.54)	(0.63)	(-0.52)	(-3.31)
$\mathbf{1}_{UK}$	1.43	1.14	12.21	-1.11	3.78	5.32	4.06	2.49	0.68
	(0.34)	(0.26)	(3.60)	(-0.37)	(1.12)	(1.13)	(0.79)	(1.12)	(0.76)
$\mathbf{1}_{EU}$	9.74	0.84	-7.04	1.94	-0.27	7.20	-2.24	-2.63	-1.15
	(1.68)	(0.12)	(-1.52)	(0.46)	(-0.05)	(1.15)	(-0.27)	(-0.76)	(-0.51)
$\mathbf{1}_{JP}$	5.01	0.06	2.29	-3.88	3.68	-3.50	-13.22	0.21	0.10
	(1.01)	(0.01)	(0.48)	(-0.98)	(0.88)	(-0.71)	(-1.84)	(0.07)	(0.15)
$\mathbf{1}_{US}$	-2.83	-5.18	6.90	2.41	-0.77	-0.93	3.17	1.88	0.63
	(-0.83)	(-1.29)	(2.19)	(0.87)	(-0.29)	(-0.27)	(0.72)	(0.91)	(0.91)

(b) Intraday hourly returns

Table A.2. Macro 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

$$ret_{t,n} = a^n + b_1^n \mathbb{1}_{\text{U.K.}} + b_2^n \mathbb{1}_{\text{EU}} + b_3^n \mathbb{1}_{\text{JP}} + b_4^n \mathbb{1}_{\text{U.S.}} + \varepsilon_t^n$$

where $\mathbb{1}_i$ is an employment, GBP or inflation announcement dummy for country i, as discussed in the main body of the online appendix.

	18	19	20	21	22	23	24	01	02	03	04	05	06	07	08
μ	-0.62	0.15	-0.38	-0.28	-0.24	0.17	0.62	1.18	3.39	0.92	-0.70	0.32	1.22	0.33	0.68
	(-0.72)	(0.32)	(-0.62)	(-0.60)	(-0.50)	(0.46)	(1.56)	(2.86)	(6.11)	(1.14)	(-0.97)	(0.50)	(1.89)	(0.47)	(0.65)
$\mathbf{1}_{BoE}$	0.53	6.64	2.40	0.99	1.57	0.34	1.12	-2.56	1.17	-0.03	-0.40	-0.99	0.07	-4.82	-0.16
	(0.27)	(3.31)	(1.06)	(0.57)	(1.27)	(0.35)	(0.93)	(-2.22)	(0.70)	(-0.01)	(-0.18)	(-0.52)	(0.03)	(-1.85)	(-0.05)
$\mathbf{1}_{ECB}$	1.08	-2.19	4.04	-0.11	1.35	-2.32	-1.28	-1.86	-1.48	0.01	5.75	-1.15	4.41	6.68	-10.93
	(0.60)	(-0.95)	(1.01)	(-0.06)	(0.86)	(-1.81)	(-0.76)	(-1.16)	(-0.75)	(0.00)	(1.78)	(-0.41)	(1.76)	(1.37)	(-1.66)
$\mathbf{1}_{BoJ}$	-0.48	0.38	2.18	4.45	-0.22	2.23	1.58	-0.15	0.41	-1.33	1.55	-1.29	-0.41	-3.04	4.47
	(-0.11)	(0.12)	(1.01)	(2.19)	(-0.13)	(1.24)	(0.72)	(-0.08)	(0.17)	(-0.41)	(0.53)	(-0.56)	(-0.13)	(-1.31)	(0.94)
$\mathbf{1}_{FOMC}$	-0.23	2.44	2.21	-2.18	-2.67	1.42	0.77	3.90	3.45	-1.31	1.76	1.02	1.49	1.84	-3.67
	(-0.07)	(1.32)	(1.11)	(-1.16)	(-1.42)	(0.93)	(0.38)	(1.96)	(1.17)	(-0.42)	(0.62)	(0.36)	(0.46)	(0.71)	(-1.07)

(a) Overnight hourly returns

	09	10	11	12	13	14	15	16	17
μ	-3.03	-1.36	-1.28	1.08	0.28	-0.89	1.30	0.18	-1.12
	(-2.28)	(-0.85)	(-1.02)	(0.98)	(0.25)	(-0.66)	(0.69)	(0.23)	(-3.24)
$\mathbf{1}_{BoE}$	1.27	-2.08	6.05	-6.23	-8.43	-2.74	-0.87	-0.53	0.85
	(0.31)	(-0.40)	(1.47)	(-1.89)	(-2.18)	(-0.53)	(-0.16)	(-0.23)	(0.74)
$\mathbf{1}_{ECB}$	-5.07	7.64	-8.21	0.89	8.41	0.46	-0.48	2.07	0.22
	(-0.59)	(0.93)	(-1.52)	(0.20)	(1.46)	(0.07)	(-0.06)	(0.56)	(0.14)
$\mathbf{1}_{BoJ}$	-2.96	-4.97	-6.51	0.26	-1.06	2.73	11.19	-3.48	-0.32
	(-0.46)	(-0.82)	(-1.30)	(0.06)	(-0.19)	(0.48)	(1.20)	(-1.03)	(-0.29)
$\mathbf{1}_{FOMC}$	4.89	11.26	8.40	3.31	4.90	12.50	-5.45	-0.01	-1.55
	(0.79)	(1.80)	(1.80)	(0.86)	(0.93)	(1.37)	(-0.51)	(-0.00)	(-1.01)

(b) Intraday hourly returns

Table A.3. Central Bank 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

$$ret_{t,n} = a^n + b_1^n \mathbb{1}_{\text{U.K.}} + b_2^n \mathbb{1}_{\text{EU}} + b_3^n \mathbb{1}_{\text{JP}} + b_4^n \mathbb{1}_{\text{U.S.}} + \varepsilon_t^n$$

where $\mathbb{1}_i$ is a central bank announcement dummy for country i, as discussed in the main body of the online appendix.

	CTC	CTO	OTC	OD	OR
NEG	-18.05	-2.74	-15.68	3.68	-6.55
	(0.20)	(0.70)	(0.16)	(0.04)	(0.10)
POS-LOW	-1.05	-0.87	-0.18	4.07	-8.38
	(0.92)	(0.89)	(0.98)	(0.00)	(0.02)
POS-MEDIUM	2.32	-1.33	3.52	4.55	-0.32
	(0.84)	(0.82)	(0.72)	(0.00)	(0.93)
POS-HIGH	8.97	9.57	-0.60	3.05	-4.38
	(0.38)	(0.08)	(0.94)	(0.01)	(0.19)
No Announcements	12.51	5.87	6.34	3.40	-3.08
	(0.04)	(0.08)	(0.21)	(0.00)	(0.12)

(a) Overnight hourly returns

Table A.4. Earnings Announcements

We sort evening earnings announcements into negative, positive low/medium/high days, and non-announcement days. Within each sort we compute close-to-close (CTC), close-to-open (CTO), open-to-close (OTC), overnight drift (OD) and opening return (OR) returns and report means and t-tests of the difference against zero in parenthesis. Further details are discussed in the main body on the online appendix.

	00:00-15	00:15-30	00:30-45	00:45-00	01:00-15	01:15-30	01:30-45	01:45-00	02:00-15	02:15-30	02:30-45	02:45-00
β_{RSV}	0.43	-0.72	-1.03	-0.44	-0.55	-0.25	0.43	-3.78	-10.17	-1.51	-4.10	-3.58
	(0.16)	(-0.60)	(-0.86)	(-0.36)	(-0.41)	(-0.23)	(0.34)	(-2.61)	(-5.23)	(-0.84)	(-2.22)	(-1.98)
β_{DST}	0.00	-0.01	0.13	0.11	-0.02	0.05	0.12	0.19	0.51	0.24	0.25	0.52
	(0.01)	(-0.09)	(1.60)	(1.43)	(-0.19)	(0.55)	(1.29)	(1.84)	(3.83)	(2.14)	(2.04)	(3.81)
$\beta_{RSV\times DST}$	0.06	-0.99	0.69	0.35	1.77	-0.99	-2.83	-0.38	2.06	-1.58	1.91	3.48
	(0.02)	(-0.56)	(0.43)	(0.23)	(0.99)	(-0.60)	(-1.61)	(-0.20)	(0.80)	(-0.68)	(0.78)	(1.35)
adj R^2 (%)	-0.06	-0.01	0.00	-0.05	-0.02	-0.02	-0.04	0.08	0.49	-0.11	0.01	0.06

	03:00-15	03:15-30	03:30-45	03:45-00	04:00-15	04:15-30	04:30-45	04:45-00	05:00-15	05:15-30	05:30-45	05:45-00
β_{RSV}	-13.84	-4.01	2.94	0.83	2.65	-0.70	1.64	-0.58	-1.27	-1.69	4.89	0.82
	(-5.23)	(-1.57)	(1.13)	(0.35)	(1.08)	(-0.31)	(0.69)	(-0.27)	(-0.56)	(-0.69)	(2.10)	(0.38)
β_{DST}	-0.12	0.21	0.25	-0.13	-0.05	-0.31	0.11	-0.17	0.20	-0.14	-0.11	0.11
	(-0.62)	(1.12)	(1.36)	(-0.74)	(-0.24)	(-1.88)	(0.73)	(-1.06)	(1.37)	(-0.99)	(-0.72)	(0.78)
$\beta_{RSV\times DST}$	0.49	4.90	-4.52	-5.50	-2.47	0.58	-0.36	2.87	0.99	1.87	-5.35	-1.20
	(0.14)	(1.36)	(-1.25)	(-1.63)	(-0.71)	(0.19)	(-0.11)	(0.98)	(0.33)	(0.58)	(-1.74)	(-0.41)
adj R^2 (%)	0.62	0.00	-0.01	0.02	-0.02	0.04	-0.01	0.00	-0.01	-0.01	0.03	-0.02

(b)

Table A.5. Natural Experiments: European Hours.

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

$$r_{t,n}^{96} = \mu_n + \beta_n^{RSV} RSV_{t-1,close} + \beta_n^{DST} \mathbb{1}_{DST,t} + \beta_n^{RSV\times DST} RSV_{t-1,close} \times \mathbb{1}_{DST,t} + \varepsilon_{t,n} \quad n = 1, \ldots, 24$$

where the dummy variable takes on a value of 1 in summer time (DST active) and 0 in winter time (DST not active) and daylight savings is seen from a U.S. perspective. Estimates are in basis points. t-statistics reported in parenthesis are computed from HAC robust standard errors.

XII. OA: Figures

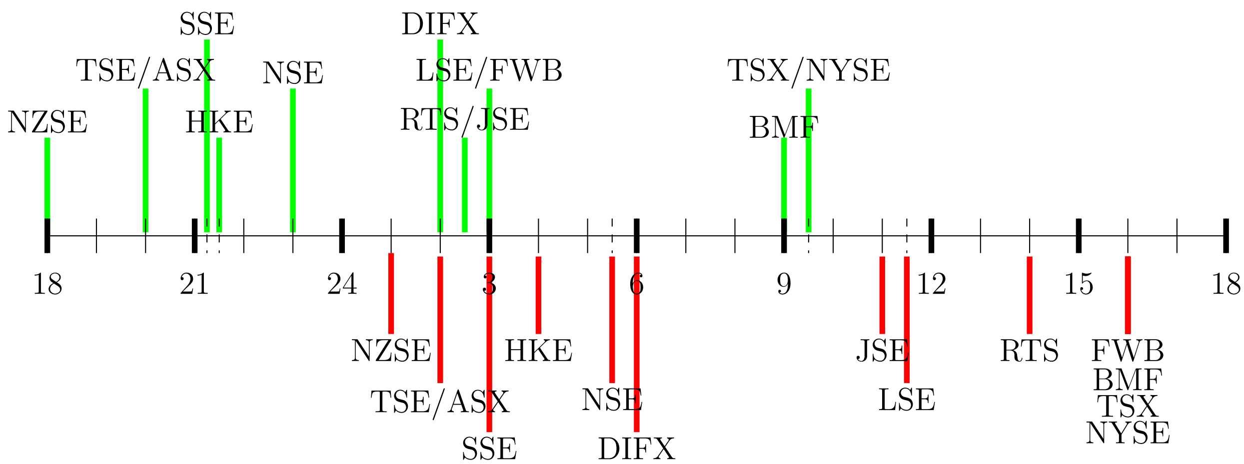
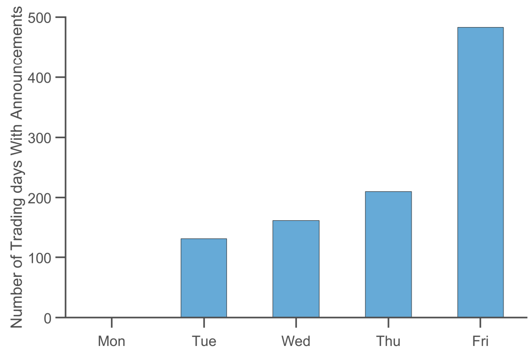
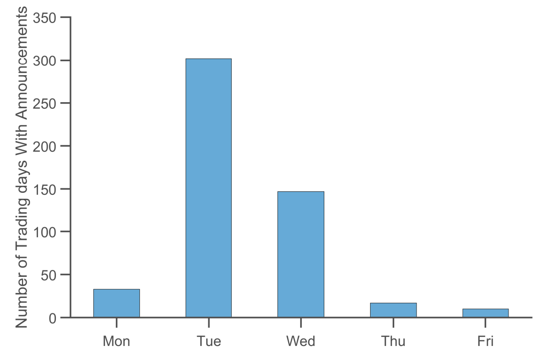


Figure A.1. Global Equity Market Trading Hours

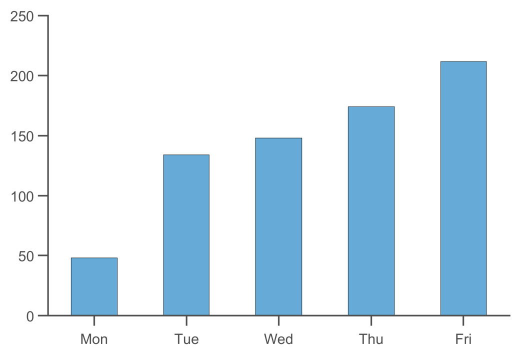
Figure displays opening and closing times for 14 global equity markets in June 2019. Green bars indicate opening times and red bars indicate closing times. The abbreviations are NYSE=New York Stock Exchange,TSE=Tokyo Stock Exchange, LSE=London Stock Exchange, HKE=Hong Kong Stock Exchange,NSE=National Stock Exchange of India , BMF=Bovespa Bolsa de Valores Mercadorias & Futuros de Sao Paulo,ASX=Australian Securities Exchange, FWB=Frankfurt Stock Exchange Deutsche Borse, RTS=Russian Trading System, JSE=Johannesburg Stock Exchange, DIFX=NASDAQ Dubai, SSE=Shanghai Stock Exchange, NZSX=New Zealand Stock Exchange, TSX=Toronto Stock Exchange. Opening and closing times are collected from the public websites of the exchanges and reported in Eastern Standard Time (ES). Several of the opening times shift by one or two hours when U.S. DST is not active (see table A.1 for details).



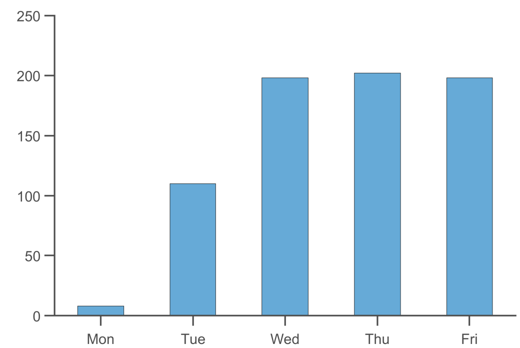
(a) U.S. Macro Announcements



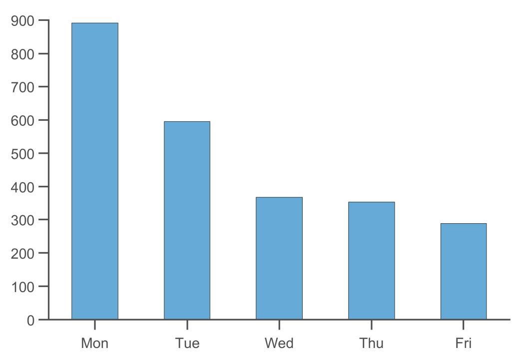
(b) FOMC Announcements



(c)
Negative U.S. Earnings Announcements



(d)
Positive U.S. Earnings Announcements



(e) Days
with no U.S. Earnings Announcements

Figure A.2. Announcements per Weekday
Figure displays the number of trading days with announcements for each day of the Week.

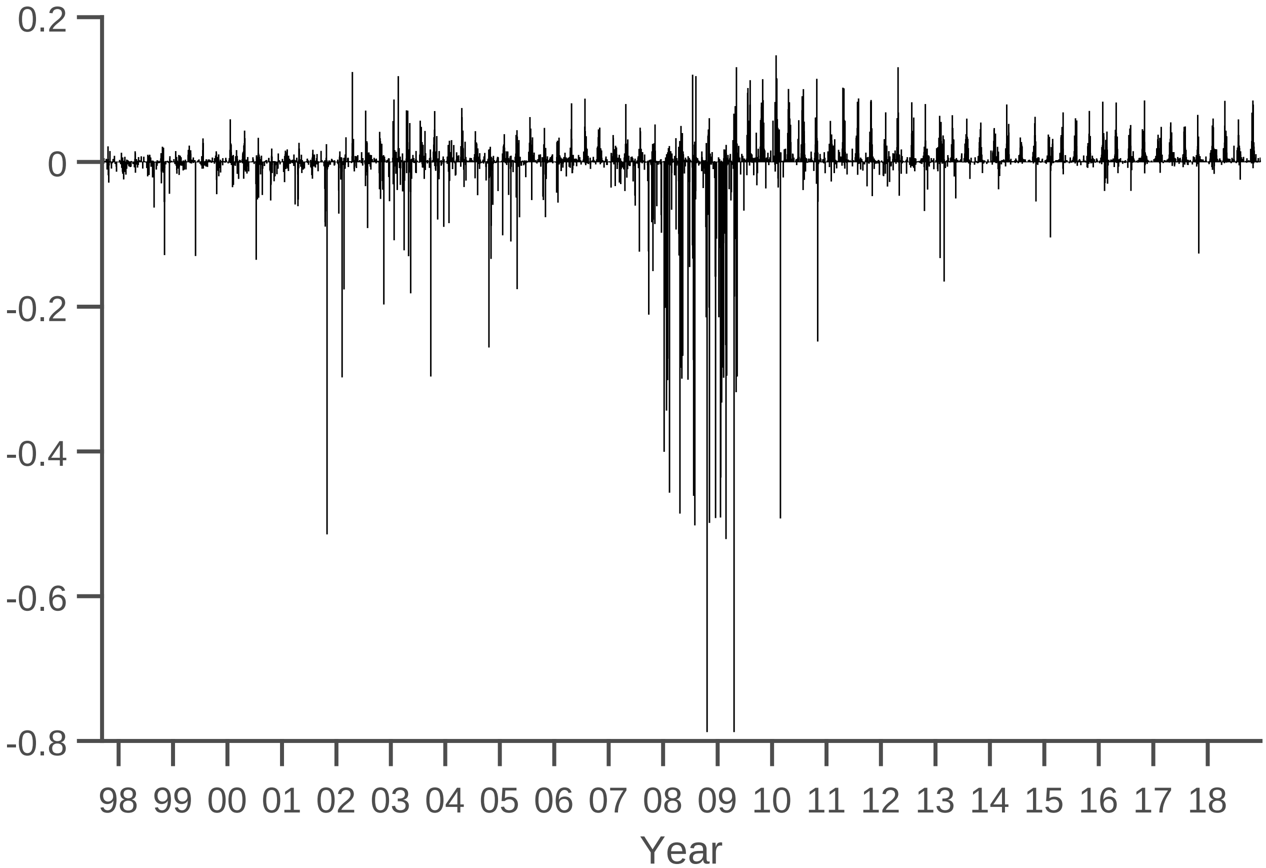
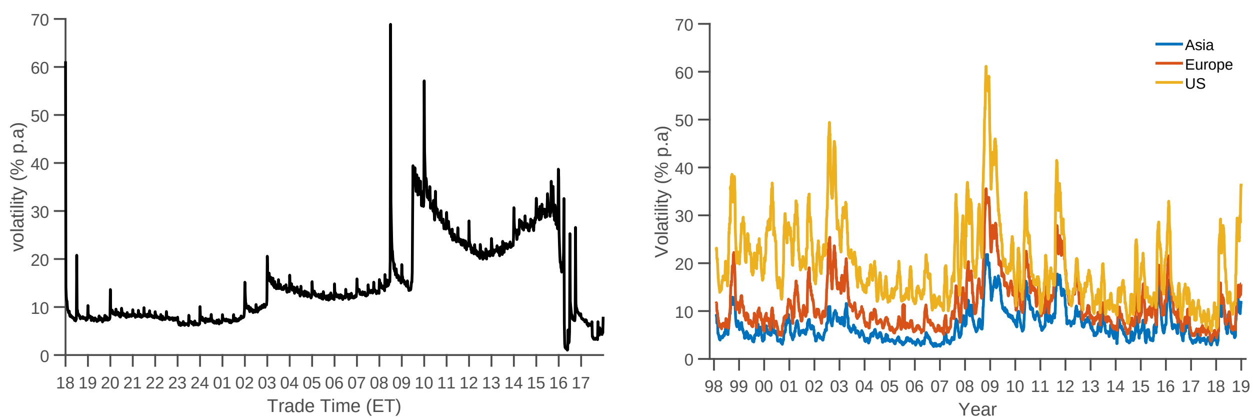


Figure A.3. SUE score

Figure displays the SUE score for the S&P 500 index.

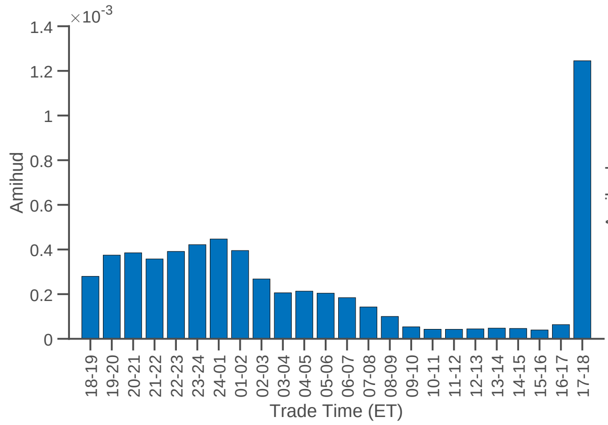


(a) Average intraday volatilty

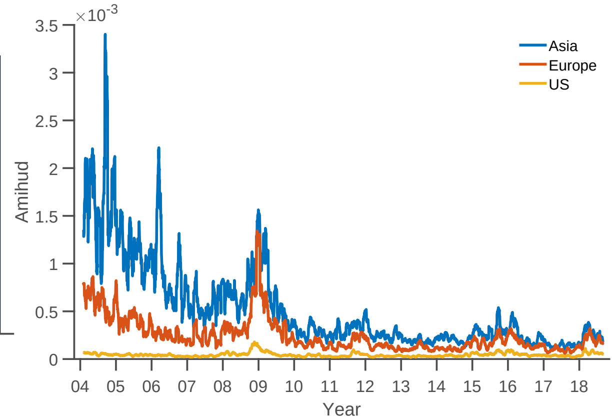
(b) Volatility, 1998 - 2018

Figure A.4. Realised Volatility

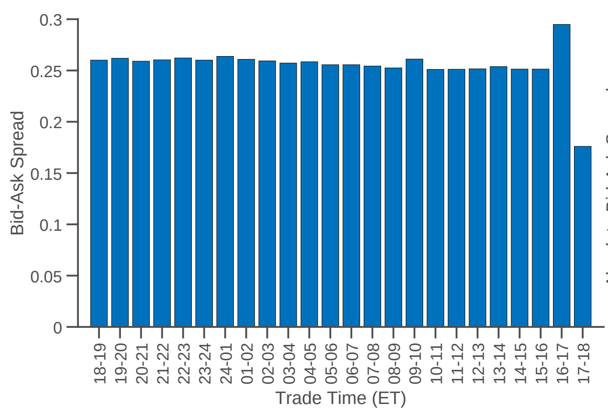
Figure displays the average intraday realized volatility of the E-mini as well as time series of the realized volatility for the Asian, European and U.S. trading hours. The volatility is annualized and displayed in percentage points.



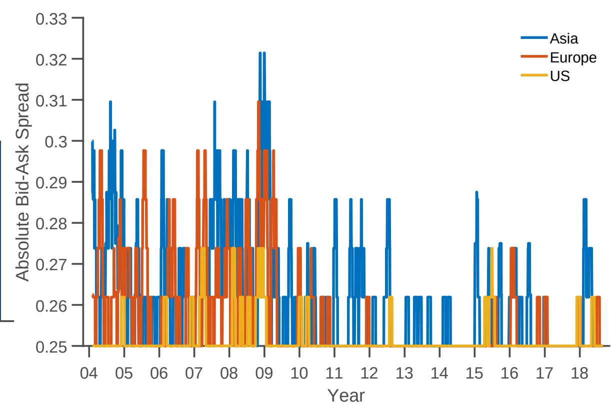
(a) Average intraday Amihud



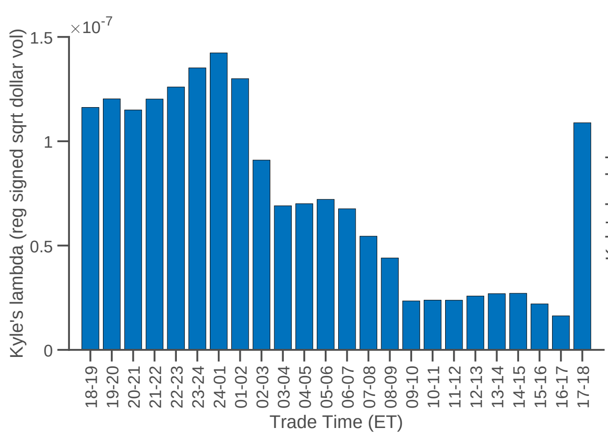
(b) Amihud, 2004 - 2018



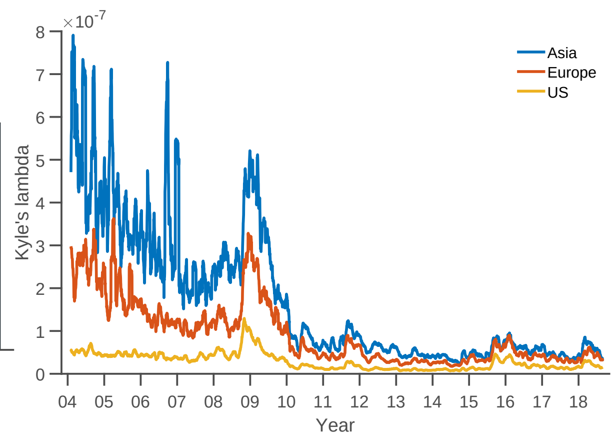
(c) Average intraday Bid-ask spread



(d) Bid-ask spread, 2004 - 2018



(e) Average intraday Kyle's lambda



(f) Kyle's lambda, 2004 - 2018

Figure A.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.