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The Overnight Drift

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Abstract

This paper documents that U.S. equity returns are large and positive during the opening hours of European markets. These returns are pervasive and highly economically and statistically significant. Consistent with models of inventory risk, we demonstrate a strong relationship with order imbalances at the close of the preceding U.S. trading day. Rationalizing unconditionally positive "overnight drift" returns, we uncover an asymmetric reaction to demand shocks: market sell-offs generate robust positive overnight reversals, while reversals following market rallies are much more modest. We argue that demand shock asymmetry can arise in inventory management models with time-varying market maker risk-bearing capacity. (*JEL* G12, G13, G14)

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Since the advent of electronic trading in the late 1990s, U.S. S&P 500 index futures have traded close to 24 hours a day. In this paper, we document that, despite the 24-hour nature of the market, returns do not accrue linearly around the clock. In fact, the largest positive returns are between 2:00 a.m. and 3:00 a.m. U.S. eastern time (ET).[1] This hour corresponds to the opening of European markets and its annualized average return is 3.7% (1.48 basis points [bps] per day). We dub this positive average return the "overnight drift" and argue it is most likely generated by the overnight resolution of order imbalances from the end of the preceding U.S. trading day.

We begin by dissecting trading during the U.S. overnight session and introduce a number of tests that demonstrate that returns during the 2:00 – 3:00 window are special in both economic and statistical terms. First, inspired by the data mining literature, we conduct a bootstrap exercise to estimate the distribution of test statistics of average hourly returns. Considering the distribution of point and t-statistic estimates for all hours we find a clear bimodal distribution, with the 2:00 – 3:00 return corresponding to the higher mode. Strikingly, the 2.5$^{\text{th}}$ percentile of overnight drift return estimates (and associated t-statistics) lie above the respective 97.5$^{\text{th}}$ pooled percentile. Second, accounting for multiple testing concerns, we consider Bonferroni and Benjamini-Yekutieli adjusted critical values and show that the *only* hour that remains consistently significant in full the sample and in subsamples is 2:00 – 3:00.

Next, following the fund alpha literature, we study the persistence of overnight drift returns: they are positive in 20 of 23 years since 1998 and statistically significant in 17 of these. In contrast, for example, opening hour returns between 9:00 and 10:00 are on average large and negative but only during recessionary periods and flat otherwise. Furthermore, we show that the 2:00 – 3:00 return is statistically significant on every day of the week, and in 9 of 12 months of the year, while returns during other periods of the day enter sporadically.

The theoretical market microstructure literature offers two broad types of potential explanations for the

[1]We use military time throughout the remainder of paper, so that 2:00 corresponds to 2:00 a.m., and 16:30 corresponds to 4:30 p.m.

overnight drift pattern: the presence of differentially informed traders in the market, generating asymmetric information, and inventory (risk) management by market makers. For asymmetric information alone to explain the overnight drift, (1) news revelation to informed traders would need to systematically occur between the closing of the U.S. market and the opening of the European market and (2) the information revealed overnight would need to be positive on average. We show that standard information releases, such as macroeconomic, monetary policy, and earnings announcements, do not explain the overnight drift, suggesting that asymmetric information alone is an implausible explanation for the overnight drift.

Studying potential explanations, we argue that unconditionally positive returns around the opening of European markets are consistent with predictions from models of inventory management and demand for immediacy, such as Grossman and Miller (1988) (GM). The framework of GM shows that risk-averse market makers profit by providing liquidity to investors with asynchronous trading demands, generating mean reversion in prices as market makers absorb shocks to their inventories.[2] To understand how inventory management concerns can lead to the overnight drift, we assume there is selling pressure during the day which translate into an overall negative order imbalance by the end of regular trading hours. Market makers become net buyers, bearing inventory risk until they are able to sell to new market participants arriving overnight; however, they demand compensation for this in terms of positive expected returns.

A natural question that arises is: why do price reversals not occur earlier upon the opening of overnight markets? The answer is that, even though overnight volumes have grown steadily over our sample period, the close of regular trading at 16:15 marks the only time of the day when volumes jump discontinuously down. Even in recent years, volumes during Asian open hours remain substantially below volumes at the U.S. close: between 2009 and 2020, trading volumes in regular Asian hours (18:00 – 2:00) were 50 to 100 times lower than volumes during U.S. trading hours. Indeed, recasting the trading day in *volume*

[2] The CME does not designate "specialist" market makers in E-mini futures. Instead, effective market makers are any participants willing to post limit orders on both sides of the order book and hence supplying liquidity (immediacy) to other traders in the market.

time, where each period has a fixed number of contracts traded, returns increase linearly in signed volume until around 60,000 contracts, corresponding to the average number of contracts traded by 3:00.[3] In other words, it takes market makers roughly 60,000 contracts to offset end-of-day order imbalances as of the previous day, with this rebalancing occurring earlier during the night as trading increases during Asian market hours. Conditioning on end-of-day order imbalances, we show that the relationship between signed volume and returns in volume-time is approximately linear but asymmetric; thus, recast in volume time, demand shock asymmetry is a more general feature of the data observable throughout Asian and European hours.

We study in greater detail predictions from GM-type models, which state that returns for providing immediacy should be higher when order imbalances are larger or uncertainty is higher. To utilize as much data as possible and to account for a time-trend in volumes, we define our main proxy for order imbalance as relative signed volume, computed as signed volume over gross volume, and denoted by RSV_t.[4] On average, close-to-close RSV_t is negative consistent with the idea that the futures market is traded as a hedging instrument for the underlying.

Sorting our full sample based on closing RSV_t^{close}, sampled between 15:15 and 16:15, we show that order imbalances at U.S. close are followed by overnight price reversals as predicted by inventory models and that price reversals following market sell-offs are much stronger than following market rallies. Moreover, price reversals are accompanied by contemporaneous trading flows in the expected direction.[5] We also study the additional intuitive prediction that market makers should not require a liquidity premium for holding zero inventory, and therefore order imbalances close to zero should have little price impact.

[3] As pointed out by Easley, de Prado, and O'Hara (2012), "in the high-frequency world, trade time, as captured by volume, is a more relevant metric than clock time" and models of immediacy and inventory risk, such as Grossman and Miller (1988), are implicitly set in volume time as it is assumed that a fixed number of trades occur in each period.

[4] Our findings are robust to tests based on signed volume over the sample period 2007 and 2020 for which total gross volumes were relatively stable.

[5] While hourly RSV_t's are negative during regular trading hours, they are economically small at market close. However, overnight imbalances are positive and strongly statistically significant between 2:00 and 3:00, mirroring unconditionally positive returns during this hour.

Consistent with this idea, when closing imbalances are approximately zero, we find reversal returns that are economically small and statistically indistinguishable from zero.

Next, we study the relationship between overnight returns and uncertainty. In double sorts on RSV_t^{close} and the end-of-day level of the VIX, we show that, conditional on the level of the VIX, average overnight returns are higher following days with greater negative end-of-day order imbalances. Conversely, conditional on the size of negative end-of-day order imbalance, average overnight returns are higher following days with greater end-of-day levels of the VIX. That is, consistent with the predictions of models of immediacy, price reversals are larger following days with larger end-of-day order imbalances and even more so if the large order imbalances coincide with periods of elevated uncertainty.

Double sorts on order imbalances and uncertainty also reveal that the distribution of the VIX is similar across days with positive and negative order imbalances, suggesting that the asymmetry in price reversals is unlikely driven by a correlation between order imbalances and the *level* of asset return variance. Instead, we speculate that this asymmetry is related to market makers' time-varying risk-bearing capacity. The literature on financial intermediation has proposed a number of mechanisms that can generate variation in effective risk aversion, including regulatory constraints, risk-management constraints, and funding constraints. Studying a simple extension to the benchmark GM model, we show that demand shock asymmetry arises when dealers face value-at-risk (VaR) constraints as in Danıelsson, Shin, and Zigrand (2004) and Adrian and Shin (2010, 2014). In the data, negative end-of-day imbalances are associated with positive *changes* in return variance.[6] Positive shocks to volatility increase the likelihood that dealer constraints bind, magnifying their effective risk aversion during sell-offs and increasing required compensation for providing immediacy. During market rallies the opposite intuition holds.[7]

We confirm our inventory risk conjecture more formally by estimating high-frequency predictability

[6] This is the so-called "leverage effect," which is the well-studied empirical fact that equity volatility tends to rise when returns are negative and fall when returns are positive (see, e.g., Black 1976).

[7] Alternatively, if the permitted VaR is given as a fraction of equity, rather than as a dollar amount, the VaR constraint becomes tighter when market maker equity declines. Brunnermeier and Pedersen (2009) show that similar dynamics can also arise when market makers have to post (cash) margins to fund levered positions.

regressions of returns on end-of-day order imbalances, and find statistically and economically significant loadings on the hours when the London and Frankfurt financial markets open. Thus, high-frequency returns become predictable as market makers transact with new participants arriving overnight, trading away order imbalances remaining from the previous U.S. trading day. Exploiting high-frequency predictability regressions further, we conduct a natural experiment to test the relationship between the overnight price reversals and the arrival of overnight traders. In particular, we exploit the fact that while the U.S. observes daylight savings time (DST), Japan does not, so that, as seen from the perspective of a U.S. trader, the timing of the opening of the Japanese market changes exogenously from 19:00 in winter to 20:00 in summer.[8] Indeed, accounting for DST, return predictability around Tokyo open shifts forward by one hour when moving from winter to summer time, so that exogenous variation in the time of the arrival of liquidity traders leads to predictable variation in the returns earned overnight. Expanding the natural experiment to also include the 3 weeks of the year when DST is asynchronous between the U.S. and Europe, we again find that the overnight return predictability shifts to the 4:00 – 5:00 hour (the first hour of regular trading in London and Frankfurt when the U.S. – Europe time difference is 4 hours).

We conclude by studying a set of trading strategies that exploit overnight price reversals. Pre-transaction costs, a trading strategy that goes long the S&P 500 futures between 2:00 and 3:00 earns a Sharpe ratio of 1.1 and accounting for bid-ask spreads this is reduced to -0.5. Extending the trading interval to the subperiod between 1:30 and 3:30 increases the pretransaction cost Sharpe ratio to 1.3 but with an associated post-transaction Sharpe ratio equal to 0.3. This is exactly what models of inventory risk predict: market makers position their limit order books to incentivize trades that bring their inventory closer to their targets, and do so by making the trade, which pays the bid-ask spread, unprofitable.

Finally, we note that although the documented high-frequency return patterns of this paper are not easily profitable, the persistent presence of the overnight drift suggests that the intraday timing of portfolio

[8]The Tokyo Stock Exchange trades from 9:00 to 15:00 in Japan standard time.

adjustments should be an important consideration for asset managers and institutional investors. Indeed, market developments suggest that arbitrageurs are trying to capitalize on the patterns identified in this paper, with NightShares launching two exchange-traded funds (ETFs) in June 2022, targeted specifically at earning the overnight drift, citing financing costs and end-of-day order imbalances as driving forces behind the pattern.

Briefly, we relate our work to existing literature. Numerous studies have documented that equities, in the time series, earn a substantial proportion of their returns during the overnight period compared to the regular U.S. trading-hours (e.g., Cliff, Cooper, and Gulen 2008; Kelly and Clark 2011), while Bondarenko and Muravyev (2022) confirm our finding that the lion's share of close-to-close equity futures returns are earned around the opening hours of European markets.

In the cross-section, Heston, Korajczyk, and Sadka (2010) study high-frequency periodicity in firm level returns documenting persistent intraday return reversals, which the authors argue arise because investors have predictable demand for immediacy at certain points within the day. Lou, Polk, and Skouras (2019) document firm level reversal patterns between intraday and overnight returns: overnight (intraday) returns predict subsequent overnight (intraday) returns positively, while overnight (intraday) returns predict subsequent intraday (overnight) returns negatively. The authors link this pattern to a "tug of war" between retail investors trading at the beginning of the day and institutional investors who trade at the end of the day. Bogousslavsky (2021), on the other hand, studies institutional constraints and a cross-section of intraday pricing anomalies.

Finally, we motivate our empirical design from a literature that studies demand for immediacy and inventory risk (Grossman and Miller 1988; Vayanos 2001; Brunnermeier and Pedersen 2009; Rostek and Weretka 2015). A common prediction of these models links price reversals to temporary order imbalances absorbed by liquidity providers.[9] Indeed, the Duffie (2010) presidential address reviews price dynamics

[9]For a textbook treatment, we refer the reader to Foucault, Pagano, and Röell (2013).

with “slow-moving” capital and highlights that “Even in markets that are extremely active, price dynamics reflect slow capital when viewed from a high-frequency perspective.”

1. Data

Our primary focus is data on intraday trades and quotes for S&P 500 futures contracts traded on the Chicago Mercantile Exchange (CME). The initial S&P 500 futures contract was introduced by the CME in 1982, trading both by open outcry and electronically during regular U.S. trading hours concurrently with the cash market.[10] This “big” futures contract (henceforth SP) was originally quoted with a multiplier of \$500 per unit of underlying, so that if the index trades, for example, at \$500, the value of the SP contract is \$250,000. As the index level rose over time, the SP contract became expensive to trade at this multiplier and the contract multiplier was cut to \$250 times the index on November 3, 1997.[11] In September 1993, the SP contract began trading electronically outside regular hours via the CME GLOBEX electronic trading platform. The S&P 500 E-mini futures contract (henceforth ES) was introduced on September 9, 1997 and is quoted at 50 times the index, that is, one-fifth of the big SP contract. The “E” in E-mini is for electronic as trading takes place only on the CME GLOBEX platform which facilitates global trade for (almost) 24 hours a day, 5 days a week. The two futures contracts have quarterly expiries on the third Thursday in March, June, September, and December. The most traded contract is almost always the front contract (the contract closest to expiry). Only when the front contract is close to expiry is the back contract (the contract second closest to expiry) the more traded. This is because market participants roll their positions in advance of the expiry. We always use the most traded contract.

Exact trading times on CME platforms have changed over time, but today, trades are executed continuously from Sunday (18:00) to Friday (17:00), with a daily maintenance as of 2020 between 17:00 and

[10] Regular trading hours are defined by the open outcry or pit session, which trades between 9:30 and 16:15.
[11] 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.

18:00.[12]

Our primary data source exploits tick-by-tick data on trades and quotes for the ES contract from Refinitiv Datascope Select, which we complement with data directly obtained from the CME.[13] The trades data set includes the trade price, trade size, and trade time. The quotes data set 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 time stamps to U.S. eastern time (ET), and define the intraday (ID) and overnight (ON) trading sessions relative to the opening hours of the U.S. cash equity market. We identify the direction of trades by comparing the trade price to the most recent quoted prices of the top level in the limit order book: buy (sell) orders trade at the best available ask (bid) price. Our sample period with 24-hour trading starts in January 1998 and ends in December 2020. Market depth for the first five levels of the order book is available since 2009.

Panel A of Figure 1 displays within-the-month average daily trading volume for the SP and ES contracts where the ES is further split by volumes within ON and ID trading sessions. We measure volume as the total number of contracts traded in the most liquid contract, multiplying the volume for the SP contract by 5 (10 prior to 1998) to make its volume comparable to the ES. The figure shows that, since the advent of electronic trading, volume in the SP has trended down over time. Instead, the trading volume in the ES (plotted in red for ON and green for ID) was growing in the run up to the 2008 financial crisis, and thereafter stabilized at around 1-2 million contracts traded per day. 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 2002, it increased somewhat linearly to around 15% in 2010 and remained

[12]Between November 1994 and December 2012, the trading week began on Sunday at 18:30 and closed on Friday at 16:15. The trading day (other than Sundays) ran from 18:00 one day to 17:30 the following day with maintenance break between 16:15 – 16:30. From December 2012 to December 2015, trading began half an hour earlier on Sundays (18:00) and closed one hour later Fridays (17:15 ET). A scheduled maintenance break occurred from 23:00 to 00:00 on Tuesday through Friday from October 1998 to September 2003.

[13]Refinitiv Datascope Select was formerly known as Thomson Reuters Tick History.

flat until 2018. In 2018, with the level of the index above 2000, using the index multiplier of 50, this implies $15 billion traded daily during the overnight session. We also note that in the final years of our sample (2019, 2020), the share of overnight trading in the ES has again increased and stands at around 20% of total volumes.

$\left[\text{Insert figure 1}\right]$

2. Returns around the Clock

This section studies intraday returns computed from the most liquid E-mini contract, which is almost always the front month contract, except in expiration months when contracts are rolled. Returns are computed from mid quotes of best bid-offers. Our sample period spans January 5, 1998 to December 31, 2020 (23 years).

2.1. Main result

The nth log return on day t is defined as

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

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 $n = N$ correspond to 18:00 when a new trading day begins as defined by the CME. We work interchangeably with hourly returns ($N = 24$), 15-minute returns ($N = 96$), 5-minute returns ($N = 288$), and 1-minute returns ($N = 1,440$).[14]

The gray bars in Figure 2 display hour-by-hour log returns, and the black line depicts cumulative 5-minute log returns, averaged across all days in our sample. Estimates are *annualized* in percentage

[14]Our last observation on Fridays is at 18:00. Our first observation on Sunday is at 18:01. Thus the weekend return is incorporated into the first overnight return on Mondays.

points and show that ON returns are positive, on average, between the hours of 00:00 and 4:00. Thirty minutes prior to the opening of the cash market at 9:30 equity returns are initially large and negative and become smaller in magnitude but remain persistently negative until 12:00. We dub negative return realizations between 9:00 and 10:00 "opening hour" returns. The ID period is then characterized by a flat return profile until 15:00, which is followed by a sequence of positive returns that turn strongly negative after the maintenance break.

This overnight return pattern is surprising. The dotted line in Figure 2 plots the cumulative average return profile one would expect if information arrived continuously and returns accrued linearly, which contrasts starkly to the realized return profile displayed in back. On average, the CTC log return is 5.9%, which is also the average yearly log return on the S&P 500 cash index (excluding dividends).[15] More than half of this return is generated during the ON session: from 16:15 to 9:30 equity returns averaged 3.6% p.a. More striking than this, the return earned during the 2:00 to 3:00 hour averaged 3.7% p.a. We dub this return sequence the "overnight drift" (OD). Figure 3 displays a more granular view of returns around the OD. Here, we see a persistent sequence of positive returns, which are clearly visible in almost every interval between 1:00 and 4:00, showing that the positive average return between 2:00 and 3:00 is not driven by within-the-hour outliers but instead represents a continuous *drift* over this interval of the overnight trading session.

What is special about this hour? Table 2 collects opening and closing times for 14 global equity markets, in the local time zone and in corresponding eastern time (ET). As regular U.S. trading hours on GLOBEX close, New Zealand, Australia, Japan, Singapore, and then China open between 18:00 and 21:30. Day trading in these venues closes between 2:00 and 3:00, at which point Dubai, Russia, London, and Europe open. Thus, the OD coincides with the opening of regular trading on Euronext, Eurex, and the Frankfurt Deutsche Börse, as well as premarket trading on the London Stock Exchange, all occurring

[15] Standard equity futures contracts do not give the owner the right to dividend claims.

at 2:00. This observation highlights the geographical nature of 24-hour trading and provides a first clue toward a potential explanation.

[Insert figure 2 and 3 here]

2.2. *Summary statistics*

Stacking hourly returns in the vector $\vec{r}$ and denoting by D a dummy matrix containing appropriately located 0's and 1's, we estimate the 1×24 vector of mean log returns μ via the projection $\vec{r} = D\mu^\top + \varepsilon$. Table 1 reports estimates for μ and t-statistics computed from HAC robust standard errors. We also report p-values adjusted for multiple testing, medians, standard deviations, skewness, and kurtosis estimates.

Consider panel A of Table 1, which collects ON return statistics. Average returns for the hours {24-01, 01-02, 02-03} are equal to {0.46, 0.43, 1.5} *bps per hour per day* with corresponding t-statistics equal to {2.8, 2.8, 7.1}, respectively. Because of the minimum tick size, median returns computed from quotes are often zero during the night. However, even the median quote return for the OD hour is large and positive equal to 0.64 bps.[16] Consider now panel B of Table 1, which collects ID return statistics. The opening hour return is strongly negative, equal to -1.2 bps with a t-statistic of 2.6, and the 17:00 – 18:00 return is equal to -0.43 bps with a t-statistic of -3.6. The remaining ID returns are flat and statistically indistinguishable from zero.

Within the 24 subperiods of the day, there is reasonably large variation in average returns across hourly windows. Indeed, while the hours {24-01, 01-02, 02-03} are striking in both economic and statistical terms, other windows are statistically significant at the 10% level over the full sample. This is to be expected since we are simultaneously testing more than one null hypothesis, and it is well known that an appropriate significance level, such as $\alpha = 0.05$, is not valid due to an inflated probability of committing a type I error. We account for the multiple testing nature of our analysis in two ways.

[16] The Internet Appendix (IA) reports findings for returns computed from volume weighted average prices (VWAPs) that are very close to returns computed from quotes.

First, we conduct a bootstrap exercise partitioning the day into 24 hourly subperiods as in Table 1. Distributions of test statistics are calculated using a block bootstrap (BS) sampling 10,000 times, with the optimal block length chosen following Patton, Politis, and White (2009). Panel A of Figure 4 plots the distribution of all hourly returns pooled together, while panel B plots the distribution of returns from 2:00 to 3:00. Solid lines represent 95% confidence intervals. Dotted lines represent median estimates for specific hours. Each histogram is normalized such that it represents a probability density function estimate; that is, the sum of the bar areas is equal to one. In terms of economic magnitudes the OD return lies well above the upper 97.5% interval. More striking, comparing panel A to panel B, the lower 2.5% BS interval for the distribution of OD estimates lies *above* the pooled 97.5% interval. Panel C repeats this exercise but plots the distribution of all hourly pooled t-statistics, while panel C plots the distribution of t-statistics for the OD hour. Here, the conclusion is the same: the statistical significance of the OD returns is extreme compared to all other hours. Moreover, panels A and C are clearly bimodal, which is because of the unusually large returns realized between 2:00 and 3:00. Making this point clear, panels E and F compute the test statistics equivalent to panels A and C after removing 2:00 – 3:00. In these plots the second mode disappears, further highlighting the unusual nature of the OD hour.

[Insert table 1 and figure 4 here]

Second, we account for multiple testing by using the Bonferroni (BF) correction to control the family-wise error (FWER) and the Benjamini-Yekutieli (BY) procedure to control for the false discovery rate (FDR).[17] Accounting for the multiple testing problem, we find that only the OD hour and the 17:00 – 18:00 hour are significant, and this holds for both the BF and the BY methods.[18] More specifically, using the BF correction the significance level is adjusted to α/m where $m = 24$ hours is the number of tests. At

[17] The FWER is the probability of making one or more type I errors. The FDR is the expected ratio of the number of type I errors to the total number of rejections of the null. Harvey, Liu, and Saretto (2020) provides a recent survey of multiple testing procedures in the context of financial economic applications.

[18] We note that between 1998 and 2012 trade was closed between 17:30 and 18:00, and in 2020 the maintenance break was moved to 17:00 – 18:00. In the following we do not investigate the 17:00 – 18:00 hour, as it is of little economic importance. Moreover, this hour is not significant when computing returns from trading prices instead of quotes (see Table I in the IA).

the 5% level, the BF adjusted significance level is $0.05/24 = 0.0021$, and it is $0.01/24 = 0.00042$ at the 1% level. With a p-value of $1.1 \cdot 10^{-12}$, the *OD* hour is extremely statistically significant. The BY method is a "step-up" procedure that computes null specific thresholds starting from the least significant hypothesis and working up until significant alternative hypotheses are detected. The BY thresholds are reported in Table A.4 (IA) at the 10%, 5%, and 1% levels and shows that the *OD* hour is the only significant return hour at the 1% level.

In summary, the evidence presented so far demonstrates that 2:00 – 3:00 is a special hour of the day, in both economic and statistical terms, and very far from what one should expect to see just by luck.

2.3. Subsample analysis and persistence

In addition to concerns related to multiple testing, one also could be suspicious that the "outperformance" of *OD* returns compared to other hours is sample specific or a result of data-mining.

A simple first test to address this concern splits the sample in two and recomputes Figure 2; see Figure 5. Panel A considers the sample period January 1998 – December 2010 and in panel B the sample period is January 2011 – December 2020. One observes that the *overall* pattern of 24-hour returns across subsamples is quite different. On the one hand, in the first sample period, opening hour returns are large, negative and significant after accounting for multiple testing using a BF adjustment (highlighted bars in dark grey) but are slightly positive and insignificant in the second sample period. On the other hand, returns between 17:00 – 18:00 are insignificant in the first sample period but become significant in the second sample period. However, both samples share the common characteristic that *OD* returns are large, positive, and significant at the 5% level.[19]

[Insert figure 5 here]

Second, a common approach used in the fund management literature to distinguish skill (outperfor-

[19]Subsample statistics are reported in the IA.

mance) from luck is to study persistence in funds α (see, e.g., Fama and French 2010). Analogously, Figure 6 displays the cumulative log returns to a \$1 initial investment that trades during various subperiods of the day. Panel A considers long positions in the hours {24-01, 01-02, 02-03}, and panel B considers the cumulative returns that go *short* at the opening and 17:00 – 18:00 hours of the day.

A passive *CTC* investment in E-mini futures (not shown) bears well-known business cycle risk, as evidenced by large negative returns in the aftermath of the dot-com bubble, the 2008 financial crisis, and more recently during the early stages of the COVID pandemic.[20] By contrast, a \$1 investment that holds E-mini futures for *only* one hour during the *OD* period would have returned \$2.4 by December 2020 and displays little variation (it is highly persistent). A \$1 investment trading either 24:00 – 1:00 or 1:00 – 2:00 would have yielded around half this value, implying that the *OD* accounts for 50% of the total return earned for holding E-mini futures over the extended window 24:00 – 3:00.[21] Panel B reveals that opening hour returns are persistently negative during recessions or states of distress (2000-2003, 2007-2008, 2020) but are otherwise flat. Section A.1.2 in the IA also shows that opening hour returns are only significantly negative on Thursdays and Fridays, suggesting that they are due to a day-of-the-week effect in bad states of the world. Returns between 17:00 – 18:00, on the other hand, are persistent but are smaller economically, comparable in size to the returns earned between 24:00 – 1:00 and 1:00 – 2:00.

[Insert figure 6 here]

Examining the overnight session further, Figure 7 shows average returns year by year for the hours {24-01, 01-02, 02-03}.[22] Panel C shows that *OD* returns were positive in 20 of 23 years. Interestingly, the largest yearly average *OD* return (10.7% p.a.) occurred in 2020, during the initial year of the COVID pandemic. The *OD* is slightly negative in the recessionary years of 2002 and 2008, and again in 2019. The bottom panels report $(1-p)$ values from t-tests against the null of zero. Panel E shows that, at the 10%

[20] A \$1 investment in E-mini futures *CTC* would have returned \$3.8 by December 2020.
[21] A detailed analysis of investment returns with and without transaction costs is delayed until Section 5.
[22] Figure A.5 in the IA reports year-by-year results for the hours 9:00 – 10:00 & 17:00–18:00.

level, the OD is significant in 17 of 23 years. Splitting the sample year by year highlights the statistical and economic consistency of 2:00 – 3:00 returns compared to 12:00 – 1:00 or 1:00 – 2:00 returns. Indeed, while the 2 hours that precede the regular opening hours in London are mostly positive, they are much smaller economically and are rarely significant at conventional levels. Moreover, Section A.1.2 in the IA studies these findings along a number of different dimensions and demonstrates that positive statistically significant average returns during 2:00 – 3:00 are a systematic feature of the data, present on all days of the week and 9 of 12 months of the year.

While observing significant positive or negative return hours is certainly interesting, developing a unified explanation for all hours of the day is beyond the scope of this paper. Instead, we will focus on the overnight return patterns straddling the opening of European markets, paying special attention to 2:00 – 3:00, which in economic and statistical terms is the salient hour of the day, thus allowing us to test theory driven hypotheses consistently over the entire sample.

[Insert figure 7 here]

3. Inventory Management and Price Reversals

In this section, we study a potential explanation for the overnight return patterns documented above. To frame the discussion, we begin from the frictionless benchmark in, for example, Glosten and Milgrom (1985). Glosten and Milgrom (1985) consider the bid and ask price setting problem of a risk-neutral, zero-profit (competitive) market specialist (market maker) and show that, in the absence of any frictions, such as inventory costs and asymmetric information, the bid price equals the ask price and the expected return earned by the market maker is indeed zero. Phenomena like the overnight drift – that is, high-frequency price reversals with a nonzero unconditional mean – must thus arise when one or more of the assumptions in the frictionless Glosten and Milgrom (1985) benchmark case are violated.

The first strand of the market microstructure literature relaxes the assumption of no asymmetric information (for an overview, see, e.g., Menkveld 2016). Glosten and Milgrom (1985) show that, when risk-neutral, competitive market makers face informed traders, the optimal bid-ask spread is not zero, and is increasing in the amount of information present in the market. Thus, for the overnight drift to arise as a result of asymmetric information, news revelation to informed traders has to systematically occur between the U.S. market close and the European market open – so that market makers set a lower bid at U.S. market close and a higher ask at European market opens – and the information revealed overnight has to be positive on average. In the IA, we show that the overnight drift cannot be explained by standard information releases, including macroeconomic, monetary policy and earnings announcements, suggesting that overnight revelation of information is an unlikely source of the overnight drift.

The second strand of literature focuses on the impact of market maker inventories (see, e.g., Stoll 1978; Amihud and Mendelson 1980; Ho and Stoll 1981, 1983; Mildenstein and Schleef 1983; O'Hara and Oldfield 1986; Grossman and Miller 1988; Shen and Starr 2002) and the costs of maintaining those inventories. This literature finds that, even in the absence of financing constraints, market makers that either face nonlinear costs (Amihud and Mendelson 1980; Shen and Starr 2002) or are risk averse (O'Hara and Oldfield 1986) set bid-ask spreads in a way that reflects their inventory positions. In such models, the setting of the bid and the ask prices depends on both the contemporaneous demand and supply and the future expected value of the security. Price reversals can thus arise in models of inventory (risk) management due to variation in either order imbalances over time or expectations of the future value of the security (information revelation).

Finally, most recently, the market microstructure literature has studied the link between funding liquidity – that is, how constrained market makers are in funding their inventories – and market liquidity provision. Gromb and Vayanos (2002); Weill (2007); Brunnermeier and Pedersen (2005); Attari, Mello, and Ruckes (2005); Brunnermeier and Pedersen (2009) feature models in which capital-constrained market makers (or market makers with costly capital) undersupply market liquidity, leading to time variation in market returns due to order imbalances, fundamental information revelation and market maker capital constraints. Given the implausibility of information revelation alone as the source of the overnight drift, in this section, we focus on the implications of the inventory risk-management-based models for market microstructure.

More concretely, consider the following stylized example. News is announced during the U.S. intraday trading session that results in selling pressure at market close. Orders transact at the best available bids and, consequently, execute at successively lower prices down the order book. As the sell-off unfolds, prices drop below fundamental values because risk-averse market makers bear inventory risk. Market makers are compensated for bearing that risk through high expected returns, earned when they offload their excess inventory to new customers arriving overnight.

Grossman and Miller (1988) (GM) provide a framework that models such "liquidity events" through the supply and demand for immediacy. In GM, buyers and sellers arrive at different points in the trading day, which generates transient imbalances between buy and sell volumes. Market makers offer immediacy to incoming traders by absorbing order imbalances and subsequently trading them away. In our context, compensation for bearing inventory risk (a liquidity premium) is earned through expected returns for offloading positions to new customers arriving overnight; that is, prices drop from S_0 to S_1 as the market sells off intraday and rebounds from S_1 to S_2 as trading begins in overseas time zones. Defining the overnight return as $R_{ON} = (S_2 - S_1)/S_1$, conditional expected returns based on date $t = 1$ information are given by

$$E\left[R_{ON}|\mathcal{F}_1\right] = \begin{matrix}\text{Dollar Order}\\ \text{Imbalance}\end{matrix} \times \begin{matrix}\text{Return}\\ \text{Variance}\end{matrix} \times \begin{pmatrix}\text{Risk-Bearing}\\ \text{Capacity}\end{pmatrix}^{-1}. \tag{2}$$

Models of the GM type provide an intuitive link between liquidity provision, demand for immediacy and price formation. The basic prediction of GM-type models is that the expected returns to providing immediacy are higher when (1) order imbalances are larger; (2) when payoffs are more uncertain; and (3) when the total risk-bearing capacity of market makers is lower. In the following, we study our proposed explanation by testing these predictions.

3.1. End-of-day volumes

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

Quantifying intraday magnitudes in the recent sample, panel C plots average volumes for all hours of the day during 2020. With the index level at 3,000 (late May & early June) closing volume in the 5-minute interval 16:10 - 16:15 averaged $85,000 \times 50 \times 3,000 \sim$ US\$ 13 billion. By comparison, panel D zooms in on the overnight hours showing that volumes are an order of magnitude smaller. Cumulative volumes in the 8-hour period between 18:00 and 3:00 total $13,500 \times 50 \times 3,000 \sim$ US\$ 2 billion so that, even in 2020, overnight trading represents a small fraction of the volume in the 5-minute interval preceding the maintenance break.

The key takeaway from Figure 8 is an economically large downward jump in intraday volume at United States close and that overnight trading activity is between 50 to 100 times lower compared to the U.S. trading hours. From an inventory management perspective, this makes order imbalances at close particularly risky since the extreme trading volumes leading up to the close of trading in the United States at 16.15 can generate large inventory imbalances. Such imbalances cannot be immediately traded away when the overnight session starts at 18:00 because the overnight trading activity is much lower. Moreover, even in recent years, order imbalances can last most of the overnight period and cannot be resolved until European trading begins.

[Insert figure 8 here]

3.2. Volume time

In the previous section, we showed that returns earned during the OD hour account for the bulk of total overnight returns and argued that this pattern is inconsistent with returns accruing linearly over time. Instead, the high returns earned during the OD hour are in line with the basic idea of GM-style models, which imply that, conditional on an order imbalance, prices revert as new participants arrive and market makers offload their inventories. In clock time, the speed of mean reversion depends on the volume of new participants because market makers cannot manage inventory imbalances when trading activity is low. Conversely, when trading activity is high, market makers can offload quickly.

In this context, a natural alternative to *clock time* is to measure time elapsed in terms of the trading volume as first proposed by Mandelbrot and Taylor (1967).[23] Specifically, we consider *volume time*, which advances one increment for every contract traded and thus equals cumulative trading volume. Volume time is a type of *activity time*, like tick time, advancing slowly when few contracts are traded (Asian hours) and quickly when many contracts are traded (U.S. hours). By definition, trade activity is constant in volume time and we therefore expect order imbalances to revert linearly to zero in volume time. Thus, we also expect price reversals induced by inventory management to be linear when measured in volume

[23] Mandelbrot and Taylor (1967) argue that price changes follow a Pareto distribution in clock time but are normally distributed in volume time. This result was later generalized by Ané and Geman (2000). More recently, Kyle and Obizhaeva (2016) propose and test "market microstructure invariance," which states that the distributions of risk transfers and transaction costs are constant across assets when measured in business-time (activity time).

time.

From the perspective of inventory risk models, the empirical measure of order imbalance would be net inventory held by market makers. As these are not observable, we proxy for them from signed volume defined as

$$SV_t^i = \#buy\ orders - \#sell\ orders, \tag{3}$$

where # of orders is defined as the number of contracts, t is the day, and i is the period during the day. Note that SV_t^i is measured in dollar units consistent with Equation (2), and the sample period is 2007–2020 since total volume was relatively stationary during this period (see Figure 1). Table A.7 of the IA shows the intraday properties of SV_t^i, while panels A and B of Figure A.6 show the distribution and time series of SV_t^i at U.S. close.

Figure 9 displays cumulative log returns (computed from VWAPS) and cumulative signed volume in both clock time and volume time, sorted by SV_t^{close}, which is the signed volume measured in the last hour before the maintenance break between 15:15 and 16:15. Panels A and C are in clock time, and we clearly see that price reversals are strongest at the opening of Asian (19:00 and 20:00) and European markets (2:00 and 3:00 ET) when volume jumps up, and that returns quickly flatten off after the initial hours of European trade. Panels B and D are in volume time. Following negative (positive) closing order imbalances, both signed volume and returns increase (decrease) essentially monotonically. Following market sell-offs, most of the overnight return is earned by the point at which 60,000 contracts are traded, or in other words, around the time when European markets open.

Corresponding positive closing order imbalances generate a smaller price impact than negative closing order imbalances, even if order flow is quite symmetric following positive versus negative end-of-day imbalances. Thus, viewed from the perspective of *volume* time, we observe an almost linear but *asymmetric* demand shock response throughout Asian and European hours.

[Insert figure 9 here]

3.3. Economic magnitudes

Next, we evaluate the *quantitative* plausibility of an inventory risk hypothesis. From the data, we can observe three of the four terms that enter Equation (2): the expected overnight returns $E[R_{ON}|\mathcal{F}_1]$, the end-of-day dollar order imbalance, and the (conditional) return variance. The final component – the risk-bearing capacity of the market – is difficult to observe directly. Instead, we note that the risk-bearing capacity can be expressed as $\binom{\text{Risk-Bearing}}{\text{Capacity}} = \frac{N+1}{ARA}$ where N is the number of market makers providing immediacy and ARA is absolute risk aversion common across market makers. Recall further that the coefficient of relative risk aversion (RRA) is approximately the ARA multiplied by wealth, which allows us to recast Equation (2) as a prediction for the RRA of the market makers in this market

$$\text{RRA} = \frac{E[R_{ON}|\mathcal{F}_1]}{\substack{\text{Dollar Order}\\ \text{Imbalance}} \times \substack{\text{Return}\\ \text{Variance}}} \times \overline{\text{Wealth}}, \tag{4}$$

where $\overline{\text{Wealth}}$ denotes total capital of the market makers, $(N+1)\times\text{Wealth}_i$, that is allocated to supporting equity market trades. While market participants' capital allocations to particular trades are notoriously hard to measure, we can follow the literature on financial intermediation (see, e.g., Adrian and Shin 2014) by proxying for $\overline{\text{Wealth}}$ and proxy with the equity value-at-risk (VaR) of large dealers.[24] The total equity VaR of large dealers proxies for how much capital is at risk for these intermediaries when they provide liquidity in equity markets, and is thus closely related to the total risk-bearing capacity of market makers in the market.[25]

We obtain the quarterly time series of average broker-dealer equity VaR from Bloomberg in order to

[24] At the end of 2020, the five largest dealer banks were Bank of America, Citibank, JP Morgan, Goldman Sachs, and Morgan Stanley. As in Adrian and Shin (2014), for firms that report VaRs at the 95% confidence level, we scale the VaR to the 99% using the Gaussian assumption.

[25] We discuss in the IA the assumptions behind using equity value-at-risk as a proxy for dealer capital committed to equity futures trades.

perform a proxy calculation of implied market maker RRA. Figure A.9 in the IA shows that the time series of equity VaR varies between US\$ 50 billion and US\$ 750 billion between 2000.Q1 and 2020.Q4, peaking in the financial crisis and rising again during the COVID-19 crisis. Average equity VaR during the sample period 2007Q1 – 2020Q4 was equal to US\$ 300 billion, which we take as our proxy for $\overline{\text{Wealth}}$. Then, from panel B of Figure 9, we take the realized overnight return, measured in volume time, equal to $\sim 17\%$ p.a. as a proxy for expected overnight returns conditional on a market sell-off. From panel D of Figure 9 we obtain the corresponding resolved overnight market maker imbalance of $\sim 1,500$ contracts that, with the index level at 2,000, equates to a dollar imbalance of $1,500 \times 50 \times 2,000 =$ US\$ 150 billion. We measure $\left(\frac{\text{Return}}{\text{Variance}}\right)$ as the unconditional level of the VIX^2 in our sample, which was $20\%^2$. The implied market maker relative risk aversion is therefore

$$RRA = \frac{0.17}{150 \times 0.04} \times 300 = 8.5. \tag{5}$$

To put this estimate in context, Greenwood and Vayanos (2014) perform a similar conversion of Treasury arbitrageurs' ARA to RRA to estimate a range of [7.6, 91.2] for the RRA. For mortgage-backed security arbitrageurs, Malkhozov, Mueller, Vedolin, and Venter (2016) perform a similar calculation, coming up with an estimate of 88. Our "back-of-the-envelope" calculation suggests that, an inventory risk explanation is plausible not only from a qualitative perspective, but also from a quantitative one.[26]

[26]Prior empirical literature has also studied the plausibility of inventory risk explanations though in more limited settings. Madhavan and Smidt (1993); Hansch, Naik, and Viswanathan (1998); Naik and Yadav (2003) find, in small samples of intraday data, that market makers control risk by mean-reverting their inventory positions toward target levels. Using 11 years of daily data on NYSE specialist inventory positions and trading revenue, Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010) directly test for the relationship between funding and market liquidity and find that both aggregate market-level and specialist firm-level spreads widen when specialists have large positions or lose money. They further document that, consistent with models of time-varying risk-bearing capacity, these effects are nonlinear.

3.4. End-of-day order imbalance

We now study in more detail the prediction of GM-type models that states that returns for providing immediacy should be higher when order imbalances are larger. To utilize as much data as possible, and following much of the empirical literature, in the remainder of the paper, we use relative signed volume as our main proxy for order imbalance, measured as signed volume over total volume

$$RSV_t^i = \frac{SV_t^i}{TV_t^i} \in [-1, 1], \tag{6}$$

where $TV_t^i = \#buy\ orders + \#sell\ orders$ accounts for the increasing trend in total trading volume over the sample 1998–2020.[27]

Table 3 reports summary statistics for hourly RSV_t. On average, close-to-close RSV_t is equal to -2.4% and is highly volatile. Negative $CTC\ RSV_t$'s are consistent with the idea that the futures market is traded as a hedging instrument for the underlying. However, while RSV_t's are negative during the day, they are largely positive between 1:00 and 4:00. During the OD hour, average RSV_t is 2.4% with a t-statistic of 6.7, mirroring the unconditional positive returns during this hour. In the following, we use the last hour preceding the maintenance break (15:15 – 16:15) to measure *closing* order imbalances, which we write as RSV_t^{close}.[28]

[Insert table 3 here]

Figure 10 sorts all trading days into groups based on closing imbalances. For each group, panel A reports returns during Asian hours (18:00 – 1:00), panel B reports returns during EU open (1:00 – 04:00), and panels C & D report returns during the OD hour (2:00 – 3:00). The sorting is performed such that

[27] In the IA, we present counterparts to all of the results that follow using SV_t as an alternative measure of imbalances (for the sample 2007–2020 as above). The results are quantitatively similar using either measure and thus robust to whether or not we standardize by volume.

[28] Panels C and D of Figure A.6 show the distribution and time series of RSV at U.S. close. RSV_t^{close} is stationary around zero throughout the sample period and its variance is stable.

the groups are approximately equal in size, and the black bars represent 95% confidence intervals.[29]

In summary, Figure 10 shows that (*i*) order imbalances at U.S. close are followed by overnight price reversals as predicted by inventory models; and (*ii*) price reversals are much stronger following market sell-offs, giving rise to an unconditional positive overnight drift.

Using RSV_t^{close} as a sorting variable the conditional return pattern resembles a step function centered around zero. Figure A.7 in the IA shows that, when sorting on SV_t^{close}, the conditional return pattern is monotonic, albeit with an asymmetric slope. More importantly, in both cases, negative closing imbalances generate statistically significant positive overnight returns.

[Insert figure 10 here]

Equation (2) contains an additional intuitive prediction that order imbalances close to zero should have little price impact. Indeed, market makers should not require a liquidity premium for holding zero inventory. Panel D examines this prediction by zooming in on OD returns based on RSV_t^{close} straddling zero. Consistent with an inventory channel, when closing imbalances are approximately zero we find reversal returns that are economically small and statistically indistinguishable from zero.

3.5. Volatility risk

The second prediction of Equation (2) is that expected overnight returns are increasing in the return variance of the risky asset. This is because risk-averse market makers demand a higher premium for holding larger price risk. To allow for differential effects on volatility because of demand shock asymmetry, we split the sample into days with positive and negative closing order imbalances and then construct double sorts – based on terciles of RSV and volatility – within each subsample. Panel A (B) of Table 4 reports double sorts conditional on negative (positive) RSV_t^{close} days. Double-sorted return averages are reported based

[29]Note that RSV_t^{close} is defined as buys minus sells so that a negative imbalance implies that dealers are long and from Equation (2) overnight expected returns should therefore be positive.

on terciles of RSV_t^{close} and the closing level of the VIX sampled at 16:15 each day.[30] Within each set, we also report average RSV_t^{close} and VIX levels ($A1, A2, B1, B2$). Double-sorted OD return averages are reported ($A3, B3$) along with high minus low differences and p-values testing the difference against zero.

We first note that the distribution of the EOD VIX appears quite symmetric conditional on positive versus negative RSV_t^{close} days. Thus, an asymmetric price impact is unlikely to be due to a correlation between order imbalance and the level of asset return variance.[31] Considering panel A (positive RSV_t^{close}), there is really no clear pattern in 3×3 sorted OD return averages. Panel B (negative RSV_t^{close}), on the other hand, is consistent with our priors from Equation (2): (i) Conditional on the level of the VIX, moving from low to high RSV_t^{close} states, the OD return averages are increasing. (ii) Conditional on the level of the RSV_t^{close}, moving from low to high RSV_t^{close} states, the OD return averages are also increasing. The only exception is in high VIX states where the impact of RSV_t^{close} is large but flat. Moreover, the high-minus-low return spreads are in the anticipated direction and statistically significant in 5 of 6 cases. Thus, as predicted by GM-style models, price reversals are larger following days with large end-of-day order imbalances and even more so if the large order imbalances coincide with periods of heightened uncertainty.

[Insert table 4 here]

3.6. Demand shock asymmetry

Consistent with the literature on downward-sloping demand curves and imperfect liquidity provision, we have shown that demand shocks have a temporary price impact that reverts over time. However, we have also shown a strong asymmetry in price impact in response to positive versus negative demand shocks. This asymmetry generates a positive unconditional overnight return that, in *clock* time, is concentrated in

[30] Tick-by-tick quotes for the VIX index are sourced from Refinitiv and complemented with data from the CBOE.

[31] While *changes* in the VIX are highly negatively correlated with returns, the correlation between the *level* of the VIX and returns (order imbalance) is quite low.

the hour from 2:00 to 3:00 (the OD). In Section 3.2, we then showed that recast in *volume* time, demand shock asymmetry is a more general feature of the data observable throughout Asian and European hours.

To the best of our knowledge, such an asymmetry is novel to the literature. Now, recall from Equation (2) that the conditional expected return to providing immediacy is the product of three terms: the end-of-day order imbalance, the conditional variance of returns, and the inverse of the risk-bearing capacity of the market makers. Table 4 shows that the first two terms are unlikely to contribute to the asymmetric response to positive and negative demand shocks: the distribution of demand shocks around zero is roughly symmetric and the distribution of the VIX conditional on the sign of the demand shock is roughly similar. Instead, the asymmetric response to positive and negative demand shocks may be driven by contemporaneous changes in the risk-bearing capacity of the market makers. This may arise through two different channels.

First, since there are no designated market makers for E-mini contracts, institutions that normally act as market makers have not obligation to continue doing so in the face of large sell-offs. That is, during large sell-offs, institutions that act as market makers may choose to exit the market, reducing the total risk-bearing capacity of the market maker segment.

Second, those market makers that choose to remain during large sell-offs may reduce their individual risk limits in response to deteriorating market conditions. Section A.3 in the IA outlines how increases in volatility, which accompany market sell-offs, may translate into higher effective risk aversion when market makers face value-at-risk (VaR) constraints. Increases in volatility tighten the VaR constraint for market makers, translating into higher effective risk aversion. Conversely, decreases in volatility do not translate into lower effective risk aversion once the VaR constraint is no longer binding. Thus, an asymmetry in the pass-through of positive versus negative volatility shocks can generate an asymmetry in return reversals following demand shocks.

Third, market makers may face an asymmetry in funding costs as in Brunnermeier and Pedersen

(2009), who argue that decreases in risk-bearing capacity arise when market liquidity and funding liquidity interact in flight-to-quality episodes, with capital required for trading evaporating when market returns are negative. Indeed, during prolonged periods of market sell-offs, the CME increases the required initial margins for futures positions.

Each of these mechanisms may contribute to time variation in effective risk aversion; we leave further investigation of return reversal asymmetry for future research.

4. High-Frequency Return Predictability

Section 2 documented our central empirical finding and Section 3 adopted a sorting-based approach to test our explanation. In this section, we study further the link between overnight *expected returns* and EOD order imbalances within a high-frequency predictability framework.

4.1. High-frequency predictability and order imbalance

Panel A of Table 5 reports point estimates from univariate regressions of hourly realized returns during the overnight session (18:00 – 6:00) on closing imbalances:

$$r^H_{t,n} = \mu_n + \beta^{RSV}_n RSV^{\text{close}}_{t-1} + \epsilon_{t,n}, \quad \text{for } n = 1, \ldots, 12, \tag{7}$$

together with t-statistics computed from robust standard errors clustered within each month. Returns are measured in basis points, and $RSV^{\text{close}}_{t-1} \in [-1, 1]$. Thus, a point estimate of $\beta^{RSV}_n = -10$ implies a $+1$ bps return response to a closing imbalance of $RSV^{\text{close}}_{t-1} = -10\%$.

Consistent with an explanation based on inventory risk, we observe a strong negative relation between the closing order imbalance and returns. The relation is strongest between 2:00 and 4:00. The estimates are both economically and statistically significant. A one-standard-deviation (6.55%) decrease in RSV^{close}_{t-1} (a sell-off) induces a $6.55\% \cdot -17.49 = 1.15$ bps increase in returns between 2:00 and 3:00. We also observe a statistically significant negative relationship between 20:00 and 21:00, corresponding to the opening of Japanese (TSE) and Australian (ASX) markets.

In panel B of Table 5, we verify that order imbalance in the last hour of the U.S. trading day is the appropriate proxy for dealer inventory imbalances. We include order imbalances measured in the final three hours of the trading day (13:15–14:15, 14:15 – 15:15, and 15:15 – 16:15) as separate regressors in a multivariate extension to Equation (7). Given the high levels of trading activity during U.S. open hours, we expect order imbalances from earlier in the day to have been traded away prior to the end of the trading day and thus do not affect overnight returns. This indeed is suggested by the estimates in Table 5. For example, focusing on the 2:00 – 3:00 interval, the point estimates monotonically decline the earlier in the day the order imbalance is measured and are insignificant beyond 14:15.

[Insert table 5 here]

4.2. Falsification test

Microstructure theory predicts a link between order imbalance and returns, both contemporaneously and at lagged intervals. In inventory management models, high-frequency predictability arises as market makers adjust their quotes to resolve imbalances. The more liquid a market is, the shorter the period of predictability will be because market makers can quickly trade imbalances away. In illiquid markets, such as the corporate bond market, predictability can last several days. Microstructure theory also predicts negative autocorrelation in returns due to a host of market frictions and indeed we do observe negatively autocorrelated returns for the E-mini, but the generally large liquidity of the market implies that autocorrelation coefficients are only significant for, at most, 30 minutes.[32] However, the closing of U.S. trading hours is a special point in the trading day because volume is extremely high relative to the subsequent trading hours.

[32]See Figure A.8 in the IA.

Our proposed explanation relies on a special relationship between closing order imbalance and returns around the opening of European markets. Table 6 provides a "falsification" test for this claim. For the overnight hours, panel A estimates univariate regressions of hourly returns on 1-hour-lagged RSV_t. There is only one significant hour between 23:00 and 24:00 and the sign is positive, not negative.

Panel B extends the regression to include the previous 12 lagged hours of RSV_t for the night hours. Most of the point estimates in the table are insignificant. However, focusing on the highlighted diagonal estimates, we find economically large and statistically significant return predictability arising from order imbalances at the close of regular U.S. trading hours. More specifically, the point estimates are large at exactly the opening of the Tokyo market and the regular opening times of the European markets, even after controlling for all imbalances subsequent to the U.S. close.

[Insert table 6 here]

4.3. Demand asymmetry and volatility risk

The sorting-based approach of the previous section revealed a strong asymmetry in price impact in response to positive versus negative demand shocks, which generates an unconditional positive overnight drift return (reversal). Panel A of Table 7 explores the asymmetry in a regression design that interacts RSV_t^{close} with a dummy variable that takes on a value of one if $RSV_{t-1}^{close} < 0$ and zero otherwise:

$$r_{t,n}^{H} = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{NEG} \mathbb{1}_{NEG,t} + \beta_n^{RSV \times NEG} RSV_{t-1,close} \times \mathbb{1}_{NEG,t} + \varepsilon_{t,n}, \tag{8}$$

for $n = 1, \ldots, 12$. We find that the dummy variable is large and statistically significant during only the OD hour.

We also investigate the standard inventory risk prediction that price reversals should be amplified in states of high volatility. Testing this, we interact RSV_t^{close} with the level of the VIX index sampled at

16:15 ET,

$$r_{t,n}^{H} = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{VIX} VIX_{t-1}^{close} + \beta_n^{RSV \times VIX} RSV_{t-1}^{close} \times VIX_{t-1}^{close} + \epsilon_{t,n}, \tag{9}$$

for $n = 1, ..., 12$. Panel B of Table 7 reports the estimates, showing that ex ante volatility has a strong amplification effect on the relationship between order imbalance and overnight returns between 2:00 and 3:00. A one-standard-deviation decrease in RSV_{t-1}^{close} when $VIX_{t-1}^{close} = 20\%$ (the average VIX level throughout the sample period is 19.8%) generates a return response of $66.39 \times (-6.55\%) - 5.33 \times (-6.55\%) \times 20 = 2.6$ bps. With the VIX at its 90th percentile (30%), the return response is 6.1 basis points and with the VIX at its 10th percentile (12%) there is close to zero effect.

[Insert table 7 here]

4.4. Daylight savings tests

The results so far highlight that large negative order imbalances at the end of the U.S. trading day are subsequently resolved during the overnight trading session, as new customers arrive in the market. The 24-hour nature of the E-mini market allows us to provide additional evidence on this explanation by conducting a novel test that exploits *exogenous* variation, from the perspective of U.S.-based market makers, in the arrival time of Asia-based clients. Specifically, we exploit the fact that while both the U.S. and Europe observe daylight savings time (DST), Japan does not. From the perspective of U.S.-based market makers, clients based in Japan arrive at 19:00 during U.S. winter months (DST off) and at 20:00 during U.S. summer months (DST on). Thus, DST changes represent exogenous variation in the arrival time of Japan-based clients.

Figure 11 shows that, during the second half of our sample (January 2007 – December 2020), when the trading volume during Asian opening hours is nonnegligible, there is a spike in E-mini trading volume at

19:00, when DST is not active (dotted line), which is exactly at the opening of the Tokyo Stock Exchange (TSE). When DST is active, the increase in volume occurs instead at 20:00, which again corresponds to the opening of the TSE in the U.S. summer. Notice, also, that a secondary spike in trading volume occurs at 22:30, when the TSE reopens after its lunch break during U.S. winter months, and at 23:30, when the TSE reopens after its lunch break during the U.S. summer months.[33]

[Insert figure 11 here]

We now test more formally whether changes in the arrival time of Asia-based clients translates into a change in the timing of overnight returns. Panel A of Table 8 reports the estimated coefficients from a regression of hourly overnight returns between 18:00 and 23:00, 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,

$$r_{t,n}^{H} = \mu_n + \beta_n^{RSV} RSV_{t-1,close} + \beta_n^{DST} \mathbb{1}_{DST,t} + \beta_n^{RSV \times DST} RSV_{t-1,close} \times \mathbb{1}_{DST,t} + \varepsilon_{t,n}, \tag{10}$$

for $n = 1, \ldots, 12$, where the dummy variable takes on a value of one in summer time (DST active) and zero in winter time (DST not active), with daylight savings seen from a U.S. perspective. The sample period is 1998.1 to 2020.12.

Consistent with the hypothesis that DST creates exogenous variation in the arrival time of Asia-based clients, we see that the effect of RSV moves forward by one hour when the U.S. goes from winter to summer time. To see this, consider first U.S. winter time, where the DST dummy equals zero. Here, Australia opens at 18:00, TSE opens at 19:00, and Singapore opens at 20:00 (also, Shanghai opens at 20:15 and Hong Kong opens at 20:30). As expected, the effect of RSV is negative in hours with market openings where new agents arrive, specifically, $\beta_n^{SRV} = \{-9.34; -13.46; -6.70\}$ for the hours 18:00 – 19:00,

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

19:00 – 20:00, and 20:00 – 21:00.

Next, in U.S. summer time, where the DST dummy equals one, there are no major market openings at 18:00; TSE opens at 20:00, Australia opens at 19:00 or 20:00, and Singapore opens at 21:00.[34] Now, we find the effect of RSV by summing $\beta_n^{RSV} + \beta_n^{RSV \times DST} = \{1.43; -1.43; -6.85\}$ and, indeed, we see that the effect of RSV shifts in accordance with DST.

We can likewise exploit the fact that DST is observed in both Europe and the U.S. The standard time difference between New York and London is 5 hours but throughout our sample period, the U.S. and Europe have switched to DST at different times, typically 1 week apart. Panel B of Table 8 reports estimates of hourly overnight returns between 24:00 and 5:00 regressed on closing signed volume and a time difference dummy:

$$r_{t,n}^{H} = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{DIFF} \mathbb{1}_{DIFF,t} + \beta_n^{RSV \times DIFF} RSV_{t-1,close} \times \mathbb{1}_{DIFF,t} + \varepsilon_{t,n}, \tag{11}$$

for $n = 1, \ldots, 12$, and where the dummy variable takes on a value of zero when the time difference between London and New York is 5 hours and a value of one when the time difference is 4 hours. We find that the predictability of RSV disappears in the hour 2:00 – 3:00 on days when the U.S. - EU time difference is only four hours. Predictability due to an overnight return reversal shifts by two hours to 4:00 – 5:00, which is the first hour of regular trading in London and Frankfurt when the U.S. - EU time difference is 4 hours. We observe fewer than 300 trading days here; thus, the point estimate is not well measured. However, the main takeaway of the European daylight savings test remains: when the U.S. and Europe are out of their usual 5-hour time-difference synchronization, consistent with the idea that liquidity traders are no longer entering the market at this time, predictability during the OD hour disappears.

[Insert table 8 here]

[34] Australia does not switch to winter (summer) time on exactly the same date as the U.S. switches to summer (winter) time. Therefore, seen from a U.S. perspective, Australia opens at 19:00 for short periods during the spring and fall.

5. Trading Overnight Reversals

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

$$R^L_{j,[t_1,t_2]} = \frac{P_{j,t_2} - P_{j,t_1}}{P_{j,t_1}}, \tag{12}$$

where P denotes the price of the ES contract. The analogous short position earns $R^S = -R^L$. Mid quotes are used to compute returns excluding transaction costs. Transaction costs are incorporated from bid-ask quotes in Refinitiv data and returns are computed from quotes as

$$R^L_{j,[t_1,t_2]} = \frac{P^{\text{bid}}_{j,t_2} - P^{\text{ask}}_{j,t_1}}{P^{\text{ask}}_{j,t_1}} \quad , \quad R^S_{j,[t_1,t_2]} = -1 \times \frac{P^{\text{ask}}_{j,t_2} - P^{\text{bid}}_{j,t_1}}{P^{\text{bid}}_{j,t_1}}. \tag{13}$$

We consider the following strategies:

- long CTC: t_1=16:15 $\rightarrow$ t_2 = 16:15;
- long CTO: t_1 = 16:15 $\rightarrow$ t_2 = 9:30;
- long OTC: t_1 = 9:30 $\rightarrow$ t_2 = 16:15;
- long OD: t_1 = 2:00 $\rightarrow$ t_2 = 3:00;
- long $OD+$: t_1 = 1:30 $\rightarrow$ t_2 = 3:30

We also consider a conditional trading strategy that "buys-the-dip" denoted by BtD, which holds the E-mini during the $OD+$ period but only on trading days following a negative order flow at market close ($RSV^{close}_{t-1} < 0$). We report findings for the sample period 2004.1 – 2020.12, since after this point the bid-ask spread during the overnight period reached its minimum tick size (see Figure A.13).

Table 9, Panel A, reports summary statistics of the trading strategies when transaction costs are excluded. Holding the ES contract continuously (the CTC strategy) since 2004.1 has yielded an average yearly return of 8.9% with a Sharpe ratio of 0.42.[35] The beta is equal to one by definition since we use the CTC return as a proxy for the market return. CTO and OTC returns contributed an approximately equal proportion to the total return earned by a passive investor holding the index: on an annualized basis, CTO returns averaged 4.6% and OTC returns averaged 4.2%. A dissection of this magnitude is not particularly surprising in itself. However, it is surprising that the OD return component is comparable in size to the CTO and OTC returns, equal to 3.8% on average. The OD strategy has a Sharpe ratio of 1.1, which outperforms the market Sharpe ratio, and arises from a combination of high excess returns and low volatility during the overnight drift period. The best performing strategy is the conditional versions of $OD+$, which holds the E-mini on $\sim$ 50% of trading days. Returns from trading the BtD strategy are considerably larger than $OD+$ returns, which we interpret as additional evidence in support of the inventory risk prediction that past RSV should predict subsequently higher expected returns, as new agents arrive in the market and liquidity suppliers offload their long positions. In addition to larger returns, the BtD strategy return variance is significantly lower and therefore the Sharpe ratio higher. Specifically, $RSV_{t-1}^{close} < 0$ has a Sharpe ratio of 1.8 compared to 1.3 of $OD+$.[36]

Table 9, panel B, reports summary statistics post transaction costs. Returns on all simple strategies are significantly lower and only the $OD+$ strategy has a positive Sharpe ratio. However, the BtD strategy remains highly profitable (Sharpe ratio of 1.1) because it only pays the bid-ask spread on half the trading days when returns are higher. This is exactly what we would expect from an inventory management perspective. Market makers earn the bid-ask spread, buying at the bid on negative closing RSV days

[35] Sharpe ratios are computed from daily risk-free rates implied by 4 week U.S. Treasury bills obtained from CRSP. Return volatilities (the denominator of the Sharpe ratio) are computed using daily data.

[36] The large number of zero returns is also what causes the large kurtosis. The positive skewness of BtD occurs because the $RSV < 0$ signal filters a significant fraction of the negative returns.

and selling at the ask during the overnight trading session. In general, market makers position their limit order books to incentivize trades that bring their inventory closer to their targets, making a contrarian trade – where a *client* would earn the bid-ask spread – less profitable.[37]

It is important to highlight that small yet persistent intraday return seasonalities can have large low-frequency effects. To illustrate this point, Figure 12 depicts the cumulative returns of the CTC, OD, $OD+$, and BtD strategies for a one dollar investment in January 2004. The overnight strategies have performed exceptionally well in the sense that they never experience large negative returns. Remarkably, the BtD strategy has positive returns during the financial crises even though the strategy never shorts the market. Panel A displays returns for a hypothetical investor who trades without costs. Trading the OD ($OD+$), a one dollar initial investment in 2004 generated a portfolio value of \$1.9 (\$2.8) in December 2020. Panel B of Figure 12 displays cumulative returns including transaction costs. The CTC return remains unchanged since 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 2004 and final sell in 2020). With transaction costs, the OD is not profitable in practice. However, the BtD strategy earns large positive returns, generating a portfolio value of \$1.9, and while it does not beat a passive position in the market, it has a significantly higher Sharpe ratio and does not experience large losses related to the business cycle.

[Insert table 9 and figure 12 here]

6. Conclusion

In this paper, we study returns to holding U.S. equity futures around the clock and document a large positive drift in returns accruing during the opening hours of regular European market trading hours.

We argue that the large, positive drift in returns is consistent with standard theories of demand

[37]Note that, while the bid-ask spread has traded at the minimum tick size post-2004.1, the market depth (number of contracts available at the best bid and ask) varies over time and can be low depending on the sample period (see Figure A.15 in the IA), limiting the effective capacity of the BtD strategy.

for immediacy and the associated liquidity provision by risk-averse market makers. Consistent with such theories, we show that overnight returns have a strong relationship with (U.S.) end-of-day order imbalances, and that the relationship is asymmetric: while large negative order imbalances at the end of the U.S. trading day are followed by large return reversals overnight, the response to large positive end-of-day order imbalances is muted. This asymmetry in return reversals following days with negative versus positive order imbalances is what generates the unconditionally positive returns around European opening times. We conjecture that the asymmetry in return reversals arise due to the time-varying risk-bearing capacity of market makers in this market, which decreases during periods of large market sell-offs. Finally, we show that the demand for immediacy hypothesis not only is qualitatively consistent with the return and order flow patterns in the data but also provides a quantitatively plausible explanation for the overnight drift.

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7. 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	−0.46	0.35	0.15	0.05	−0.03	0.04	0.46	0.43	1.48	0.35	−0.08	0.15	0.61	−0.08	0.26
t-stat	−1.43	1.80	0.68	0.25	−0.19	0.29	2.77	2.75	7.13	1.33	−0.32	0.63	2.46	−0.31	0.71
p-value	0.15	0.072	0.50	0.80	0.85	0.77	0.0056	0.0060	$1.1 \cdot 10^{-12}$	0.18	0.75	0.53	0.014	0.75	0.48
median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.64	0.00	0.00	0.00	0.00	0.00	0.00
SD	24.94	14.77	16.75	14.68	13.58	10.34	12.60	11.95	15.78	21.46	19.64	17.50	18.59	19.78	28.76
Skew	−3.73	0.26	−0.60	−3.61	−6.65	−0.67	7.38	−0.32	1.20	0.02	−0.87	−0.45	1.42	0.26	1.03
Kurt	86.76	40.61	55.29	115.02	184.65	35.32	213.51	34.03	33.77	16.90	21.73	19.83	51.11	60.80	45.80

A. Overnight

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
Mean	−1.24	−0.25	−0.23	0.41	−0.15	−0.06	0.61	0.00	−0.43
t-stat	−2.60	−0.45	−0.52	1.07	−0.37	−0.12	0.99	0.01	−3.62
p-value	0.093	0.66	0.60	0.28	0.71	0.91	0.32	1.00	0.00030
median	0.00	0.85	1.20	1.12	0.96	0.00	1.20	1.10	0.00
SD	36.11	42.28	32.96	29.17	30.52	36.80	50.79	20.91	9.16
Skew	−0.99	−0.07	−0.36	−0.48	0.51	0.31	1.25	−1.88	−0.56
Kurt	19.40	11.10	10.40	24.56	21.12	14.26	30.65	21.09	61.82

B. Intraday

Table 1. E-mini Summary statistics: Hourly returns around the clock

Summary statistics for S&P 500 E-mini futures hourly log returns. Returns are computed from mid quotes at the top of the order book and reported in basis points. Panel A displays overnight hours, and panel B displays intraday hours. Mean, medians, and standard deviations are displayed in basis point terms. t-statistics testing again the null of zero returns are computed from HAC robust standard errors. p-values indicate significance levels under a student-t distribution. The sample period is January 1998 to December 2020.

Abbreviation	Name	Open	Close	Time difference	ET open	ET close
NZSX[b]	New Zealand	10:00	17:00	16	18:00	01:00
TSE[a]	Tokyo	09:00	15:00	13	20:00	02:00
ASX[b]	Australia	10:00	16:00	14	20:00	02:00
SGX[a]	Singapore	09:00	17:00	12	21:00	05:00
SSE[a]	Shanghai	09:15	15:00	12	21:15	03:00
HKE[a]	Hong Kong	09:30	16:00	12	21:30	04:00
NSE[a]	India	09:15	15:30	9.5	23:45	06:00
DIFX[a]	Dubai	10:00	14:00	8	02:00	06:00
RTS[a]	Russia	09:30	19:00	7	02:30	14:00
FWB	Frankfurt	08:00	20:00	6	02:00	14:00
JSE[a]	South Africa	08:30	17:00	6	02:30	11:00
LSE	London	08:00	16:30	5	03:00	11:30
BMF[b]	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 2. Open and closing times of global equity cash indexes

The table displays opening and closing times for 15 global equity markets, in the local time zone and in the corresponding eastern time zone (ET) for June, 2018. The abbreviations are NYSE=New York Stock Exchange, TSE=Tokyo Stock Exchange, LSE=London Stock Exchange, HKE=Hong Kong Stock Exchange,NSE=National Stock Exchange of India, BMF=Bovespa Bolsa de Valores Mercadorias & Futuros de Sao Paulo, ASX=Australian Securities Exchange, FWB=Frankfurt Stock Exchange Deutsche Börse, RTS=Russian Trading System, JSE=Johannesburg Stock Exchange, DIFX=NASDAQ Dubai, SSE=Shanghai Stock Exchange, SGX= Singapore Exchange, NZSX=New Zealand Stock Exchange, TSX=Toronto Stock Exchange. Opening and closing times are collected from the public website of each exchange. *a* 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. *b* denotes Locations south of the 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.

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	−1.12	−0.01	−0.78	−0.51	−0.04	−0.87	−0.13	0.94	2.39	0.54	0.15	0.07	−0.00	0.97	0.27
t-stat	−3.62	−0.03	−2.20	−1.44	−0.12	−1.69	−0.34	2.30	6.71	1.99	0.56	0.26	−0.00	4.78	1.69
Median	−1.37	0.00	−0.42	−0.09	0.00	0.00	0.00	0.56	1.53	0.13	−0.02	0.11	0.00	0.70	0.19
SD	23.13	26.53	27.03	26.98	27.90	38.71	29.79	31.27	26.31	21.27	20.92	20.25	18.74	15.37	12.14
Skew	0.11	0.01	0.09	−0.02	−0.00	−0.05	0.06	0.01	0.11	0.12	0.04	0.01	−0.07	0.22	0.42
Kurt	4.32	3.82	3.96	4.00	3.87	4.33	3.93	4.01	4.96	7.01	6.97	6.54	6.92	6.67	8.88

A. Overnight

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	CTC
Mean	−0.46	−0.44	−0.39	−0.21	−0.48	−0.36	0.03	0.81	−1.00	−2.36
t-stat	−5.74	−5.75	−4.21	−1.92	−4.32	−3.36	0.33	6.12	−2.80	−1.14
Median	−0.50	−0.39	−0.28	−0.21	−0.38	−0.42	−0.03	0.78	−1.68	−0.91
SD	6.04	5.80	7.00	8.22	8.48	8.28	7.20	9.97	46.71	136.19
Skew	−0.54	−0.33	0.35	0.31	0.22	1.53	0.50	0.23	0.04	−0.12
Kurt	16.83	8.31	7.85	7.69	7.00	21.40	9.97	12.03	3.52	4.00

B. Intraday

Hour	15:00-15:15	15:15-15:30	15:30-15:45	15:45-16:00	16:00-16:15	15:15-16:15
Mean	−0.33	0.24	0.49	−0.29	0.96	0.24
t-stat	−1.95	1.47	3.02	−1.93	7.04	2.70
Median	−0.02	0.00	0.15	−0.32	0.77	0.28
SD	12.88	12.40	12.24	11.42	10.29	6.55
Skew	0.10	0.09	−0.07	−0.02	0.43	0.03
Kurt	4.59	4.42	3.96	4.52	6.90	3.82

C. EOD

Table 3. Summary statistics: relative signed volume around the clock

Summary statistics for S&P 500 E-mini futures hourly relative signed volume defined as

$$RSV_t = \frac{\#buy\ orders - \#sell\ orders}{\#buy\ orders + \#sell\ orders} \in [-100\%, 100\%],$$

which states order imbalance relative to total volume in percentages. Panel A displays overnight hours and panel B displays intraday hours. Panel C displays RSV_t in quarterly intervals between 15:00 and 16:15 and in the final column reports summary statistics for RSV_t^{close} which is relative signed volume measured between 15:15 and 16:15. Mean, medians, and standard deviations are displayed in percentages. The sample period is January 1998 to December 2020.

	VIX low	VIX med	VIX high	VIX low	VIX med	VIX high
	A1. Average RSV			*A2. Average VIX*		
RSV low	1.23	1.29	1.20	12.71	19.16	31.56
RSV med	4.04	4.10	4.06	12.60	18.32	30.41
RSV high	9.55	9.43	9.37	12.49	18.04	28.11

	A3. OD average returns				
	VIX low	VIX med	VIX high	high - low	p-value
RSV low	0.59	0.80	2.33	1.74	.54
RSV med	-2.41	1.96	6.02	8.43	.00
RSV high	-0.12	-0.11	-1.96	-1.84	.44
High-Low	0.71	0.91	4.30		
p-value	.59	.67	.22		

	B1. Average RSV			*B2. Average VIX*		
RSV low	-1.33	-1.32	-1.40	13.17	19.24	28.44
RSV med	-4.03	-4.12	-4.11	12.88	18.78	29.63
RSV high	-9.56	-10.07	-9.66	12.88	19.19	30.63

	B3. OD average returns				
	VIX low	VIX med	VIX high	high - low	p-value
RSV low	0.88	4.93	12.66	11.78	.00
RSV med	3.23	6.33	13.03	9.80	.00
RSV high	4.42	8.93	7.01	2.60	.31
High-Low	3.54	3.99	-5.64		
p-value	.02	.09	.12		

Table 4. Double sorts on relative signed volume and closing VIX

We split the sample into positive (panel A) and negative (panel B) closing relative signed volume. Within each set, we double-sort trading days into terciles of relative signed volume RSV and the closing level of the VIX. Within each set we report average RSVs and VIX levels ($A1, A2, B1, B2$). Double-sorted overnight drift OD return averages are reported ($A3, B3$) along with high minus low differences and p-values testing the difference against zero. The sample period is January 1998 to December 2020.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
RSV 3:15-4:15	-1.89	-5.58	-6.81	-2.29	2.33	0.22	-1.64	-5.75	-17.46	-17.96	4.55	1.40
	(-0.67)	(-1.95)	(-4.16)	(-1.05)	(1.61)	(0.13)	(-1.79)	(-3.19)	(-8.14)	(-6.01)	(1.07)	(0.55)
μ	-0.18	0.38	0.15	0.16	0.07	0.05	0.34	0.41	1.45	0.32	-0.05	0.03
	(-0.44)	(3.03)	(1.23)	(1.46)	(0.60)	(0.37)	(2.06)	(2.71)	(7.19)	(1.21)	(-0.16)	(0.13)
Adj. R^2(%)	.00	.07	.07	.01	.02	.00	.01	.11	.57	.31	.03	.00

A.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
RSV 15:15-16:15	-1.88	-5.67	-6.70	-2.13	2.43	0.25	-1.58	-5.65	-17.25	-17.85	4.58	1.11
	(-0.66)	(-1.94)	(-4.19)	(-1.01)	(1.67)	(0.15)	(-1.81)	(-3.13)	(-8.10)	(-6.02)	(1.07)	(0.46)
RSV 14:15-15:15	-0.12	2.17	-2.68	-4.51	-2.74	-0.84	-1.63	-2.52	-5.45	-2.89	-0.64	7.56
	(-0.03)	(0.41)	(-1.04)	(-2.14)	(-1.20)	(-0.58)	(-1.10)	(-1.30)	(-3.26)	(-1.19)	(-0.39)	(3.83)
RSV 13:15-14:15	3.49	0.10	0.86	-2.81	0.27	0.07	-1.26	0.28	1.04	0.95	1.39	0.30
	(1.06)	(0.11)	(0.60)	(-2.89)	(0.21)	(0.08)	(-1.24)	(0.36)	(0.60)	(0.49)	(0.86)	(0.18)
μ	-0.17	0.38	0.15	0.13	0.06	0.04	0.33	0.40	1.44	0.31	-0.04	0.05
	(-0.40)	(2.98)	(1.24)	(1.27)	(0.54)	(0.36)	(2.02)	(2.67)	(7.26)	(1.19)	(-0.15)	(0.24)
Adj. R^2(%)	-.02	.03	.04	.11	-.01	-.05	-.01	.09	.60	.27	-.02	.08

B.

Table 5. Regression: Overnight returns on closing relative signed volume

Panel A displays regression estimates of hourly overnight returns regressed on closing relative signed volume:

$$r^H_{t,n} = \mu_n + \beta^{SV}_n RSV^{close}_{t-1} + \varepsilon_{t,n} \quad n = 1, \ldots, 12.$$

Panel B estimates a multivariate extension to this regression that includes relative signed volume recorded in the final three hours of the trading day before the maintenance break. 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 parentheses are computed from robust standard errors clustered within each month. The sample period is January 1998 to December 2020.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
RSV 1H lag	-0.41	-1.31	-0.04	-0.14	0.46	0.40	2.21	0.95	0.44	0.85	0.00	0.77
	(-0.55)	(-1.46)	(-0.08)	(-0.30)	(1.25)	(1.17)	(7.89)	(1.84)	(0.76)	(0.91)	(0.01)	(0.86)
μ	-0.19	0.35	0.14	0.15	0.08	0.05	0.36	0.39	1.40	0.25	-0.04	0.03
	(-0.47)	(2.76)	(1.09)	(1.43)	(0.67)	(0.37)	(2.29)	(2.60)	(6.79)	(1.04)	(-0.13)	(0.14)
Adj. R^2(%)	.01	.05	.00	.00	.01	.01	.61	.07	.01	.01	.00	.01

A.

	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06
RSV 1H lag	-0.43	-1.31	-0.13	-0.25	0.34	0.24	2.21	0.98	0.10	0.72	0.52	0.68
	(-0.58)	(-1.51)	(-0.29)	(-0.59)	(0.97)	(0.70)	(7.98)	(2.13)	(0.18)	(0.68)	(0.61)	(0.75)
RSV 2H lag	-1.91	-0.49	1.18	-0.27	0.65	0.80	-0.34	0.03	0.96	-0.88	-1.70	0.58
	(-0.76)	(-1.32)	(1.04)	(-0.61)	(2.02)	(2.28)	(-1.46)	(0.12)	(1.43)	(-1.42)	(-1.39)	(0.46)
RSV 3H lag	0.67	0.47	0.79	0.57	-0.12	0.85	0.34	-0.71	0.27	-1.56	-0.78	-1.13
	(0.19)	(0.21)	(1.36)	(1.26)	(-0.29)	(1.84)	(0.75)	(-2.04)	(1.00)	(-1.97)	(-0.99)	(-2.58)
RSV 4H lag	1.27	-1.09	1.23	0.57	0.54	0.40	0.22	1.46	0.39	-0.18	0.52	0.60
	(0.43)	(-0.26)	(0.57)	(1.32)	(0.90)	(0.99)	(0.45)	(3.12)	(0.88)	(-0.25)	(0.57)	(0.76)
RSV 5H lag	0.12	2.87	-6.45	2.66	0.22	0.02	0.93	-0.33	0.28	1.07	0.20	-1.87
	(0.04)	(0.66)	(-3.09)	(3.28)	(0.74)	(0.05)	(2.90)	(-0.95)	(0.44)	(1.18)	(0.26)	(-2.64)
RSV 6H lag	-0.70	-1.82	-0.16	-3.07	2.11	0.59	-0.51	-0.64	1.36	0.89	-0.21	0.00
	(-0.19)	(-1.55)	(-0.05)	(-1.74)	(2.00)	(1.97)	(-0.78)	(-2.03)	(2.29)	(0.71)	(-0.29)	(0.01)
RSV 7H lag	1.53	-1.13	-1.64	-4.82	0.75	0.36	-0.49	0.13	1.30	0.50	-0.40	0.54
	(0.50)	(-0.79)	(-0.86)	(-2.74)	(0.56)	(0.47)	(-1.49)	(0.22)	(2.11)	(0.47)	(-0.58)	(0.67)
RSV 8H lag	1.42	2.78	0.93	-0.86	-1.08	1.17	2.86	-0.25	1.24	1.14	-0.69	-0.30
	(0.18)	(1.28)	(0.76)	(-0.51)	(-0.55)	(0.67)	(2.28)	(-1.00)	(1.74)	(1.00)	(-0.93)	(-0.66)
RSV 9H lag	-5.49	1.25	-5.56	0.02	-1.29	-1.55	-4.09	-3.51	-0.67	-2.19	-0.40	-1.41
	(-1.25)	(0.45)	(-1.94)	(0.01)	(-0.88)	(-0.86)	(-4.23)	(-3.23)	(-1.62)	(-1.64)	(-0.44)	(-1.62)
RSV 10H lag	2.34	2.02	-3.72	-2.21	-1.40	-0.76	-1.02	-2.93	-9.56	-1.20	1.49	0.86
	(1.29)	(0.77)	(-1.21)	(-1.06)	(-0.71)	(-0.53)	(-0.59)	(-1.61)	(-4.52)	(-3.24)	(2.19)	(1.11)
RSV 11H lag	-1.87	0.55	0.65	-4.57	-2.87	1.99	1.46	-2.52	-9.21	-2.91	-0.09	-0.46
	(-0.98)	(0.30)	(0.24)	(-2.29)	(-1.59)	(1.23)	(1.10)	(-1.53)	(-5.12)	(-1.41)	(-0.17)	(-0.94)
RSV 12H lag	-0.53	1.60	-1.04	3.26	-2.86	1.12	0.68	1.22	-4.61	-14.94	-2.74	-0.35
	(-0.34)	(1.96)	(-0.46)	(1.81)	(-1.19)	(0.63)	(0.40)	(0.81)	(-3.54)	(-5.11)	(-1.80)	(-1.03)
μ	-0.18	0.35	0.12	0.11	0.04	0.06	0.33	0.42	1.49	0.26	0.04	0.02
	(-0.42)	(2.78)	(0.94)	(1.14)	(0.31)	(0.57)	(2.15)	(2.72)	(7.88)	(0.97)	(0.14)	(0.10)
Adj. R^2(%)	-.15	-.04	.03	.09	-.07	.05	.66	.21	.83	.32	-.07	.02

B.

Table 6. Falsification test

Panel A displays regression estimates of hourly overnight returns regressed on a one-hour lag of relative signed volume. Panel B displays regression estimates of hourly overnight returns regressed on twelve lags of hourly relative signed volume. For each column, the highlighted elements represent the point estimates and t-stats on the RSV during the closing trading hour from the preceding U.S. trading day. 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 parentheses are computed from robust standard errors clustered within each month. The sample period is January 1998 to December 2020.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
RSV 15:15-16:15	-3.84	2.58	-4.75	-0.80	-0.68	2.55	-11.50	-0.85	-1.99	-3.83	-10.05	-7.12
	(-0.26)	(0.29)	(-0.64)	(-0.13)	(-0.07)	(0.47)	(-1.51)	(-0.14)	(-0.20)	(-0.30)	(-0.66)	(-0.49)
NEG	0.33	-0.14	1.26	1.06	0.56	0.52	0.10	-0.65	3.60	-0.37	-1.01	-2.30
	(0.23)	(-0.14)	(1.12)	(1.53)	(0.83)	(1.07)	(0.16)	(-1.03)	(3.46)	(-0.22)	(-0.83)	(-1.50)
RSV x NEG	-8.67	-25.90	7.06	14.35	20.07	3.46	9.07	-21.69	-6.20	-3.68	20.90	-6.56
	(-0.29)	(-1.53)	(0.52)	(1.41)	(1.36)	(0.27)	(0.86)	(-3.51)	(-0.36)	(-0.19)	(1.05)	(-0.35)
μ	-0.94	-0.05	-0.62	-0.13	-0.02	-0.08	0.56	0.47	-0.32	0.00	0.91	1.32
	(-0.99)	(-0.08)	(-1.40)	(-0.37)	(-0.06)	(-0.23)	(1.11)	(1.08)	(-0.49)	(0.00)	(1.13)	(1.48)
Adj. R^2(%)	.05	.21	.16	.07	.09	.02	.14	.17	1.33	.01	.09	.19

A.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
RSV 15:15-16:15	-45.77	-11.66	45.29	-13.05	-4.32	-12.37	30.40	-10.45	66.39	19.35	-12.85	-49.54
	(-1.48)	(-0.47)	(2.12)	(-0.72)	(-0.21)	(-0.58)	(3.21)	(-0.41)	(3.53)	(1.03)	(-0.49)	(-2.41)
VIX 15:15-16:15	-0.02	0.02	0.08	-0.01	-0.05	0.02	0.07	0.03	0.07	-0.05	-0.10	-0.06
	(-0.17)	(0.50)	(1.10)	(-0.35)	(-1.36)	(0.48)	(2.14)	(0.97)	(0.72)	(-0.74)	(-1.13)	(-0.54)
RSV x VIX	1.94	0.17	-3.05	0.62	0.49	0.71	-2.09	0.23	-5.33	-1.22	1.08	3.06
	(1.11)	(0.11)	(-2.44)	(0.60)	(0.38)	(0.56)	(-3.78)	(0.14)	(-4.23)	(-1.03)	(0.71)	(2.41)
μ	-0.22	-0.03	-1.64	0.27	0.74	-0.32	-1.00	0.10	0.15	0.79	1.86	1.60
	(-0.12)	(-0.04)	(-1.41)	(0.57)	(1.35)	(-0.41)	(-1.72)	(0.28)	(0.08)	(0.66)	(1.32)	(0.76)
Adj. R^2(%)	.05	.05	.64	-.06	.04	.01	.78	.02	2.48	.00	.16	.47

B.

Table 7. Regression: Overnight returns on closing relative signed volume and interactions

Panel A displays regression estimates of hourly overnight returns regressed on closing relative signed volume and an interaction term that takes on a value of one if $RSV_{t-1}^{close} < 0$ and zero otherwise

$$r_{t,n}^{H} = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{NEG} \mathbb{1}_{NEG,t} + \beta_n^{RSV\times NEG} RSV_{t-1,close} \times \mathbb{1}_{NEG,t} + \varepsilon_{t,n} \quad n = 1, \ldots, 12.$$

Panel B displays regression estimates of hourly overnight returns regressed on closing relative signed volume and a closing signed volume interacted with the level of the VIX from the close of the preceding day

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

Days where the time difference between London and New York is different from 5 hours are excluded. Estimates are in basis points. t-statistics reported in parentheses are computed from robust standard errors clustered within each month. The sample period is January 1998 to December 2020.

	18-19	19-20	20-21	21-22	22-23
RSV	-9.34	-13.46	-6.70	-1.46	5.43
	(-2.11)	(-1.98)	(-1.62)	(-0.36)	(2.43)
DST	-1.57	-0.08	-0.15	0.06	0.08
	(-2.13)	(-0.28)	(-0.52)	(0.29)	(0.25)
$RSV \times DST$	10.77	12.03	-1.20	-0.17	-4.54
	(2.09)	(1.80)	(-0.27)	(-0.04)	(-1.73)
μ	0.54	0.42	0.26	0.02	-0.09
	(0.68)	(1.73)	(1.09)	(0.13)	(-0.51)
Adj. $R^2(\%)$	.11	.13	.09	.01	.03

A. Asia

	24-01	01-02	02-03	03-04	04-05
RSV	-7.93	-7.21	-31.32	-1.93	6.36
	(-3.70)	(-1.44)	(-5.15)	(-0.33)	(1.23)
$DIFF$	3.56	0.59	1.24	2.28	-1.63
	(2.18)	(2.05)	(2.91)	(1.26)	(-1.08)
$RSV \times DIFF$	-7.24	31.00	37.30	15.00	-38.80
	(-0.96)	(2.53)	(1.73)	(1.50)	(-1.50)
μ	0.42	0.60	1.57	-0.11	-0.01
	(2.52)	(3.17)	(7.13)	(-0.30)	(-0.02)
Adj. $R^2(\%)$	.47	.14	.82	.07	.11

B. Europe

Table 8. Daylight saving tests

In panel A hourly overnight returns are regressed on closing relative signed volume and a dummy variable for daylight savings time:

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

where the dummy variable takes on a value of zero in winter time (DST not active) and one in summer time (DST active) and daylight savings is seen from a U.S. perspective. The Tokyo Stock Exchange (TSE) opens at 19:00, when DST is not active, and at 20:00 when DST is active. Estimates are in basis points. In panel B hourly overnight returns are regressed on closing relative signed volume and time-zone difference dummy:

$$r_{t,n}^{H} = \mu_n + \beta_n^{RSV} RSV_{t-1}^{close} + \beta_n^{DIFF} \mathbb{1}_{DIFF,t} + \beta_n^{RSV \times DIFF} RSV_{t-1,close} \times \mathbb{1}_{DIFF,t} + \varepsilon_{t,n} \quad n = 1, \ldots, 12,$$

where the dummy variable takes on a value of zero when the time-zone difference between London and New York is 5 hours (3282 observations) and a value of one when the time-zone difference is 4 hours (240 observations). t-statistics reported in parentheses are computed from robust standard errors clustered within months. The sample period is January 1998 to December 2020.

	CTC	CTO	OTC	OD	$OD+$	$RSV_{t-1}^{close} < 0$
Mean	8.95	4.62	4.20	3.75	6.21	6.07
SD	19.35	11.23	14.90	2.65	4.13	2.95
Sharpe ratio	0.42	0.34	0.23	1.10	1.30	1.78
Beta	1.00	0.37	0.63	0.02	0.04	0.02
Skew	0.01	−0.67	−0.33	1.18	2.16	4.89
Kurt	20.06	20.86	13.65	32.91	41.88	98.60

A. Without transaction costs

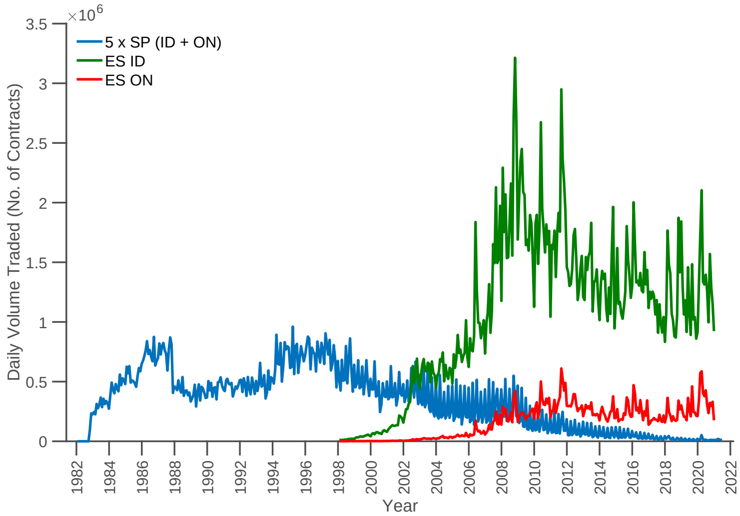
	CTC	CTO	OTC	OD	$OD+$	$RSV_{t-1}^{close} < 0$
Mean	8.95	0.38	−0.05	−0.59	1.91	4.04
SD	19.35	11.23	14.90	2.65	4.12	2.92
Sharpe ratio	0.42	−0.04	−0.06	−0.54	0.26	1.10
Beta	1.00	0.37	0.63	0.02	0.04	0.02
Skew	0.01	−0.68	−0.35	1.09	2.10	4.77
Kurt	20.06	20.84	13.67	32.81	41.61	99.87

B. With transaction costs

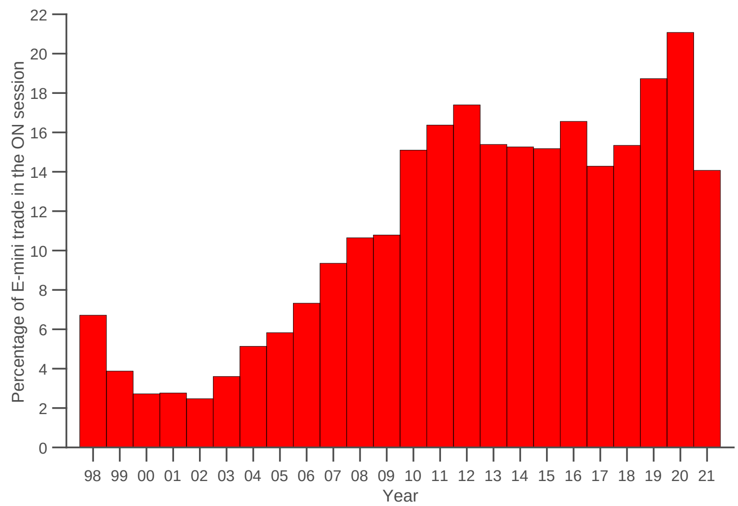
Table 9. Trading strategies

Summary statistics for returns of intraday trading strategies excluding (panel A) and including (panel **(b)**) transaction costs. CTC is continuously holding the E-mini contract. CTO is holding the contract from 16:15 to 8:30; OTC is from 9:30 to 16:15; $-OR$ is shortening the opening returns from 8:30 to 10:00; OD is the overnight drift from 2:00 to 3:00; and $OD+$ is from 1:30 to 3:30. $RSV_{t-1}^{close} < 0$ is a buy-the- dip strategy that goes long from 1:30 to 3:30 only on days following a negative closing order flow. Means and standard deviations are in annualized percentages. The Sharpe ratios use 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 costs are computed from mid quotes and returns including transaction costs are computed from the best bid and ask prices quotes. The sample period is 2004.1 to 2020.12. The trading strategies start in 2004 since this is where the overnight bid/ask spread reached its effective minimum of one tick.

8. Figures



A



B

Figure 1. Overnight versus intraday E-mini volume split
Panel A plots average daily trading volumes in the SP and ES contracts with the ES split by overnight versus intraday trading sessions. Panel B plots year-by-year average percentages of overnight volume relative to total volume for the ES contract. E-mini volumes are measured as the total number of contracts traded. The sample period for overnight trading is January 1998 to December 2020.

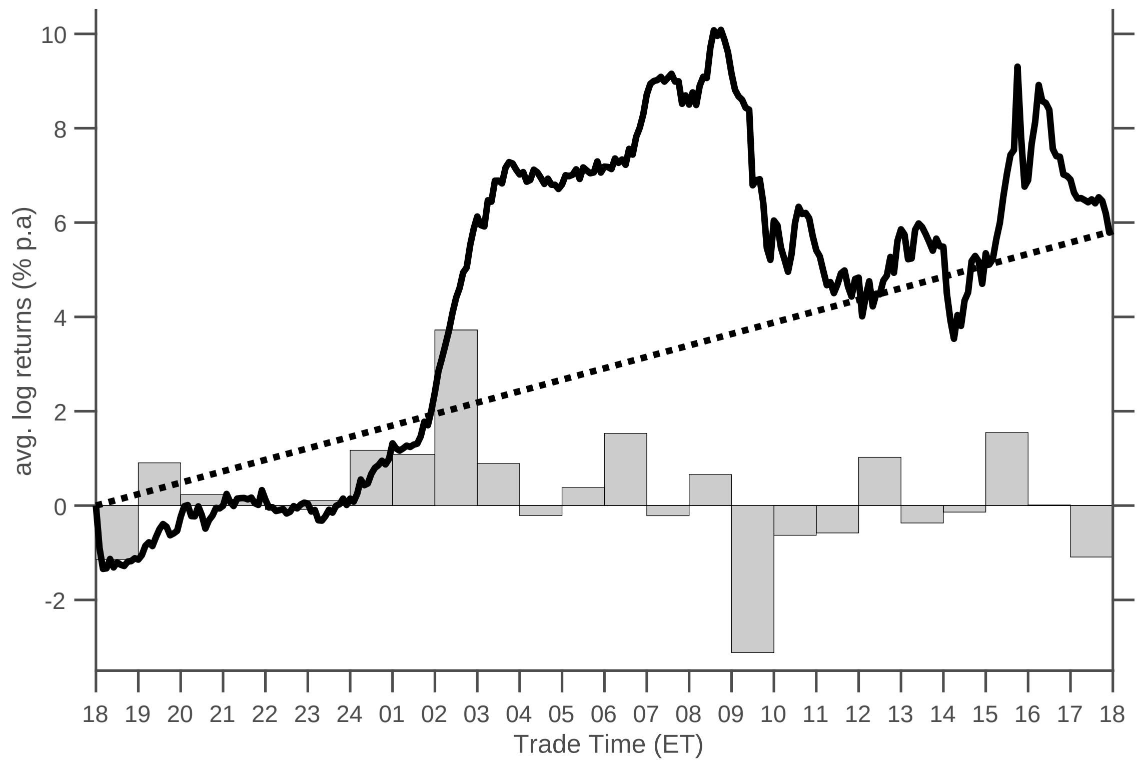


Figure 2. Intraday return averages

This figure plots the average hourly log returns (bars) and average cumulative 5-minute log returns (solid black line) holding the E-mini contract (first close-to-open and then open-to-close). The sample period is January 1998 to December 2020.

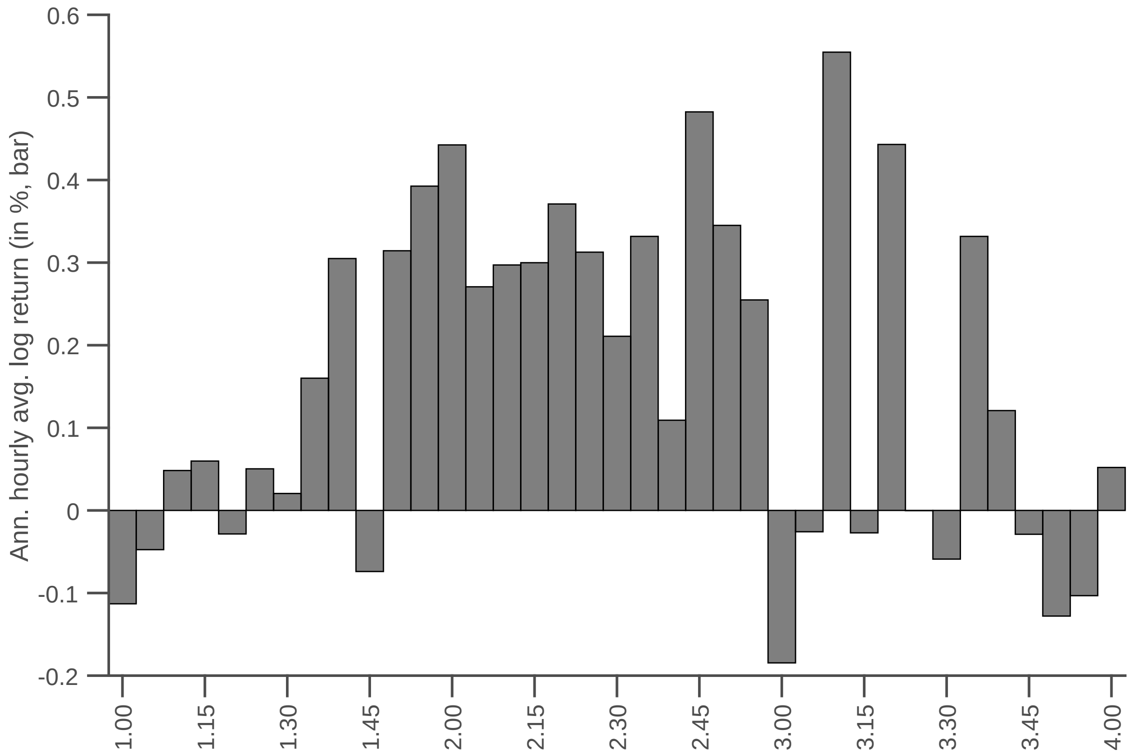
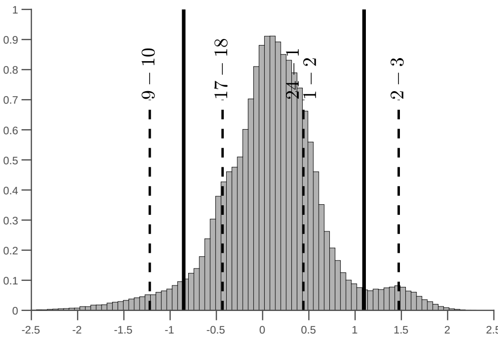
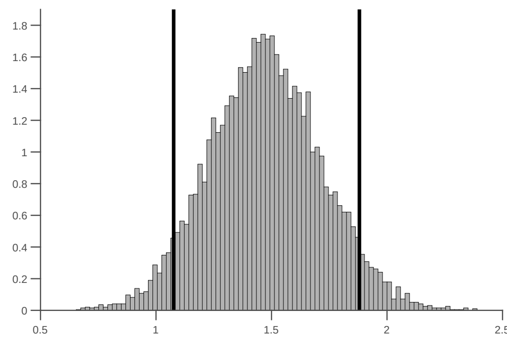


Figure 3. Intraday return averages

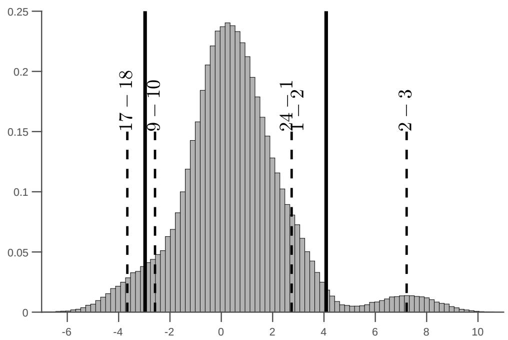
This figure plots average 5-minute returns holding the E-mini contract for the hours 1.00 – 4.00. The sample period is January 1998 to December 2020.



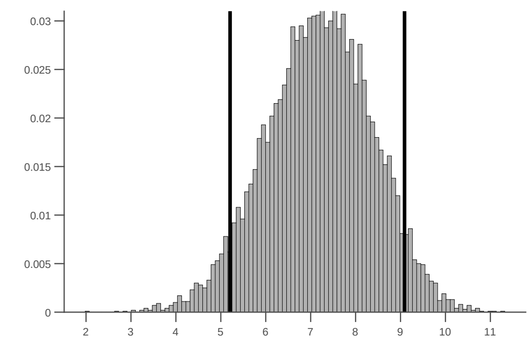
A All hours mean dist



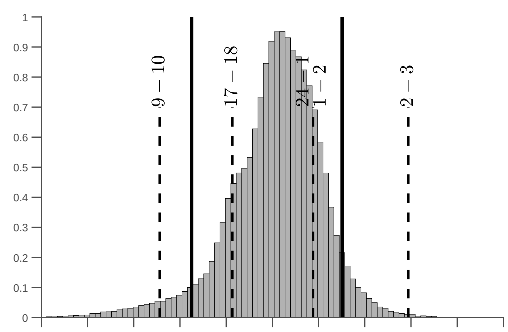
B 2:00-3:00 mean dist



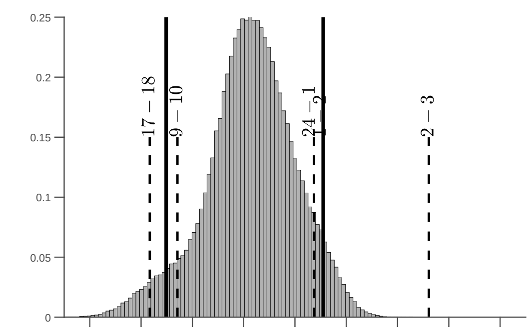
C All hours t-stat dist



D 2:00-3:00 t-stat dist



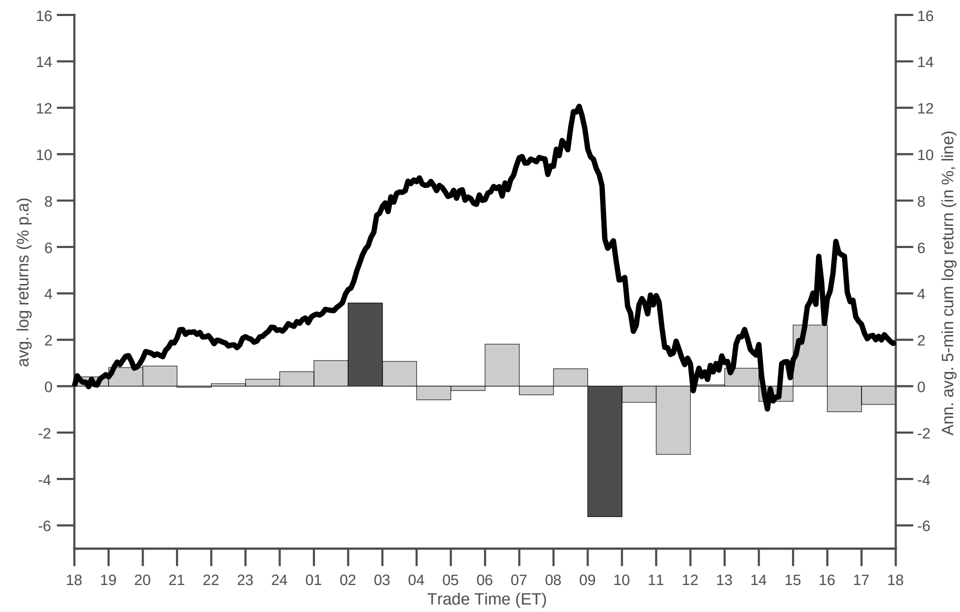
E 23-hour mean dist



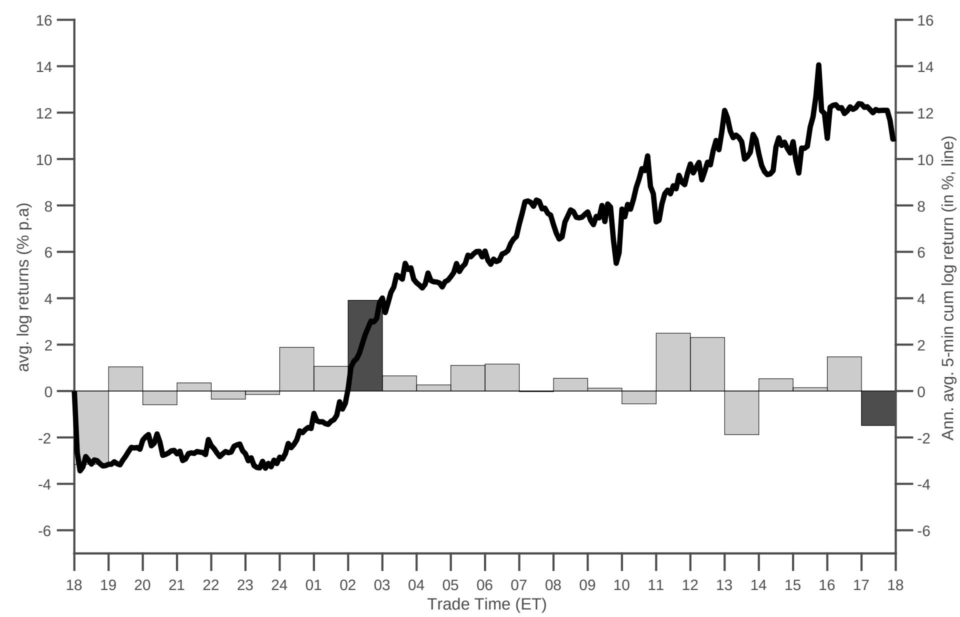
F 23-hour t-stat dist

Figure 4. Bootstrapped estimates

The distribution of hourly log return mean estimates is calculated using a block bootstrap (BS) sampling 10,000 times where days are partitioned into 24 subperiods as in Table 1. The optimal block length is chosen following Patton, Politis, and White (2009). Panel A plots the distribution of all hourly returns pooled. Panel B plots the distribution of returns from 2:00 to 3:00. Panel C plots the distribution of all hourly t-statistics pooled. Panel D plots the distribution of t-statistics for 2:00 − 3:00. Panels E and F are equivalent to panels A and C after removing returns between 2:00 and 3:00 from the 24 subperiods. Solid lines represent the 95% confidence interval. Dotted lines represent median estimates for specific hours. Each histogram is normalized such that it represents a probability density function estimate; that is, the sum of the bar areas is equal to one. The sample period is January 1998 to December 2020.



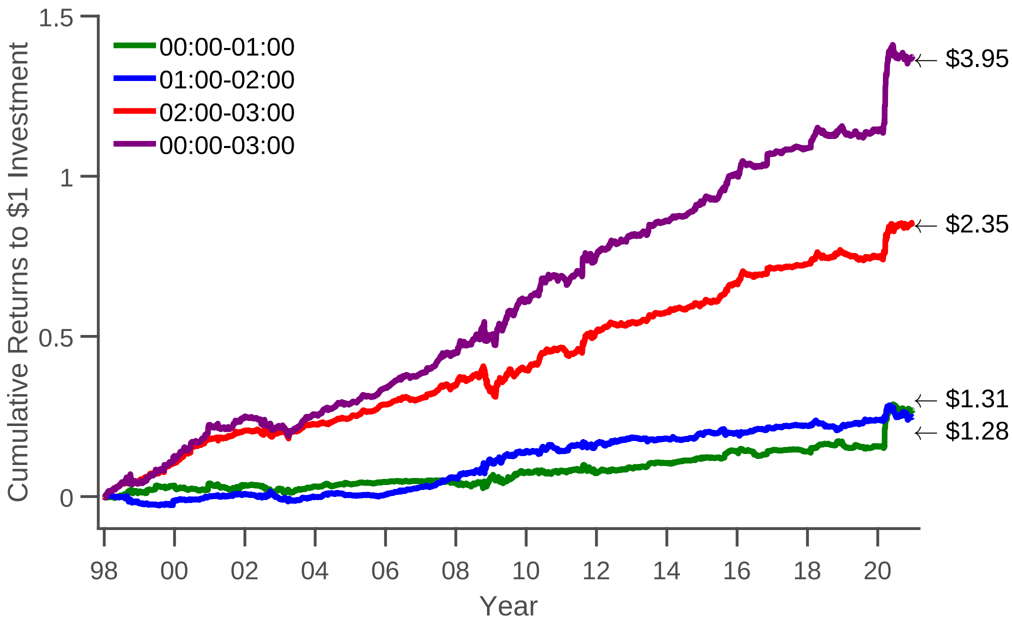
A



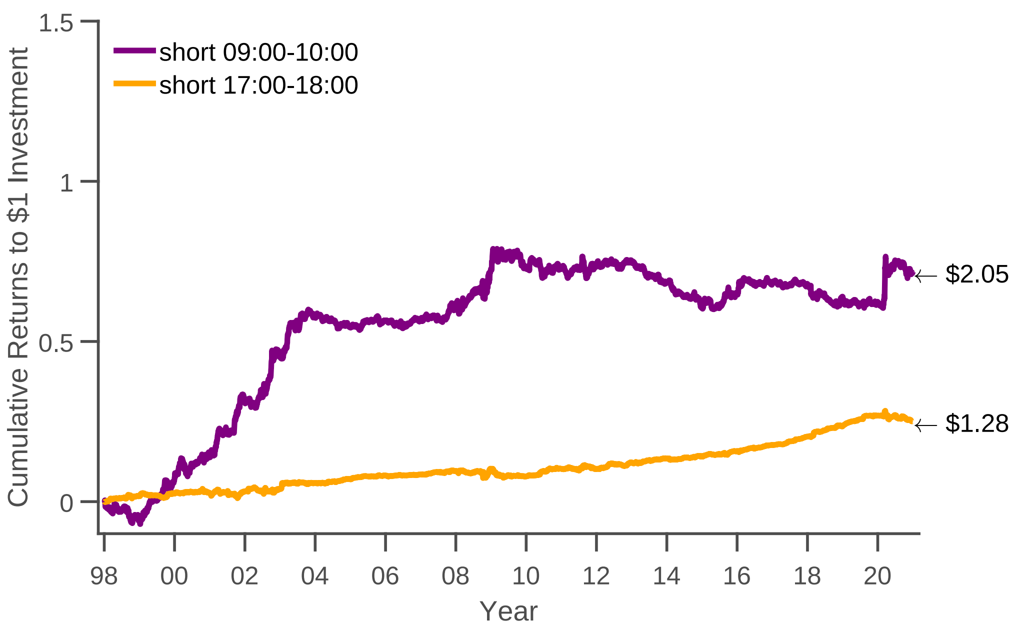
B

Figure 5. Intraday return averages: Subsamples

This figure plots the average hourly log returns (bars) and average cumulative 5-minute log returns (solid black line) holding the E-mini contract (first close-to-open and then open-to-close). Panel A plots the sample period January 1998 to December 2010. Panel B plots the sample period January 2011 to December 2020. Highlighted bars in dark grey represent Bonferroni corrected p-values, which are significant at the 5% level or less, which accounts for the multiple testing nature of our 24-hour dissection.



A



B

Figure 6. Return persistence

This figure displays the cumulative log returns to a $1 initial investment that trades various subperiods of the day. Panel A considers long positions in the hours {24-01, 01-02, 02-03} in addition to an extended window spanning 24-03. Panel B considers the cumulative returns to a short position between 9 and 10 or 17 and 18. The sample period is January 1998 to December 2020.

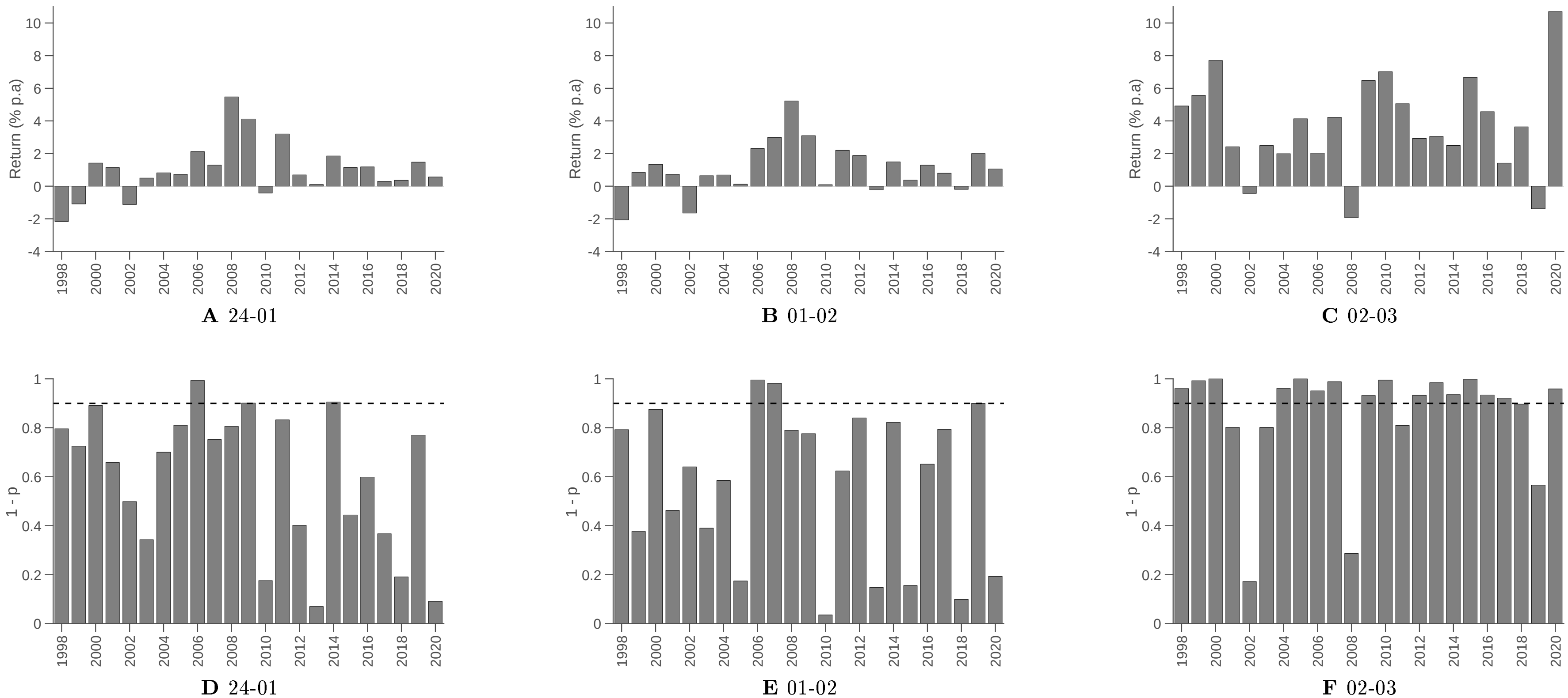


Figure 7. Year by year

This figure plots yearly average log returns (top panels) and $(1-p)$ the values from a t-test against the null hypothesis that these returns are zero (bottom panels). Panels indicate the hour of the night. The sample period is January 1998 to December 2020.

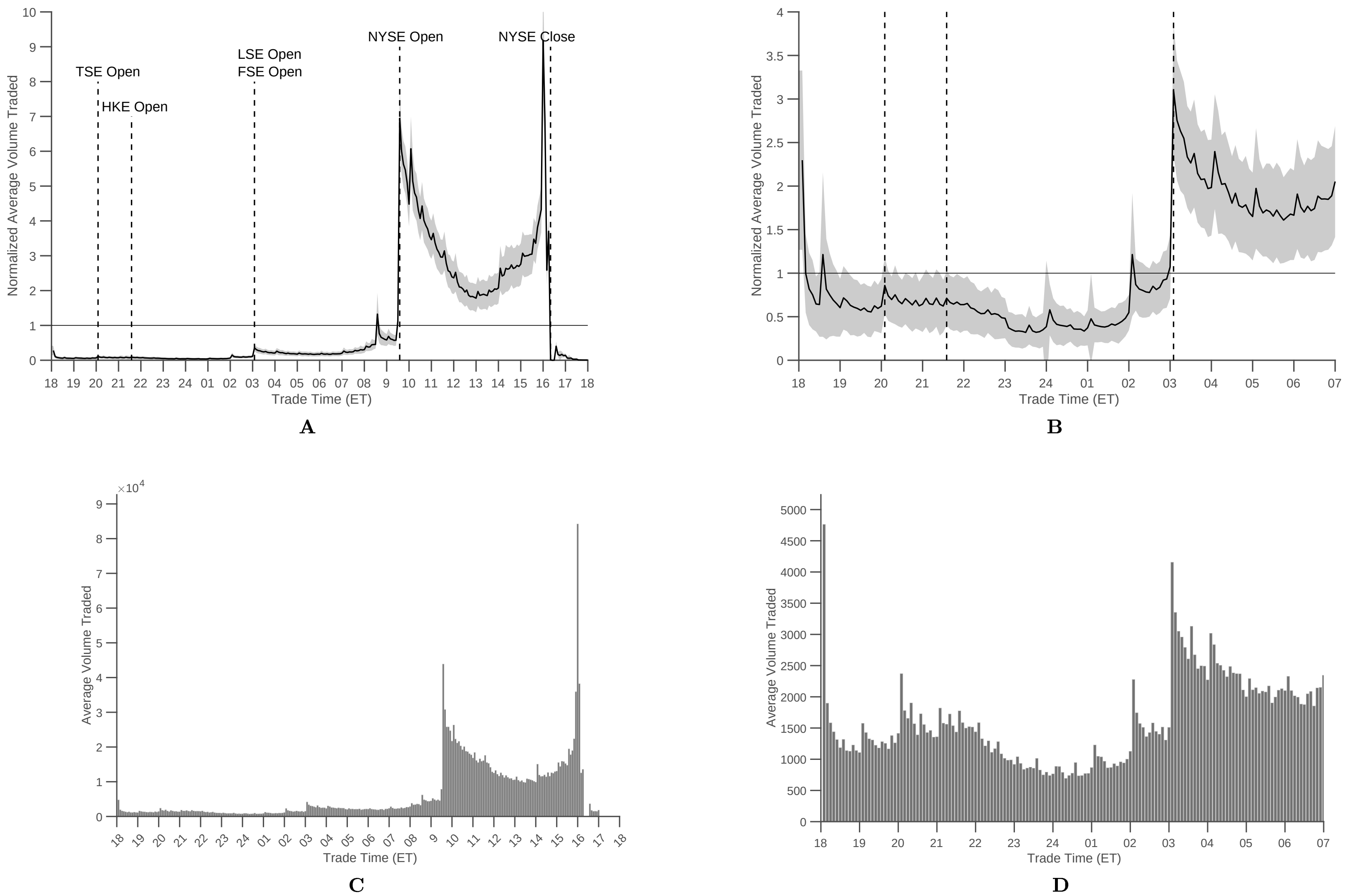
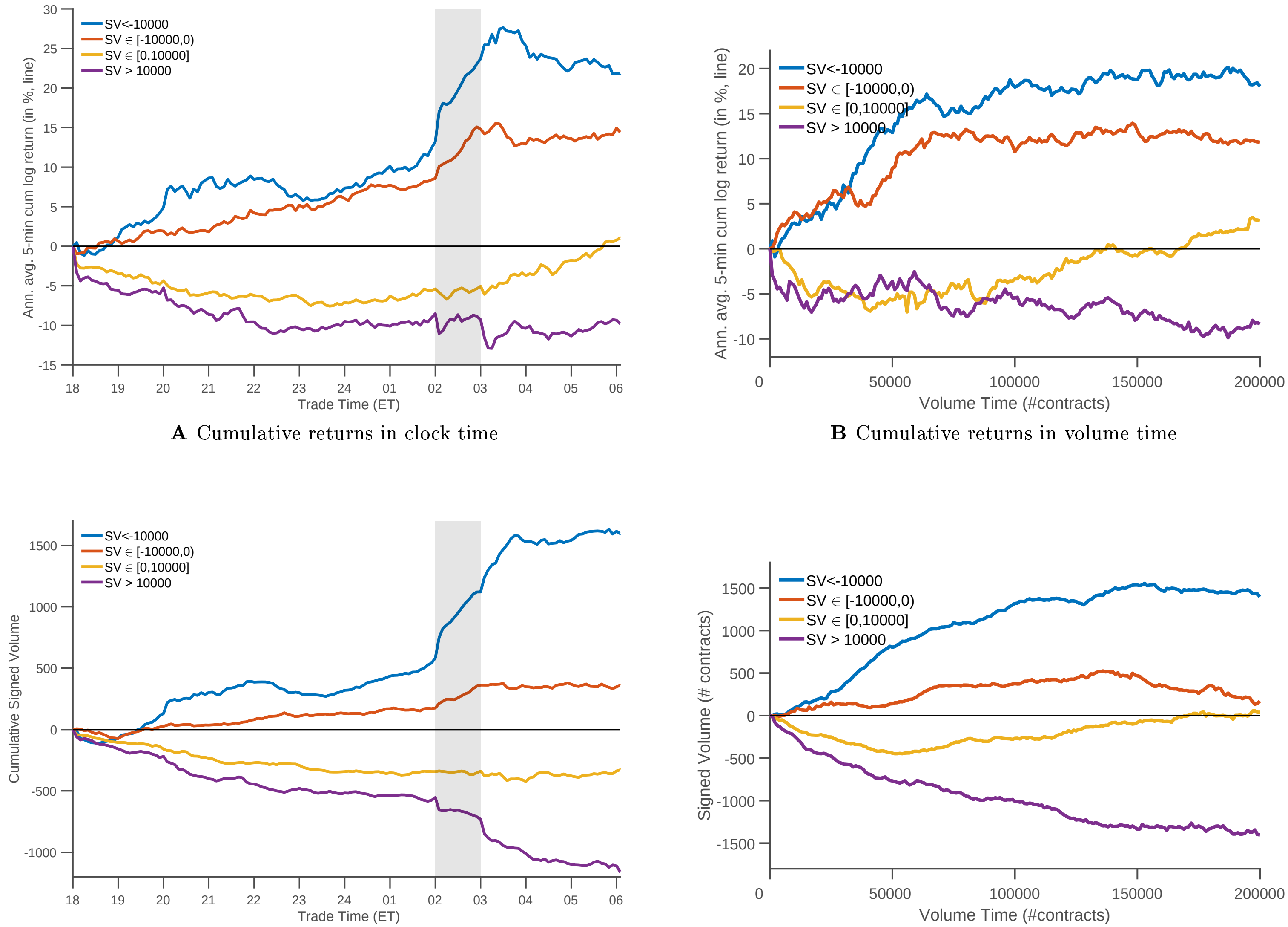


Figure 8. Intraday equity volumes

Panel A plots the average 5 minute trading volume of the E-mini for the entire trading day, showing the full intraday pattern of volume. Panel B focuses on volume outside U.S. open hours. Volumes are normalized by dividing each 5-minute volume by its daily volume, and then averaging normalized 5-minute intervals over all days in the sample. Panel C plots average volumes for all hours of the day during 2020. Panel D zooms in on average overnight volumes during 2020.



A Cumulative returns in clock time

B Cumulative returns in volume time

C Cumulative signed volume in clock time

D Cumulative signed volume in volume time

Figure 9. Volume time

This figure displays the cumulative log returns and the cumulative signed volume in both clock time and volume time and sorted by closing signed volume (SV_{t-1}^{close}) from the previous trading day. Volume time is defined such that a one increment step on the x-axis advances each time a single contract is traded. The sample period is January 2007 to December 2020.

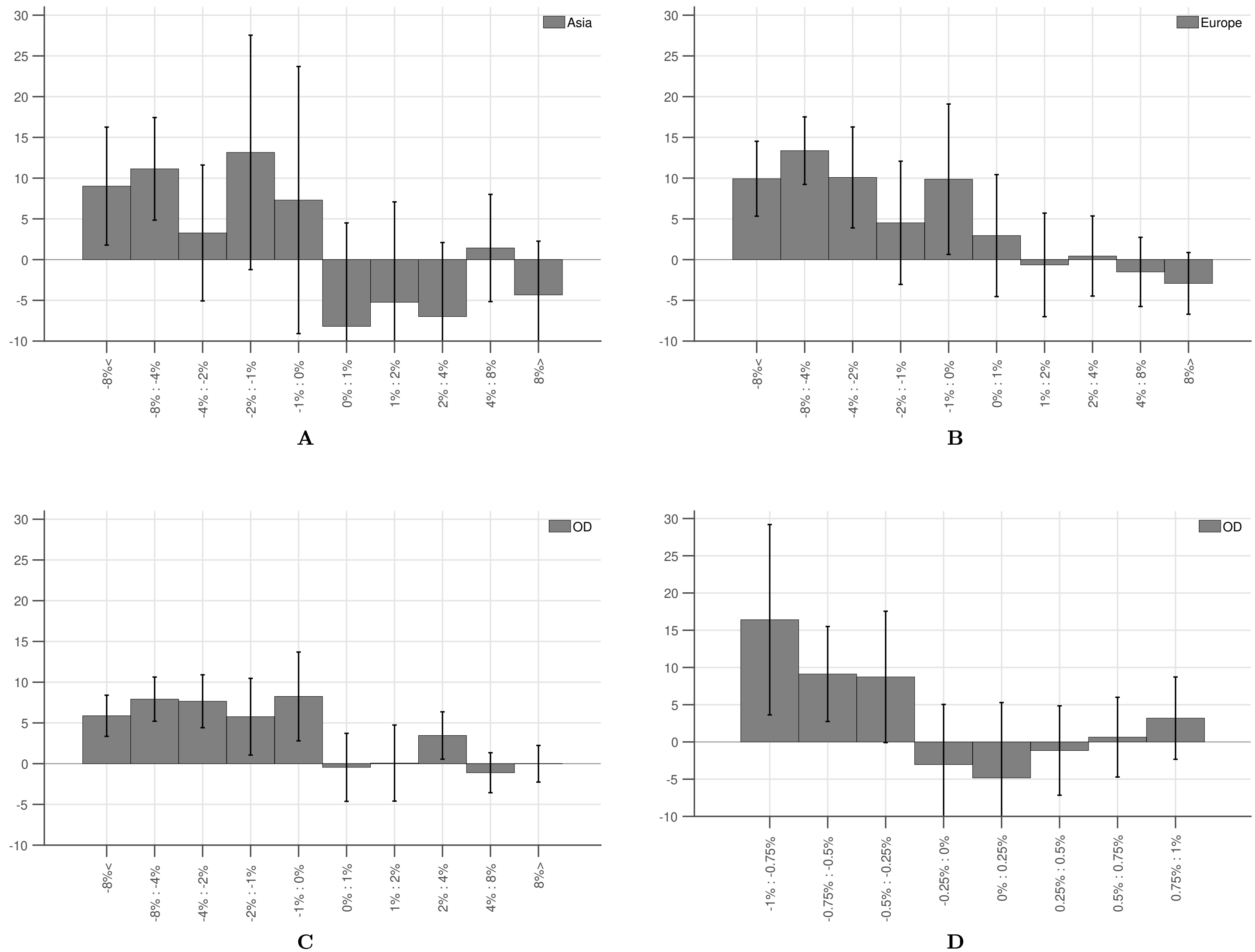


Figure 10. Average overnight returns sorted on closing imbalance

Panels A, B, and C sort all trading days based on ten sets of closing relative signed volume (RSV_{t-1}^{close}) of the preceding trading day and the average annualized returns of each group are plotted for subsequent Asian trading hours (18:00 – 2:00), for returns during European trading hours (1:00 – 4:00), and for returns during the overnight drift hour (2:00 – 3:00). Panel D zooms in on the overnight drift hour for closing order flow sorts straddling zero imbalances. The sample period is January 1998 to December 2020.

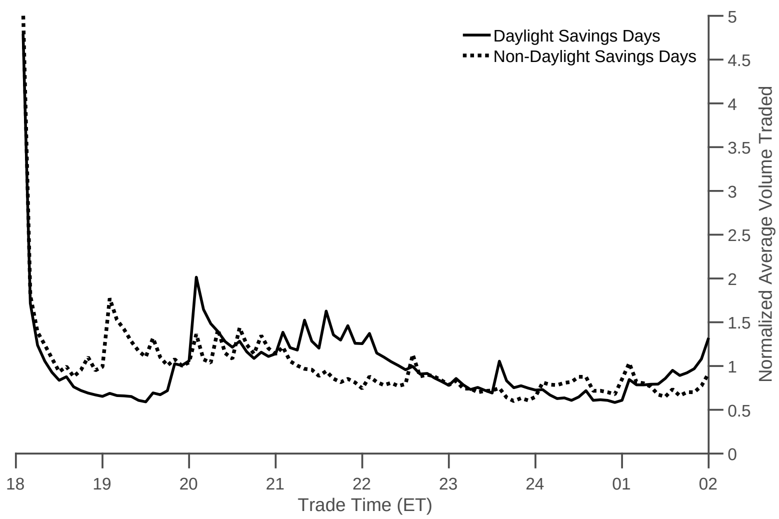
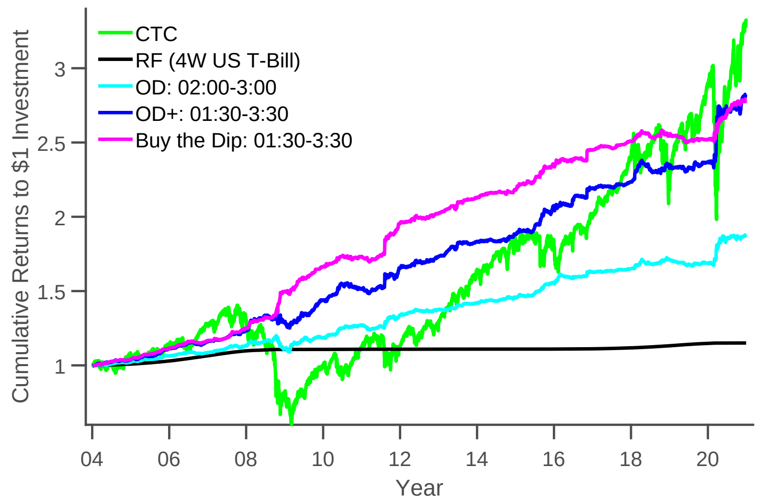
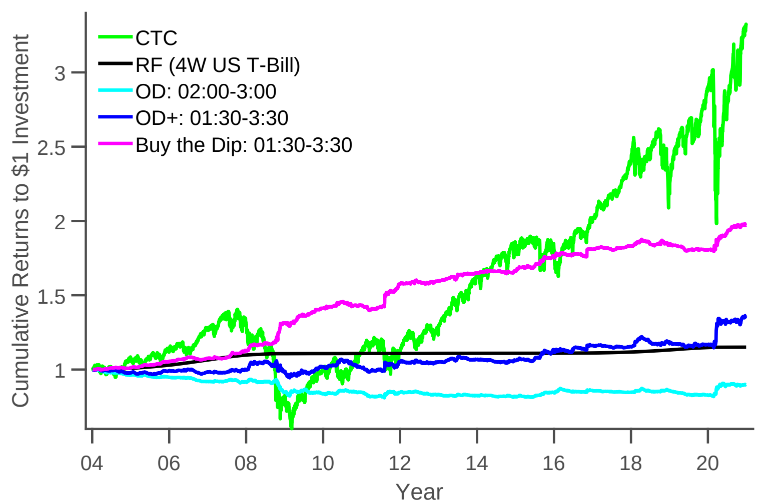


Figure 11. E-mini trading volume: Asian hours

Figure displays average trading volume in the E-mini contract for the Asian trading hours. Volumes are normalized by dividing each 5-minute volume by its daily volume, and then averaging normalized 5-minute intervals over all days in the 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, when U.S. DST is not active and at 20:00 when U.S. DST is active. TSE reopens at 22:30 (23:30) after its lunch break when U.S. DST is not active (active). All volumes are computed as averages of the 5-minute volume relative to the total daily volume. The sample period is January 2007 to December 2020.



A Without transaction costs



B With transaction costs

Figure 12. Cumulative returns with and without transaction costs

Figure displays time series of cumulative returns for a one dollar investment in various intraday trading strategies for the E-mini contract. The investment starts in 2004, when the overnight spread reached its effective minimum of one tick (0.25 index points). Panel A (B) excludes (includes) transaction costs. *CTC* is continuously holding the E-mini contract. *OD* is the strongest part of the overnight drift from 2:00 to 3:00, and *OD+* is from 1:30 to 3:30 and buy the dip goes long from 1:30 to 3:30 only on days following a negative closing order flow. The black line represents the cumulative risk-free return measured as the return of a 4-week U.S. Treasury bill. Returns excluding transaction costs are computed from the mid quotes and returns, including transaction costs are computed from the best bid and best ask price.

The Overnight Drift

Internet Appendix

Section A.1 reports supplementary results to our central empirical contribution, which is the documentation of consistent positive returns for holding U.S. equity futures around the opening of European financial markets. Section A.2 reports robustness tests related to our market making explanation. This section repeats our main inventory risk tests with an alternative measure of order imbalance. Section A.3 provides a survey of Grossman and Miller (1988) (GM) interpreting the results of that paper in the context of our setting. Section A.4 discusses a series of alternative explanations based on volatility risk, liquidity risk, the arrival of overnight news, and the resolution of uncertainty.

A.1. Supplementary results: overnight drift

A.1.1. Relationship to existing overnight literature

Figure A.1 displays cumulative close-to-close (CTC) log returns on S&P 500 futures: $1 invested at the beginning of 1983 becomes $27 dollars by the end of 2020, translating into an annual log return of 8.65%. Decomposing into intraday versus overnight components open-to-close (OTC) log returns averaged 5.12%, while close-to-open (CTO) log returns averaged 3.53% This figure updates the findings of Cliff, Cooper, and Gulen (2008) and Kelly and Clark (2011), who both document that equities earn a substantial proportion of their returns during the overnight period. Overnight return patterns are also well discussed in the financial press.[38] We note here that earning a substantial overnight return is not, in itself, that surprising. Given the length of the overnight period, one would even expect the overnight period to earn the largest return if information flowed continuously as in a Black-Scholes economy. What is surprising is that the overnight versus intraday return dissection only becomes noticeable after the advent of overnight electronic markets. Indeed, the red and blue lines track each other quite closely until after the introduction of GLOBEX and shortly before the introduction of the E-mini contract. These dates are marked by vertical dotted lines. Our discovery of an overnight drift in U.S. equities during the opening of European markets and our explanation based on demand for immediacy are closely related to this long-standing puzzle.

[Insert figure A.1 here]

A.1.2. Supplementary results: section 2

A.1.2.1. Day of the week

Panel (a) of figure A.3 plots cumulative 5-minute returns sampled for each trading day of the week. In terms of close-to-close returns, $r_{CTC}^{TUE} \sim r_{CTC}^{WED} \sim r_{CTC}^{THU}$ while returns on Mondays and Fridays are significantly lower. Considering the OD, it is clearly visible in each day of the week, and displays far less dispersion than close-to-close returns, suggesting that it is a systematic phenomenon. Panel (a) of table A.5 tests this claim formally using a regression dummy framework as above. In all days of the week, the 2:00 - 3:00 return is positive and significant at the 1% level and the magnitude of the returns is also quite similar.

Panel (b) of table A.5, on the other hand, shows that the OP returns are always negative but statistically significant only on Thursdays and Fridays with mean returns equal to -2.10 and -3.03 basis points

[38] www.bloomberg.com/news/articles/2020-06-05/the-stock-rebound-really-gets-going-after-wall-street-logs-off www.bloombergquint.com/markets/volatility-bout-puts-outsize-overnight-stock-moves-in-focus

per hour per day, with t-statistics equal to -2.02 and -2.76, respectively. Figure A.10 reports three pieces of suggestive evidence as to why the OP occurs only on Thursdays and Fridays: First, we observe more U.S. macro announcements released at 8:30 on Thursdays and Fridays. Generally, we experience large positive returns leading up to announcements, as has been documented in the literature (Savor and Wilson (2013)). We conjecture that (short-lived) price reversals following the macro announcements partly explain the negative opening returns. Second, we do not observe many FOMC announcements on Thursdays and Fridays and we also know that returns typically are positive in the hours leading up to FOMC announcements, which subsequently do not revert (Lucca and Moench (2015)). Third, we observe that most negative earnings announcement days are Thursdays and Fridays. In summary, while OP returns are concentrated in the final days of the week, OD returns are systematically positive and significant on each day of the week.

[Insert figure A.3 and A.10 and table A.5 here]

A.1.2.2. Month of the year

Panel (b) of figure A.4 plots average cumulative 5-minute returns across the trading day for the futures contract roll months March, June, September and December. While ID returns display significant variation, in particular the OP is large and negative in September, equal to -3.45%, opening returns are either slightly positive or negative in other months. The OD, however, is clearly visible in all months. More formally, table A.6 reports the statistical significance within each calendar month. Consistent with figure A.4, the OD drift is positive in all months of the year and statistically significant at conventional levels in 9 out of 12 months.

[Insert figure A.4 and table A.6 here]

A.2. Supplementary results: section 3 & 4 of paper

Sections 3 and 4 conducted a number of tests of the relationship between the overnight drift and trading imbalances as predicted by inventory risk models along the lines of Grossman and Miller. In these sections, we primarily measured end-of-day (EOD) order imbalances in terms of RSV and the sample period was 1998–2020. In this part of the IA we present counterparts to the results of the main body but using SV instead. We use the sample period 2007–2020, since total volumes were relatively stationary over this period; see figure A.6.[39] Using the SV measure in the early sample period would be problematic, since trading volume has increased by more than a factor of 1000 since the early 2000's; thus, an order imbalance of 1000 contracts would be massive in 1998 when the E-mini had just started trading but it would be small in 2020.

Table A.7 reports summary statistics for hourly SV_t. On average, close-to-close SV_t is equal to -2,217 contracts (t-stat = -3.27), is highly volatile, and negatively skewed. Indeed, the median SV_t is actually positive. Negative $CTC\ SV_t$'s are consistent with the idea that the futures market is traded as a hedging instrument for the underlying. However, while SV_t's are negative during the day, they are largely positive overnight. During the OD hour, SV_t is equal to 124 contracts with a t-statistic of 4.23, mirroring the unconditional positive returns during this hour. Panel (c) zooms in on the signed volume during the closing hour of U.S. trading. In the following, we use the last hour preceding the maintenance break to

[39] Closing order imbalances can be very extreme, as seen in 2006 where there was a net sell-off of more than 250,0000 contracts in the last hour of trading: *A sense of calm that returned to the market Tuesday disappeared in the final minutes of trading as stocks gyrated and reversed earlier gains.* See `www.money.cnn.com/2006/05/23/markets/markets_newyork/index.htm`.

measure *closing* order imbalances. Thus, SV_t^{close} denotes the order imbalance based on all trades sampled during the hour 15:15 – 16:15.

[Insert table A.7 here]

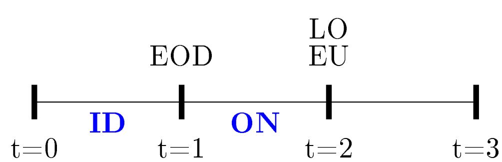
Consistent with the findings for the sample period January 1998 – December 2020 using RSV_t^{close}, figure A.7 shows that sorting days based on SV_t^{close}, positive overnight returns occur only on nights following market sell-offs (negative end-of-day order imbalances). Price reversals following market *rallies* are much more modest; thus, we have uncovered a strong demand asymmetry between long and short inventory positions. Consistent with the prediction of GM that higher price uncertainty should command a higher liquidity premium, table A.8 reports double sorts on SV_t^{close} and EOD VIX and shows that the OD returns are amplified in states of higher ex-ante volatility but only following market sell-offs. Finally, table A.9 confirms high-frequency return predictability arising at the opening of European financial markets via projections onto SV_t^{close}.

[Insert figure A.6, figure A.7, table A.8 and table A.9 here]

From inventory models we know that order flow predicts returns. However, the more liquid a market is, the shorter the period of predictability should be because liquidity providers can quickly trade imbalances away. In illiquid markets, such as the corporate bond market, you can observe predictability over days. For the E-mini, negatively autocorrelated return predictability *usually* only lasts a couple of minutes. For example, figure A.8 displays 5-minute predictability regressions of returns on lagged signed volume for lags out to one hour. Only the first 5-minute lag is significantly negative. The bottom panel shows that this pattern occurs in returns at the same frequency. What makes predictability by the order imbalance at the closing of U.S. trading hours special is that the volumes transacted are much larger than those traded in the subsequent hours. Therefore, a market maker providing immediacy in this market is faced with a (potentially) large order imbalance at the end of the day that will take a long(er) time to trade away overnight, creating a longer-horizon return predictability overnight. Indeed, this is precisely the fundamental assumption of Grossman-Miller style models: market makers have to absorb excess order flow in the near term in the hope that new trader will arrive at some point in the future.

[Insert figure A.8 here]

A.3. Grossman and Miller (1988) review



Trading Periods

There exists a risk-free asset (cash), B, with a zero rate of return, and a risky futures contract that pays S_3 at date $t = 3$ where S_3 is conditionally normally distributed. Public information about S_3 arrives before trading in period 1 and again before trading in period 2:

$$S_3 = S_2 + \epsilon_3 = S_1 + \epsilon_2 + \epsilon_3 = \mu + \epsilon_2 + \epsilon_3, \tag{A.1}$$

where news shocks $\epsilon_2, \epsilon_3 \sim \mathcal{N}(0, \sigma_t^2)$.

Assume there are N competitive market makers (MM) with a CARA utility function and identical risk aversions α. At $t = 0$ dealers hold a non-zero cash position but a zero position in the risky asset: $q_0^{MM_n} = 0$. In period $t = 1$, a representative intraday liquidity trader (ID), who holds an initial endowment of q_0^{ID} futures contracts, executes a transaction of q_1^{ID} contracts. Dealers provide immediacy at $t = 1$ by trading with the ID agent and next period $t = 2$ dealers meet a representative overnight liquidity trader (ON), who trades an offsetting amount. Denote the initial endowments of the ID and ON trader as $q_0^{ID} = \mathcal{I} = -q_0^{ON}$. Demand for immediacy thus arises because the liquidity demand by non-market-maker traders in period 1 is asynchronous with the liquidity supplied by overnight liquidity traders that arrive in period 2. The ID liquidity trader thus faces the risk of delaying execution until one period later, or offloading some of that trade now to the market makers who start with zero inventory but are willing to carry some inventory in exchange for a liquidity premium (expected transaction return).

The problem of determining equilibrium quantities and prices is solved backward in time. At $t = 2$, agent $i \in \{MM_1, \dots MM_n, ID, ON\}$ maximizes their expected utility subject to their budget constraints

$$\max_{q_2^i} E_2\big[-\exp(-\alpha W_3^i)\big] \tag{A.2}$$

$$W_2^i = B_2^i + q_2^i S_2 = B_1^i + q_1^i S_2 \tag{A.3}$$

$$W_3^i = B_2^i + q_2^i S_3 \tag{A.4}$$

$$= W_2^i + q_2^i (S_3 - S_2), \tag{A.5}$$

where the expectation is taken conditional on the information set realized at date $t = 2$. Eliminating the cash position from the problem is equivalent to

$$\max_{q_2^i} \alpha(W_2^i + q_2^i(E_2[S_3] - S_2)) - \frac{1}{2}(\alpha q_2^i \sigma_t)^2. \tag{A.6}$$

The first-order condition is

$$q_2^{*,i} = \frac{E_2[S_3] - S_2}{\alpha \sigma_t^2} \tag{A.7}$$

$$\bar{q}_2^{*,i} = \frac{E_2[S_3] - S_2}{\alpha \sigma_t^2} - q_0^i, \tag{A.8}$$

where in the second line we have written the first-order condition in "excess demand" terms

$$\bar{q}_t^i = q_t^i - q_0^i. \tag{A.9}$$

Market clearing in period 2 gives us:

$$0 = \sum_i \bar{q}_2^i = \underbrace{\left[\frac{E_2[S_3] - S_2}{\alpha \sigma_t^2} - \mathcal{I}\right]}_{\bar{q}_2^{*,ID}} + N \cdot \underbrace{\left[\frac{E_2[S_3] - S_2}{\alpha \sigma_t^2}\right]}_{\bar{q}_2^{*,MM}} + \underbrace{\left[\frac{E_2[S_3] - S_2}{\alpha \sigma_t^2} + \mathcal{I}\right]}_{\bar{q}_2^{*,ON}}. \tag{A.10}$$

Moving backward one period, at $t = 1$, the portfolio choice problem is now solved by the set of agents

$i \in \{MM_1, \ldots MM_n, ID\}$ and given by

$$\max_{q_1^i} E_1\big[-\exp(-\alpha W_2^i)\big] \tag{A.11}$$
$$W_2^i = B_1^i + q_1^i S_2 \tag{A.12}$$
$$W_1^i = B_1^i + q_1^i S_1 = B_0^i + q_0^i S_1, \tag{A.13}$$

which is equivalent to

$$\max_{q_1^i} \alpha(W_1^i + q_1^i(E_1[S_2] - S_1)) - \frac{1}{2}(\alpha q_1^i \sigma_t)^2. \tag{A.14}$$

The first-order condition in excess demand terms is given by

$$\bar{q}_1^{*,i} = \frac{E_1[S_2] - S_1}{\alpha\sigma_t^2} - q_0^i = \frac{\mu - S_1}{\alpha\sigma_t^2} - q_0^i. \tag{A.15}$$

Imposing market clearing in period $t = 1$ and remembering $q_0^{MM} = 0$ and $q_0^{ID} = \mathcal{I}$

$$\bar{q}_1^{ID} + N q_1^{MM} = 0 \tag{A.16}$$
$$(N+1)\frac{\mu - S_1}{\alpha\sigma_t^2} = \mathcal{I}, \tag{A.17}$$

and so the equilibrium clearing price is given by

$$S_1 = \mu - \mathcal{I}\sigma_t^2 \frac{\alpha}{N+1}. \tag{A.18}$$

At this point, it is worth making clear that the ID agent does not offload their entire initial position to the MM. Substituting the equilibrium price back into the optimal *demands* we see

$$q_1^{*,MM} = \frac{\mathcal{I}}{N+1} \tag{A.19}$$
$$\bar{q}_1^{*,ID} = -N q_1^{*,MM} = -\frac{N\mathcal{I}}{N+1} \tag{A.20}$$
$$q_1^{*,ID} = \mathcal{I} - N\frac{\mathcal{I}}{N+1}. \tag{A.21}$$

The larger the number of dealers present, the greater is the optimal initial position that is immediately traded. For example, with the introduction of a single EOD MM, 50% of the initial order imbalance will be carried overnight by the MM. In the CME E-mini market, on average since 2009, there are more than 30 dealers continually posting quotes at the best bid and ask, implying that 96% of imbalances, conditional on a liquidity event, will be absorbed end-of-day and carried overnight.

Now, define the return $R_{ON} = (S_2 - S_1)/S_1$ which compensates the dealer for holding inventory between $t = 1 \rightarrow t = 2$. Then, from (A.17) and using $\sigma_t^2 = Var_1[S_2] = S_1^2 Var[S_2/S_1] = S_1^2 Var[R_{ON}] =$

$S_1^2\sigma^2_{R,t}$, we have

$$(N+1)\frac{E_1[S_2]-S_1}{\alpha S_1^2\sigma^2_{R,t}} = \mathcal{I} \tag{A.22}$$

$$\Leftrightarrow \qquad \frac{E_1[S_2]-S_1}{S_1} = S_1\mathcal{I}\times\sigma^2_{R,t}\times\frac{\alpha}{N+1}, \tag{A.23}$$

which shows that expected overnight return are composed of

$$E_1[R_{ON}] = \begin{matrix}\text{Dollar Order}\\ \text{Imbalance}\end{matrix} \times \begin{matrix}\text{Return}\\ \text{Variance}\end{matrix} \times \begin{pmatrix}\text{Risk-Bearing}\\ \text{Capacity}\end{pmatrix}^{-1}. \tag{A.24}$$

From $R_{ON} = (S_2 - S_1)/S_1$, we can also consider the conditional covariance of the overnight return and the intraday order imbalance (from the perspective of period $t = 0$ such that $S_1\mathcal{I}$ is random):

$$\text{cov}_0[S_1\mathcal{I}, R_{ON}] = -\text{var}_0\left(S_1\mathcal{I}\right)\sigma^2_{R,t}\times\frac{\alpha}{N+1}, \tag{A.25}$$

which shows that the size of the reversal following the date $t = 1$ imbalance is larger when

- dollar order imbalance is larger (more variable);
- conditional variance is larger;
- dealer risk-bearing capacity is smaller.

While the size of the price reversal above is variable, the speed of the reversal happens very fast and always within one period. This is because $q_0^{ID} = \mathcal{I} = -q_0^{ON}$. Relaxing this assumption one can solve for the case $q_0^{ID} = \mathcal{I} = -\Delta q_0^{ON}$. The case of $\Delta > 1$ implies a large overnight demand, while the case $\Delta < 1$ implies a small overnight demand. It is straightforward to solve this model and we find that lower overnight demand will increase the magnitude of return reversals but the speed of mean reversion (between $t = 0$ and $t = 3$) is slower. Thus, lower overnight demand implies that overnight return reversals are not completed until later in the overnight session.

We now turn to the potential relationship between dealer risk-bearing capacity and return variance. Keeping fixed the number of dealers, we can endogenize dealer risk aversion by incorporating a value-at-risk (VaR) constraint into the market maker's problem, as is done, for example, in Danıelsson, Shin, and Zigrand (2004); Adrian and Shin (2010, 2014) and the subsequent literature. More specifically, we modify the optimization problem (A.14) to include a VaR constraint, so that the market makers solve

$$\max_{q_1^{MM_i}} \quad -\alpha\left(W_1^{MM_i} + q_1^{MM_i}\left(E_1[S_2]-S_1\right)\right) + \frac{1}{2}(\alpha q_1^{MM_i}\sigma_t)^2 \tag{A.26}$$

s.t.

$$\bar{p} \geq \mathbb{P}_1\left(\underbrace{W_1^{MM_i} + q_1^{MM_i}\left(E_1[S_2]-S_1\right)}_{=E_1\left[W_2^{MM_i}\right]} - W_2^{MM_i} \geq \text{VaR}\right). \tag{A.27}$$

That is, the market maker maximizes the expected utility of providing inter-period liquidity (as in A.14) but now subject to the probability of losses larger than the permitted value-at-risk (VaR) being lower than a pre-specified permitted probability $\bar{p}$. Denote by $\Phi(\cdot)$ the distribution function of the standard normal. Then we can rewrite (A.27) as

$$\Phi\left(\frac{-\text{VaR}}{\sigma_{W_2^{MM_i}}}\right) \leq \bar{p},$$

or, equivalently,

$$\sigma^2_{W_2^{MM_i}} \leq \left(\frac{\text{VaR}}{\Phi^{-1}\left(1-\bar{p}\right)}\right)^2 \equiv \bar{v}. \tag{A.28}$$

Here, $\sigma_{W_2^{MM_i}}$ is the volatility of period 2 wealth, given period 1 information, which, for the market makers, is given by $\sigma_{W_2^{MM_i}} = q_1^{MM_i}\sigma_t$. Denoting by $\alpha\lambda_t/2$ the Lagrange multiplier on the simplified VaR constraint (A.28), we can thus rewrite the market makers' optimization problem as

$$\max_{q_1^{MM_i}} \quad \alpha\left(W_1^{MM_i} + q_1^{MM_i}\left(E_1[S_2] - S_1\right)\right) - \frac{1}{2}(\alpha q_1^{MM_i}\sigma_t)^2 - \frac{\alpha\lambda_t}{2}\left(\bar{v} - \left(q_1^{MM_i}\sigma_t\right)^2\right) \tag{A.29}$$

$$0 = \frac{\alpha\lambda_t}{2}\left(\bar{v} - \left(q_1^{MM_i}\sigma_t\right)^2\right). \tag{A.30}$$

Thus, in the presence of a VaR constraint, the optimal demand by a market maker is given by

$$q_1^{*,MM} = \frac{\mu - S_1}{\left(\alpha + \lambda_t\right)\sigma_t^2}, \tag{A.31}$$

and the market maker's effective risk aversion becomes $\alpha + \lambda_t$. For a given level of the permitted value-at-risk and permitted probability $\bar{p}$, increases in volatility tighten the value-at-risk constraint, raising the effective risk aversion of value-at-risk constrained market makers. Similarly, if the permitted value-at-risk is given as a fraction of equity – so that $\text{VaR} = \varphi W_1^{MM_i}$ – rather than as a dollar amount, the value-at-risk constraint is tighter when the market maker equity declines.

The framework above suggests that value-at-risk may serve as a reasonable proxy for market makers' capital commitments to the trade. Value-at-risk is a measure of economic capital, that is, the capital required to absorb losses in excess of expected loss due to current risks. As noted in, for example, the BCBS white paper on "Range of practices and issues in economic capital frameworks":[40]

> Economic capital was originally developed by banks as a tool for capital allocation and performance assessment.

In other words, banks use notions of economic capital to determine the composition of the asset side of their balance sheets, both from the perspective of the relative size of different lines of business and from the perspective of allocating to business units within each line of business. We thus view that using a measure of economic capital as being appropriate in the context of evaluating market makers' risk-bearing capacity. Although bank capital regulation has famously evolved over our sample period, the major regulatory changes have a limited impact on economic capital as it relates to equity futures, since both the futures and the underlying basket of securities are exchange-traded throughout our sample period, and are on-balance-sheet items for supervised institutions.[41]

More specifically, we focus on the *equity* VaR as opposed to the *total* VaR of reporting institutions. Conversations that the Federal Reserve Bank of New York conducted with major market participants

[40] `https://www.bis.org/publ/bcbs152.pdf`

[41] Post-crisis changes to capital regulation had the biggest impact on over-the-counter, non-centrally cleared, off-balance-sheet securities.

following the implementation of post-crisis banking regulation suggest that large financial institutions allow different business lines to make day-to-day allocation decisions independently, as long as the overall economic capital allocated to that business line (and, indeed, business unit) is not exhausted. Thus, for example, the equity futures "desk" makes day-to-day trading decisions independent of the Treasury desk. We thus view using equity VaR as balancing the desired definition of what constitutes a market maker in the market against the feasibility of granularity available in the data.

Acknowledging that our calculation is by its nature an approximation, we note that, even if the true economic capital allocated to the E-mini futures market is 10 times higher, our relative risk aversion estimate is comfortably within the range previously estimated in the literature.

Completing the derivation, the modified market clearing condition in equation A.16 becomes

$$\left(\frac{\mu - S_1}{\alpha\sigma_t^2}\right) + N\left(\frac{\mu - S_1}{(\alpha + \lambda_t)\sigma_t^2}\right) = \mathcal{I} \tag{A.32}$$

from which the equilibrium EOD price is now given by

$$S_1 = \mu - \mathcal{I}\sigma_t^2\left(\frac{\alpha^2 + \alpha\lambda_t}{N(\alpha + \lambda_t) + \alpha}\right) \tag{A.33}$$

from which we identify the modified risk-bearing capacity as

$$\overline{RBC}_t = \frac{N(\alpha + \lambda_t) + \alpha}{\alpha^2 + \alpha\lambda_t} \tag{A.34}$$

Then from

$$\frac{\partial \overline{RBC}_t}{\partial \alpha} = -\frac{1}{(\alpha + \lambda)^2} - \frac{N}{\alpha^2} \tag{A.35}$$

$$\frac{\partial \overline{RBC}_t}{\partial \lambda} = -\frac{1}{(\alpha + \lambda)^2} \tag{A.36}$$

we see the sensitivity of $\overline{RBC}_t$ w.r.t risk aversion is strictly larger (in magnitude) compared to the non-constrained case, adjusted by a term that is the sensitivity of $\overline{RBC}$ w.r.t the probability of the constraint binding. The expected overnight return becomes

$$E_t[R_{ON}] = \begin{matrix}\text{Dollar Order}\\\text{Imbalance}\end{matrix} \times \begin{matrix}\text{Return}\\\text{Variance}\end{matrix} \times \overline{RBC}_t^{-1} \tag{A.37}$$

and from equations A.35 and A.36 it is straightforward to show that expected overnight returns are strictly increasing in both risk aversion and the tightness of the dealer constraint.

A.4. Alternative explanations

In this subsection we link CRSP, Computstat and IBES datasets for S&P 500 firms to build intraday and overnight earnings surprises, and consider international macro announcements from Bloomberg, and central bank announcements sourced from Bloomberg and central bank websites. We also exploit tick-by-tick trades and quotes on VIX futures (VX) sourced from Refinitiv and complemented with data from the CBOE.

A.4.1. *Volatility risk*

Figure A.11 (a) depicts average realized intraday volatility (squared log returns) from 1998.1–2020.12 sampled at a 1-minute frequency. The intraday volatility displays the well-known U-shaped pattern for Asian, European and U.S. trading hours where volatility is high at the beginning and at the end of each trading period (Andersen et al. (2018)). Across trading periods, the level of volatility is lowest during Asian trading hours and highest during U.S. trading hours, relative to the average trading volume across the 3 periods. Comparing average levels for each session, we find that the volatility of U.S. hours is more than twice as large as that of Asian hours and therefore considerably larger than estimates of return volatility using close-to-close prices. The large spike in volatility at 8:30 is caused by the spike in volume observed just after U.S. macro announcements. Figure A.11(b) plots time series of the realized volatility for each of the three trading periods. The volatility is always lowest during Asian hours and highest during U.S. hours but the difference has diminished over time as trading volume in the overnight session has picked up. The three time series are highly positively correlated, indicating that volatility increases on the same days for all three trading periods. More importantly, we do not observe an obvious link between realized quantities of risk and returns.

[Insert figure A.11 here]

A.4.2. *Overnight liquidity*

To measure liquidity risk we construct hourly estimates of 1) Kyle (1985) lambda (based on returns sampled at the 1-min frequency), 2) the Amihud price impact measure and 3) the bid-ask spread. Figure A.12 depicts the average intraday patterns of these measures as well as their time series for the Asian, European and U.S. trading hours. As expected, intraday illiquidity is lowest during U.S. trading hours when the trading activity is highest and illiquidity is highest during Asian hours when the trading activity is at its lowest. The bid-ask spread is very close to the minimum tick size (0.25 index points) at all times during the trading day. All liquidity measures experience large changes throughout the sample period. Most notably, the overnight illiquidity (Asian and European hours) has decreased strongly as overnight trading activity has picked up, and today it is much closer to the illiquidity level in regular U.S. trading hours. Second, the illiquidity increases during times of crises, as one would expect.

Considering all three measures, we do not observe intraday patterns that could rationalize the OD returns with theories of liquidity risk. We see that average intraday bid-ask spreads are almost always trading at the minimum tick size, equal to 0.25 index points. The spread is only significantly higher after 16:30 when trading resumes after the maintenance break and volumes are close to zero (see figure 8). The jumps in the bid-ask spread at 8:30 and 10:00 correspond to the U.S. macro announcements that are released at these times.

In addition, since we observe the aggregate limit order book for the market, we can also measure intraday illiquidity by computing the depth of the market. Market depth is computed as the number of contracts available in each 5-minute interval, and is reported for the first five levels on each side of the order book. Figure A.14 shows the intraday depth averaged across all days in the 2009.1-2020.12 sample. Here we observe that, at each level, the depth of the bid is equal to the depth of the ask. We also note there are three depth regimes differentiated by Asia, European and U.S. trading hours. Depth is flat in Asian hours and rises throughout European hours.

At the opening of the U.S. market, depth increases steeply, remains relatively flat during the regular U.S. hours and then spikes at the U.S. close before dropping in the overnight market. However, we also see that the overnight market remains highly *liquid*. For example, until 2:00 at the top level (L1) there are, on average, 100 contracts available, which in dollar terms with the S&P level at 2000 is equal to $10 million at the bid or ask. Considering all levels, L1 - L5 depth rises to $80 million. Indeed, a highly liquid overnight market is consistent with the large overnight volumes traded in this market, which, as noted in the introduction, have averaged in excess of $15 billion daily.

[Insert figures A.12, A.14, A.14, A.15 here]

A.4.3. Overnight news

We now consider whether overnight news released after the U.S. cash market closes is not immediately incorporated into prices during Asian hours but instead accumulates and is resolved at European open when trading volumes increase. Indeed, a large fraction of U.S. corporate earnings announcements are released after the U.S. market closes. Furthermore, Asian and European macro or central bank information released during the U.S. overnight session may signal news about U.S. growth prospects. Explanations for the overnight drift along these lines are related to a literature that shows that conditional risk premia are higher on days prior to and on days of macroeconomic announcements.[42] We study this conjecture by examining hour-by-hour returns conditional on U.S. earnings announcements, and U.S., Japanese or European macro- and central bank announcements.

A.4.3.1. Earnings announcements

We test whether 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 are 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 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. Since 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.[43] We define the daily earnings surprise of the S&P 500 index, ES_t, as the daily sum of all ES_i.[44]

Figure A.16 plots the time series of ES_t. The shocks are periodic on a quarterly basis and generally positive ($\sim$ 75% of all shocks are positive). Notably, we see large negative shocks during the financial crisis and almost exclusively positive shocks following the crisis.

To test this conjecture formally, we sort all trading days based on ES_t. We choose only announcements that are published after the U.S. market closes (16:00 ET). This is because the effect of announcements published early in the day should be incorporated into the price on that day, while announcements that occur after CTO hours could affect returns in these hours. Table A.13 reports the average returns for day $t+1$ after sorting on ES_t. We sort all trading days into 5 groups based on ES_t. In group 1, $ES_t < 0$. For groups 2-4, ES_t is positive and increasing by group. Group 5 is for days where ES_t is zero, i.e., not a single firm announced its earnings prior to these days (this was $\sim$ 46% of all trading days). The

[42] In the context of stock returns, Savor and Wilson (2014) show that equity risk premia are consistently larger on days when U.S. inflation, GDP and non-farm announcements are made. Lucca and Moench (2015), on the other hand, document a drift in the U.S. stock market that *precedes* FOMC announcements.

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

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

table contains a number of interesting findings. First, we see a strong monotonic positive relationship between earnings shocks and *CTC* returns across groups. Second, no news days have the highest CTC return, equal to 4.57 % p.a., with a t-statistic of 1.86, and in this sense "no news is good news." Third, negative shocks are not incorporated into the price until the U.S. market opens, while positive shocks are incorporated immediately during the *CTO* period. However, most importantly for the focus of this paper, we do not detect a post-close information effect: the *OD* is not driven by earnings announcements since it is positive and significantly different from zero for all 5 sets of days.

[Insert figure A.16 and table A.13 here]

A.4.3.2. Macro and central banks

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

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

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

For central banks, we collect announcement dates and times from the websites of the following central banks: (*i*) the Federal Reserve; (*ii*) the Europe Central Bank; (*iii*) the Bank of England; (*iv*) the BoJ. FOMC target rate announcements are released at or very close to 14:15 ET. ECB target announcements are at 6:45 ET, followed by a press conference at 7:30 ET. BoE announcement days often coincide with ECB days and the announcements are at 7:00 ET. Finally, BoJ announcements do not occur at a regular time but target rate decisions are generally announced between 22.00 and 1.00 ET. Our sample period is January 1998 to December 2020.

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

$$r^H_{t,n} = a^n + b^n_1 \mathbb{1}_{\text{U.K.}} + b^n_2 \mathbb{1}_{\text{EU}} + b^n_3 \mathbb{1}_{\text{JP}} + b^n_4 \mathbb{1}_{\text{U.S.}} + \varepsilon^n_t, \tag{A.38}$$

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

Panel (a) of table A.14 reports estimates for macro announcements. The intercept during the *OD* hour (2:00–3:00) is estimated to be 1.52 bps with a t-statistic of 5.98, i.e., the drift is present on non-announcement days and thus not driven by macro announcements. Furthermore, none of the announcement dummies are statistically different from the non-announcement days in this hour. The U.K. macro dummy is economically large and significantly *negative* at the 10% level at 3:00 (which is 8:00 in London). More generally, we fail to detect an announcement effect in any of the overnight hours. U.S. announcements occur at 8:30 and indeed we see a large positive return of 3.22 bps with a t-statistic of 2.29. Panel (b) of table A.14 reports estimates for central bank announcements. Again, the intercept is unaffected at 2:00-3:00 and we obtain an estimate of 1.40 bps with a t-statistic of 6.52. The BoE dummy is economically large and marginally significantly *positive* between 4:00 - 5:00, consistent with central bank announcement premia. The FOMC dummy is large but insignificant.

[Insert table A.14 here]

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

A.5. 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	0.45	0.16	−0.04	−0.06	−0.20	−0.06	0.54	0.50	1.51	0.39	−0.14	0.14	0.39	−0.01	0.28
t-stat	1.08	0.73	−0.14	−0.22	−0.85	−0.28	2.41	2.29	5.78	1.32	−0.47	0.54	1.47	−0.05	0.75
p-value	0.28	0.46	0.89	0.83	0.39	0.78	0.016	0.022	$9.8 \cdot 10^{-9}$	0.19	0.64	0.59	0.14	0.96	0.45
median	0.00	0.14	0.08	0.10	0.15	0.14	0.17	0.44	0.77	0.05	0.31	0.29	0.35	0.58	−0.22
Sdev	13.40	14.59	16.92	16.22	15.65	12.59	13.74	13.67	17.21	22.32	20.63	17.89	18.69	19.40	28.51
Skew	1.16	−0.53	−1.39	−3.46	−5.42	−0.83	5.96	−0.54	0.88	0.15	−0.83	−0.92	1.23	0.49	1.44
Kurt	25.66	33.90	37.49	85.42	121.25	28.07	152.23	28.61	31.58	15.26	20.24	17.54	38.40	47.81	47.59

A.

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
Mean	−1.33	−0.08	−0.27	0.48	−0.11	−0.13	0.52	−2.65	−0.61
t-stat	−2.96	−0.15	−0.61	1.28	−0.27	−0.29	0.87	−0.96	−1.08
p-value	0.0031	0.88	0.54	0.20	0.79	0.77	0.39	0.34	0.28
median	−0.57	1.36	1.12	0.87	1.18	0.78	1.41	0.78	−0.63
Sdev	34.05	41.83	32.95	28.48	30.40	35.83	49.42	24.97	14.84
Skew	−0.28	−0.04	−0.38	−0.09	0.33	0.28	1.27	−3.95	1.19
Kurt	11.97	9.78	10.44	20.56	20.74	13.32	30.95	26.23	14.10

B.

Table A.1. Summary statistics: returns computed from trades
Summary statistics for S&P 500 E-mini futures hourly returns occurring overnight. Returns are computed from volume-weighted average prices. Panel (a) displays overnight hours and panel (b) displays intraday hours. Mean, medians and standard deviations are displayed in basis points. Sample period is January 1998 — December 2020.

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	0.16	0.30	0.45	−0.02	0.04	0.12	0.25	0.44	1.42	0.42	−0.23	−0.07	0.72	−0.15	0.30
t-stat	0.42	1.10	1.52	−0.09	0.22	0.71	1.29	2.13	5.43	1.22	−0.66	−0.24	2.14	−0.40	0.55
p-value	0.68	0.27	0.13	0.93	0.83	0.48	0.20	0.033	$6.1 \cdot 10^{-8}$	0.22	0.51	0.81	0.033	0.69	0.58
median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00
Sdev	22.18	15.47	16.83	11.98	11.70	9.73	11.43	11.57	15.37	21.52	20.10	17.87	18.66	20.84	31.58
Skew	−1.07	1.11	0.53	0.64	−2.68	1.14	1.58	−0.51	−0.03	−0.24	−0.71	−0.80	1.80	1.93	−0.44
Kurt	91.88	44.88	67.03	31.11	78.24	33.47	39.93	39.76	31.88	19.14	16.50	18.77	21.34	64.84	22.42

A. Overnight

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
Mean	−2.24	−0.28	−1.17	0.02	0.31	−0.26	1.05	−0.44	−0.31
t-stat	−3.27	−0.32	−1.82	0.04	0.51	−0.36	1.12	−1.06	−1.74
p-value	0.0011	0.75	0.075	0.97	0.61	0.72	0.26	0.29	0.081
median	−1.13	0.00	0.00	0.00	0.00	0.00	1.88	0.00	0.00
Sdev	39.09	48.14	36.43	31.75	34.93	42.50	58.38	23.36	10.35
Skew	−0.67	−0.11	−0.32	−1.21	0.90	0.54	1.10	−1.84	−0.73
Kurt	13.02	9.99	8.65	20.16	19.55	11.88	24.75	17.37	55.42

B. Intraday

Table A.2. Summary statistics: January 1998 — December 2010

Summary statistics for S&P 500 E-mini futures hourly returns. Returns are computed from mid quotes at the top of the order book. Panel (a) displays overnight hours and panel (b) displays intraday hours. Mean, medians and standard deviations are displayed in basis points. t-statistics testing again the null of zero returns are computed from HAC robust standard errors. Sample period is January 1998 — December 2010.

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	-1.26	0.42	-0.23	0.14	-0.14	-0.06	0.75	0.42	1.55	0.26	0.11	0.44	0.46	-0.01	0.22
t-stat	-2.34	1.52	-0.72	0.38	-0.48	-0.26	2.56	1.74	4.65	0.62	0.27	1.30	1.27	-0.03	0.47
p-value	0.019	0.13	0.47	0.70	0.63	0.79	0.011	0.082	$3.4 \cdot 10^{-6}$	0.54	0.79	0.19	0.20	0.98	0.64
median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sdev	28.09	13.81	16.64	17.57	15.69	11.09	13.97	12.43	16.29	21.38	19.02	17.00	18.49	18.32	24.62
Skew	-5.27	-1.28	-2.10	-5.10	-8.46	-2.24	11.31	-0.12	2.55	0.37	-1.10	0.09	0.91	-2.92	4.95
Kurt	76.92	30.51	39.21	120.04	206.83	35.56	300.85	28.13	35.46	13.93	30.06	21.34	91.21	49.21	117.26

A. Overnight

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
Mean	0.05	-0.22	0.99	0.92	-0.75	0.21	0.06	0.59	-0.59
t-stat	0.08	-0.34	1.78	1.83	-1.61	0.38	0.08	1.76	-4.03
p-value	0.94	0.74	0.075	0.067	0.11	0.70	0.93	0.079	$5.6 \cdot 10^{-5}$
median	1.19	1.71	2.10	1.26	1.15	0.95	0.94	1.20	-0.46
Sdev	31.77	33.16	27.78	25.41	23.57	27.69	38.78	17.19	7.33
Skew	-1.66	0.11	-0.36	1.42	-1.32	-0.82	1.54	-1.68	0.07
Kurt	35.71	9.81	14.10	33.83	13.53	16.66	42.14	28.75	60.80

B. Intraday

Table A.3. Summary statistics: January 2011 — December 2020

Summary statistics for S&P 500 E-mini futures hourly returns. Returns are computed from mid quotes at the top of the order book. Panel (a) displays overnight hours and panel (b) displays intraday hours. Mean, medians and standard deviations are displayed in basis points. t-statistics testing again the null of zero returns are computed from HAC robust standard errors. Sample period is January 2011 — December 2020.

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	−0.46	0.35	0.15	0.05	−0.03	0.04	0.46	0.43	1.48	0.35	−0.08	0.15	0.61	−0.08	0.26
t-stat	−1.43	1.80	0.68	0.25	−0.19	0.29	2.77	2.75	7.13	1.33	−0.32	0.63	2.46	−0.31	0.71
p-value	0.15	0.072	0.50	0.80	0.85	0.77	0.0056	0.0060	$1.1 \cdot 10^{-12}$	0.18	0.75	0.53	0.014	0.75	0.48
BY 10% threshold	0.0088	0.0077	0.014	0.023	0.024	0.022	0.0033	0.0044	0.0011⋆	0.0099	0.020	0.015	0.0066	0.021	0.013
BY 5% threshold	0.0044	0.0039	0.0072	0.012	0.012	0.011	0.0017	0.0022	0.00055⋆	0.0050	0.0099	0.0077	0.0033	0.011	0.0066
BY 1% threshold	0.00088	0.00077	0.0014	0.0023	0.0024	0.0022	0.00033	0.00044	0.00011⋆	0.00099	0.0020	0.0015	0.00066	0.0021	0.0013

A. Overnight

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
Mean	−1.24	−0.25	−0.23	0.41	−0.15	−0.06	0.61	0.00	−0.43
t-stat	−2.60	−0.45	−0.52	1.07	−0.37	−0.12	0.99	0.01	−3.62
p-value	0.093	0.66	0.60	0.28	0.71	0.91	0.32	1.00	0.00030
BY 10% threshold	0.0055	0.018	0.017	0.011	0.019	0.025	0.012	0.027	0.0022⋆
BY 5% threshold	0.0028	0.0088	0.0083	0.0055	0.0094	0.013	0.0061	0.013	0.0011⋆
BY 1% threshold	0.00055	0.0018	0.0017	0.0011	0.0019	0.0025	0.0012	0.0026	0.00022

B. Intraday

Table A.4. Benjamini–Yekutieli Thresholds

The table provides Benjamini–Yekutieli (BY) corrected significance levels (thresholds) for the null hypotheses of the S&P 500 E-mini futures average hourly log returns being zero. The BY procedure is a method for handling multiple testing problems. Specifically, it aims to control the false discovery rate, which is the expected ratio of the number of type I errors to the total number of rejections of the null. The BY method is a "step up" procedure that computes null specific thresholds starting from the least significant hypothesis and working up until significant alternative hypotheses are detected. This implies that every test has a unique threshold (see Harvey, Liu, and Saretto (2020) for a recent survey of multiple testing procedures in the context of financial economic applications). In the table, returns are computed from mid quotes at the top of the order book and reported in basis points. Means are displayed in basis points. t-statistics testing again the null of zero returns are computed from HAC robust standard errors. p-values indicate significance levels under a student-t distribution. BY thresholds are shown at the 10%, 5% and 1% level. A threshold is denoted with a $\star$ if the corresponding p-value of a test is below the given threshold. Panel (a) displays overnight hours and panel (b) displays intraday hours. Sample period is January 1998 — December 2020.

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	-3.65	0.67	0.71	0.00	0.15	0.32	-0.30	-0.10	1.54	1.22	0.06	-0.20	0.81	1.29	0.17
t-stat	(-2.39)	(1.51)	(1.50)	(0.00)	(0.43)	(0.99)	(-0.93)	(-0.27)	(3.23)	(1.89)	(0.11)	(-0.40)	(1.54)	(2.49)	(0.21)
Tuesday	0.89	0.75	0.26	0.93	-0.07	0.07	0.51	1.03	1.55	-0.29	-0.88	1.32	1.03	0.28	-0.19
t-stat	(1.36)	(1.99)	(0.61)	(2.30)	(-0.23)	(0.23)	(1.61)	(2.93)	(3.26)	(-0.53)	(-1.50)	(2.59)	(1.70)	(0.49)	(-0.27)
Wednesday	-0.15	0.13	-0.12	-0.15	0.13	0.14	0.65	0.01	1.69	0.03	0.34	0.37	0.24	-0.17	-1.03
t-stat	(-0.42)	(0.30)	(-0.27)	(-0.37)	(0.36)	(0.48)	(2.17)	(0.03)	(3.94)	(0.04)	(0.61)	(0.72)	(0.42)	(-0.28)	(-1.24)
Thursday	-0.22	1.38	1.41	-0.56	-0.16	-0.23	0.63	0.45	1.32	0.10	0.43	-0.90	0.50	-1.42	0.93
t-stat	(-0.57)	(2.93)	(2.54)	(-0.97)	(-0.34)	(-0.79)	(1.76)	(1.36)	(2.83)	(0.17)	(0.72)	(-1.58)	(1.01)	(-2.14)	(1.06)
Friday	0.62	-1.20	-1.48	0.01	-0.19	-0.10	0.79	0.74	1.28	0.79	-0.36	0.09	0.47	-0.31	1.48
t-stat	(1.39)	(-2.63)	(-2.90)	(0.02)	(-0.44)	(-0.32)	(1.43)	(1.92)	(2.60)	(1.28)	(-0.63)	(0.17)	(0.84)	(-0.58)	(1.39)

A. Overnight hourly returns

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
Monday	-1.21	0.15	-1.29	0.43	-0.53	-0.00	0.22	-0.08	-0.50
t-stat	(-0.92)	(0.13)	(-1.30)	(0.53)	(-0.60)	(-1.04)	(0.14)	(-0.13)	(-2.42)
Tuesday	-0.01	0.03	0.93	-0.58	-0.33	-0.88	-0.36	-0.15	-0.73
t-stat	(-0.01)	(0.02)	(0.99)	(-0.70)	(-0.40)	(-0.79)	(-0.25)	(-0.24)	(-2.15)
Wednesday	0.12	-0.67	1.57	1.15	-0.40	2.09	-2.39	-0.47	-0.56
t-stat	(0.12)	(-0.56)	(1.71)	(1.54)	(-0.43)	(1.85)	(-1.58)	(-0.81)	(-1.79)
Thursday	-2.10	0.44	-0.19	0.24	1.38	-0.60	2.12	0.34	-0.30
t-stat	(-2.02)	(0.34)	(-0.20)	(0.26)	(1.43)	(-0.55)	(1.43)	(0.53)	(-1.03)
Friday	-3.03	-1.19	-2.28	0.81	-0.88	0.02	3.53	0.37	-0.07
t-stat	(-2.76)	(-0.99)	(-2.24)	(0.93)	(-1.02)	(0.02)	(2.62)	(0.57)	(-1.44)

B. Intraday hourly returns

Table A.5. 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. Sample period is January 1998 — December 2020.

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	-0.52	0.53	0.43	-0.01	-0.15	-0.39	-0.86	-0.08	1.28	-0.97	0.47	0.56	1.26	-0.12	-0.34
t-stat	(-0.45)	(0.87)	(0.70)	(-0.03)	(-0.28)	(-1.05)	(-1.83)	(-0.19)	(2.05)	(-1.07)	(0.58)	(0.65)	(1.63)	(-0.15)	(-0.28)
February	-0.33	1.19	-0.57	0.06	-0.39	-0.43	0.29	1.09	2.06	0.07	-0.90	-0.79	0.51	1.17	-2.14
t-stat	(-0.36)	(2.09)	(-0.69)	(0.13)	(-0.83)	(-1.16)	(0.55)	(2.82)	(2.73)	(0.08)	(-1.10)	(-1.18)	(0.66)	(1.54)	(-1.75)
March	-4.49	-0.08	0.08	-1.61	-0.36	-0.10	2.13	0.84	2.13	1.48	-0.08	-0.22	-0.65	-0.44	2.81
t-stat	(-2.64)	(-0.07)	(0.10)	(-1.23)	(-0.43)	(-0.15)	(1.84)	(1.32)	(2.14)	(1.47)	(-0.06)	(-0.23)	(-0.55)	(-0.40)	(1.76)
April	-0.87	0.21	-0.10	0.51	0.07	0.17	0.59	0.22	2.40	0.09	-0.28	1.49	0.13	1.72	0.51
t-stat	(-0.83)	(0.46)	(-0.10)	(0.88)	(0.14)	(0.44)	(1.21)	(0.39)	(3.87)	(0.10)	(-0.37)	(2.11)	(0.17)	(2.16)	(0.36)
May	-0.34	0.73	0.27	-0.26	0.47	0.04	0.54	0.39	1.11	0.43	-0.60	0.23	-0.27	0.52	-0.92
t-stat	(-0.42)	(1.40)	(0.51)	(-0.51)	(1.14)	(0.11)	(1.46)	(0.90)	(1.91)	(0.58)	(-0.83)	(0.37)	(-0.43)	(0.72)	(-0.88)
June	-0.82	0.89	0.51	0.31	0.06	0.25	0.47	0.09	1.92	0.45	-0.64	0.45	-0.09	-0.17	0.45
t-stat	(-0.99)	(2.11)	(0.57)	(0.54)	(0.09)	(0.63)	(0.99)	(0.18)	(2.94)	(0.57)	(-0.79)	(0.70)	(-0.14)	(-0.25)	(0.42)
July	-0.34	0.06	-0.25	-0.29	0.79	0.44	-0.50	0.29	1.37	-0.19	0.84	0.19	1.24	1.16	-0.42
t-stat	(-0.45)	(0.17)	(-0.56)	(-0.59)	(1.73)	(1.32)	(-1.51)	(0.81)	(2.57)	(-0.26)	(1.10)	(0.29)	(1.81)	(1.48)	(-0.38)
August	-2.12	-0.19	0.32	0.12	-0.21	-0.34	0.62	0.80	0.95	0.51	0.08	-1.03	0.73	-0.02	-0.41
t-stat	(-2.35)	(-0.46)	(0.49)	(0.20)	(-0.43)	(-0.68)	(1.44)	(1.59)	(1.33)	(0.52)	(0.11)	(-1.46)	(1.16)	(-0.03)	(-0.34)
September	0.68	0.11	-0.39	0.38	-0.14	-0.45	0.22	0.62	2.71	-1.24	0.56	0.23	-2.17	-0.98	-0.46
t-stat	(0.44)	(0.15)	(-0.47)	(0.53)	(-0.26)	(-1.01)	(0.50)	(1.01)	(3.63)	(-1.11)	(0.58)	(0.26)	(-2.49)	(-1.12)	(-0.37)
October	-2.12	-0.19	0.32	0.12	-0.21	-0.34	0.62	0.80	0.95	0.51	0.08	-1.03	0.73	-0.02	-0.41
t-stat	(-2.35)	(-0.46)	(0.49)	(0.20)	(-0.43)	(-0.68)	(1.44)	(1.59)	(1.33)	(0.52)	(0.11)	(-1.46)	(1.16)	(-0.03)	(-0.34)
November	2.24	0.40	0.03	0.60	-0.08	0.32	1.20	0.07	0.63	1.61	0.04	-0.05	1.64	-1.57	1.70
t-stat	(2.04)	(0.57)	(0.04)	(0.84)	(-0.11)	(0.56)	(2.12)	(0.14)	(0.73)	(1.62)	(0.04)	(-0.06)	(1.54)	(-1.62)	(1.33)
December	2.30	-0.07	0.88	-0.03	-0.44	-0.23	0.75	1.26	1.05	1.48	1.88	0.79	0.27	-1.02	0.56
t-stat	(2.56)	(-0.09)	(1.57)	(-0.08)	(-0.68)	(-0.51)	(1.32)	(2.61)	(2.19)	(1.93)	(2.62)	(1.13)	(0.40)	(-1.38)	(0.53)

A. Overnight hourly returns

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
January	-1.45	-3.15	-0.82	0.41	1.51	0.94	1.09	-0.31	-0.72
t-stat	(-0.81)	(-1.57)	(-0.56)	(0.34)	(1.01)	(0.62)	(0.63)	(-0.34)	(-1.41)
February	-1.12	-0.96	0.55	0.65	-2.05	0.41	0.57	-0.87	-0.36
t-stat	(-0.72)	(-0.51)	(0.35)	(0.57)	(-1.26)	(0.25)	(0.29)	(-0.96)	(-0.00)
March	-3.41	4.54	0.97	2.18	-2.69	1.71	1.37	-0.64	-0.82
t-stat	(-1.48)	(2.13)	(0.54)	(1.37)	(-1.95)	(0.90)	(0.59)	(-0.65)	(-1.82)
April	-1.04	1.06	-0.17	1.15	-0.15	-1.49	1.15	2.75	0.09
t-stat	(-0.77)	(0.62)	(-0.11)	(0.97)	(-0.12)	(-1.04)	(0.70)	(2.63)	(0.21)
May	-0.24	-0.72	0.37	0.66	-0.77	-0.41	0.29	-0.75	-0.55
t-stat	(-0.19)	(-0.39)	(0.29)	(0.58)	(-0.73)	(-0.30)	(0.17)	(-1.07)	(-1.76)
June	-0.06	0.17	0.62	-1.63	0.23	-1.44	-1.90	0.34	-0.59
t-stat	(-0.04)	(0.10)	(0.51)	(-1.58)	(0.20)	(-1.01)	(-1.26)	(0.48)	(-2.17)
July	-0.60	-1.73	-1.63	-0.88	2.83	-1.01	2.28	-0.66	-0.15
t-stat	(-0.46)	(-1.02)	(-1.00)	(-0.78)	(2.38)	(-0.73)	(1.14)	(-0.77)	(-0.32)
August	-1.59	-0.30	-0.94	0.76	1.20	-1.33	-0.87	0.82	-0.49
t-stat	(-1.14)	(-0.16)	(-0.67)	(0.62)	(1.04)	(-0.92)	(-0.41)	(1.15)	(-1.28)
September	-3.45	-0.34	0.70	-0.68	0.68	1.22	-0.77	-0.18	-0.12
t-stat	(-1.98)	(-0.17)	(0.48)	(-0.53)	(0.48)	(0.70)	(-0.37)	(-0.17)	(-0.33)
October	-1.59	-0.30	-0.94	0.76	1.20	-1.33	-0.87	0.82	-0.49
t-stat	(-1.14)	(-0.16)	(-0.67)	(0.62)	(1.04)	(-0.92)	(-0.41)	(1.15)	(-1.28)
November	-1.56	1.24	-0.46	0.06	0.59	1.06	0.68	0.13	-1.26
t-stat	(-0.92)	(0.68)	(-0.32)	(0.04)	(0.40)	(0.55)	(0.26)	(0.14)	(-3.33)
December	-0.38	1.37	-1.28	-0.17	-2.48	-0.93	-0.44	-0.03	-0.21
t-stat	(-0.24)	(0.75)	(-0.87)	(-0.15)	(-1.88)	(-0.55)	(-0.24)	(-0.02)	(-0.70)

B. Intraday hourly returns

Table A.6. 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. Sample period is January 1998 — December 2020.

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	−102.69	38.49	−25.64	7.58	−27.50	−14.10	27.03	34.03	123.89	−3.92	0.14	20.09	12.63	5.81	10.29
t-stat	−4.14	1.85	−1.04	0.31	−1.21	−0.80	1.61	1.95	4.21	−0.09	0.00	0.57	0.33	0.12	0.12
Median	−71.00	14.00	−17.00	−4.00	15.00	0.00	3.00	26.00	67.00	−1.00	0.00	36.00	27.00	75.00	27.00
Sdev	1,496.30	1,230.72	1,501.57	1,473.38	1,353.31	1,077.16	1,019.88	1,057.16	1,768.44	2,721.70	2,387.59	2,147.20	2,245.48	2,849.86	4,979.66
Skew	−1.78	−2.90	−1.07	−1.95	−1.93	−1.22	0.88	0.06	−0.52	−0.15	−0.43	−0.44	−0.44	0.05	0.23
Kurt	35.73	84.00	18.47	46.37	42.41	31.55	27.17	17.53	17.47	10.02	12.51	10.24	9.38	14.11	9.56

A. Overnight

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	CTC
Mean	−568.13	−709.04	−466.78	−83.86	−278.26	−156.65	−290.89	251.78	−21.50	−2,217.19
t-stat	−3.04	−2.87	−2.24	−0.49	−1.73	−0.83	−0.99	2.10	−1.78	−3.27
Median	−313.00	−267.00	70.00	144.00	−6.00	38.00	249.00	433.00	0.00	765.00
Sdev	11,095.61	14,532.35	12,322.54	10,314.53	9,654.53	11,383.17	17,667.79	6,950.99	719.57	40,376.68
Skew	−0.34	−0.33	−0.66	1.69	−0.07	−0.17	−0.49	−0.05	−0.81	−0.61
Kurt	6.50	8.09	8.13	51.73	7.88	10.39	7.95	5.41	43.93	6.93

B. Intraday

Hour	15:00-15:15	15:15-15:30	15:30-15:45	15:45-16:00	16:00-16:15	15:15-16:15
Mean	−138.23	57.20	218.90	−428.75	311.31	158.65
t-stat	−1.39	0.61	1.95	−2.11	2.63	0.53
Median	0.00	84.00	190.00	0.00	495.00	868.00
Sdev	5,863.72	5,600.23	6,698.96	11,940.43	6,830.89	17,957.57
Skew	0.12	−0.16	−0.21	−0.36	0.00	−0.30
Kurt	10.64	7.32	6.58	6.87	5.32	6.89

C. EOD

Table A.7. Summary statistics: signed volume around the clock

Summary statistics for S&P 500 E-mini futures hourly signed volume defined as

$$SV_t = \#buy\ orders - \#sell\ orders,$$

which states order imbalance measured in terms of number of contracts. Panel (a) displays overnight hours and panel (b) displays intraday hours. Panel (c) displays SV_t in quarterly intervals between 15:00 – 16:15 (ET) and in the final column reports summary statistics for SV_t^{close} which is signed volume measured between 15:15 – 16:15 (ET). Mean, medians and standard deviations are displayed in millions of contracts. Sample period is January 2007 — December 2020.

	VIX Low	VIX Med	VIX High	VIX Low	VIX Med	VIX High
	Panel A1: Positive SV			Panel A2: Average VIX		
SV Low	2,769.00	2,767.00	2,484.00	12.37	15.99	25.87
SV Med	8,970.00	9,196.00	8,840.00	12.40	15.79	24.08
SV High	17,597.00	20,315.50	22,295.00	13.24	18.33	28.27

			Panel A3: *OD* Average Returns		
	VIX Low	VIX Med	VIX High	High - Low	p-value
SV Low	1.52	-3.43	-1.24	-2.76	0.50
SV Med	-1.54	-0.68	6.96	8.50	0.01
SV High	0.33	-1.29	0.42	0.09	0.98
High-Low	1.19	-2.14	-1.66		
p-value	0.50	0.41	0.77		

	Panel B1: Negative SV			Panel B2: Average VIX		
SV Low	-2,747.50	-2,941.00	-3,031.00	13.84	18.41	27.14
SV Med	-9,954.50	-10,052.00	-9,802.50	12.85	16.89	25.60
SV High	-21,023.00	-25,804.00	-24,140.50	12.58	16.11	24.43

			Panel B3: *OD* Average Returns		
	VIX Low	VIX Med	VIX High	High - Low	p-value
SV Low	-0.01	1.20	13.27	13.28	0.00
SV Med	4.14	2.59	18.12	13.98	0.00
SV High	4.98	12.15	17.10	12.11	0.03
High-Low	4.99	10.95	3.83		
p-value	0.03	0.00	0.54		

Table A.8. Double sorts on signed volume and closing VIX
We split the sample into positive (panel a) and negative (panel b) closing signed volume. Within each set we double-sort trading days into terciles of relative signed volume RSV and the closing level of the VIX. Within each set we report average RSVs and VIX levels ($A1, A2, B1, B2$). Double-sorted overnight drift OD return averages are reported ($A3, B3$) along with high minus low differences and p-values testing the difference against zero. Sample period is January 2007 – December 2020.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
SV 15:15-16:15	-0.07	-0.30	-0.66	0.05	0.15	0.12	-0.35	-0.21	-1.18	-0.21	0.35	0.30
	(-0.22)	(-1.34)	(-3.11)	(0.29)	(0.87)	(0.63)	(-3.64)	(-0.80)	(-4.18)	(-0.73)	(1.48)	(1.06)
μ	-0.70	0.35	-0.15	0.10	-0.15	0.12	0.45	0.52	1.45	-0.09	0.06	0.36
	(-1.28)	(1.38)	(-0.42)	(0.66)	(-0.72)	(0.80)	(2.50)	(2.45)	(6.14)	(-0.27)	(0.13)	(0.98)
Adj. R^2(%)	0.00	0.14	0.43	0.00	0.03	0.03	0.25	0.08	1.36	0.02	0.09	0.08

A.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
SV 15:15-16:15	-0.10	-0.32	-0.67	0.06	0.16	0.12	-0.32	-0.23	-1.16	-0.21	0.34	0.26
	(-0.32)	(-1.47)	(-3.02)	(0.36)	(0.95)	(0.63)	(-3.17)	(-0.88)	(-4.23)	(-0.72)	(1.53)	(0.93)
SV 14:15-15:15	0.41	0.35	0.16	-0.63	-0.18	-0.03	-0.43	-0.00	-0.46	-0.18	0.00	0.39
	(0.67)	(1.22)	(0.31)	(-1.81)	(-0.54)	(-0.15)	(-1.44)	(-0.01)	(-1.17)	(-0.81)	(0.00)	(1.23)
SV 13:15-14:15	0.45	0.04	0.02	0.61	-0.05	0.04	-0.29	0.81	-0.13	0.11	0.14	0.96
	(0.86)	(0.15)	(0.06)	(1.87)	(-0.14)	(0.15)	(-0.80)	(1.91)	(-0.26)	(0.27)	(0.25)	(1.71)
μ	-0.68	0.36	-0.14	0.11	-0.15	0.12	0.44	0.55	1.44	-0.09	0.07	0.40
	(-1.25)	(1.38)	(-0.41)	(0.68)	(-0.74)	(0.83)	(2.53)	(2.54)	(6.07)	(-0.28)	(0.14)	(1.06)
Adj. R^2(%)	-0.04	0.12	0.35	0.23	-0.05	-0.07	0.35	0.33	1.35	-0.07	-0.01	0.28

B.

Table A.9. Regression: overnight returns on closing signed volume

Panel (a) displays regression estimates of hourly overnight returns regressed on closing signed volume:

$$r^H_{t,n} = \mu_n + \beta^{SV}_n SV^{close}_{t-1} + \varepsilon_{t,n} \quad n = 1, \ldots, 12.$$

Panel (b) estimates a multivariate extension to this regression that includes relative signed volume recorded in the final three hours of the trading day before the maintenance break. Days where the time difference between London and New York is different from 5 hours are excluded. Estimates are in basis points. t-statistics reported in parenthesis are computed from robust standard errors clustered within each month. Sample period is January 1998 – December 2020.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
SV 1H Lag	-8.63	-2.83	-0.60	5.13	5.49	7.28	4.54	7.51	4.92	-1.61	-1.95	1.29
	(-1.55)	(-1.50)	(-0.33)	(1.14)	(1.23)	(2.50)	(0.86)	(1.20)	(0.79)	(-0.47)	(-1.39)	(1.16)
μ	-0.21	0.35	0.14	0.16	0.07	0.05	0.34	0.38	1.40	0.29	-0.03	0.03
	(-0.51)	(2.77)	(1.12)	(1.54)	(0.58)	(0.47)	(2.08)	(2.44)	(6.78)	(1.20)	(-0.12)	(0.14)
Adj. $R^2(\%)$	0.11	0.06	0.00	0.22	0.23	0.57	0.12	0.28	0.07	0.01	0.05	0.02

A.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
SV 1H Lag	-8.68	-2.93	-1.43	5.65	4.50	6.29	6.04	7.11	0.51	-0.00	-1.80	1.60
	(-1.51)	(-1.59)	(-0.88)	(1.22)	(1.19)	(2.18)	(1.17)	(1.21)	(0.11)	(-0.00)	(-1.15)	(1.51)
SV 2H Lag	-0.87	-2.51	-0.67	-4.79	4.81	2.19	-2.95	1.25	11.94	-14.67	0.60	-1.45
	(-1.69)	(-1.37)	(-0.16)	(-1.50)	(1.22)	(1.97)	(-1.00)	(0.42)	(1.64)	(-3.73)	(0.18)	(-0.86)
SV 3H Lag	0.24	-0.38	-4.83	0.25	-1.29	4.38	0.30	-3.63	0.68	-2.61	-4.70	-2.80
	(0.67)	(-1.82)	(-1.52)	(0.13)	(-0.32)	(2.43)	(0.16)	(-1.65)	(0.11)	(-0.53)	(-1.27)	(-1.20)
SV 4H Lag	0.34	-0.21	-0.79	2.75	3.82	1.70	-7.45	2.30	-2.52	-16.73	-0.91	5.00
	(0.94)	(-0.99)	(-2.72)	(1.15)	(1.79)	(0.83)	(-3.16)	(0.91)	(-0.92)	(-2.43)	(-0.23)	(1.03)
SV 5H Lag	-0.20	0.12	-0.53	0.67	0.42	3.16	3.22	-2.69	-3.43	0.32	3.63	-6.70
	(-0.44)	(1.21)	(-3.23)	(2.80)	(0.20)	(1.75)	(1.76)	(-1.79)	(-0.87)	(0.05)	(0.54)	(-1.67)
SV 6H Lag	-0.46	0.01	0.10	-0.13	0.58	2.09	0.07	-0.93	0.61	-1.06	-1.27	1.29
	(-0.94)	(0.06)	(0.33)	(-1.29)	(2.04)	(1.13)	(0.03)	(-0.36)	(0.21)	(-0.17)	(-0.64)	(0.44)
SV 7H Lag	0.25	0.12	-0.23	-0.44	0.17	-0.50	-0.12	-1.36	6.02	-0.91	0.76	0.85
	(0.46)	(0.49)	(-0.86)	(-2.77)	(1.85)	(-1.84)	(-0.06)	(-0.59)	(1.55)	(-0.18)	(0.31)	(0.31)
SV 8H Lag	-0.38	0.15	0.04	0.24	-0.03	0.29	0.30	-0.71	2.42	6.77	0.85	0.95
	(-1.06)	(0.92)	(0.13)	(1.23)	(-0.18)	(1.67)	(0.93)	(-0.36)	(0.79)	(1.51)	(0.31)	(0.36)
SV 9H Lag	0.21	0.11	-0.27	0.04	-0.03	-0.07	-0.40	-1.11	-2.48	-3.47	-6.65	2.06
	(0.34)	(0.59)	(-1.37)	(0.13)	(-0.09)	(-0.32)	(-3.88)	(-4.87)	(-1.18)	(-0.90)	(-1.78)	(0.81)
SV 10H Lag	0.71	0.25	-0.29	-0.28	-0.06	-0.20	-0.31	-0.19	-1.58	-3.62	3.46	1.57
	(1.04)	(0.68)	(-1.76)	(-1.73)	(-0.35)	(-0.97)	(-1.69)	(-0.78)	(-4.44)	(-0.88)	(1.01)	(0.37)
SV 11H Lag	-2.33	0.17	-0.18	-0.05	-0.05	0.24	-0.10	-0.11	-0.77	-0.34	-3.68	-1.23
	(-1.50)	(0.42)	(-0.81)	(-0.32)	(-0.28)	(1.03)	(-0.40)	(-0.57)	(-2.92)	(-0.76)	(-1.11)	(-0.79)
SV 12H Lag	-2.63	-0.82	-0.37	0.06	-0.18	0.19	-0.02	0.35	-0.22	-0.59	-0.27	-0.26
	(-1.20)	(-1.10)	(-0.68)	(0.37)	(-1.51)	(0.89)	(-0.10)	(1.47)	(-1.28)	(-2.29)	(-1.19)	(-0.16)
μ	-0.20	0.37	0.08	0.16	0.08	0.09	0.29	0.38	1.39	0.24	0.00	0.05
	(-0.49)	(2.84)	(0.61)	(1.46)	(0.73)	(0.79)	(1.89)	(2.47)	(7.12)	(1.03)	(0.00)	(0.23)
Adj. $R^2(\%)$	0.20	0.02	0.38	0.50	0.49	1.38	1.04	0.82	1.79	0.99	0.08	0.07

B.

Table A.10. Falsification test

Panel (a) displays regression estimates of hourly overnight returns regressed on a one hour lag of signed volume. Panel (b) displays regression estimates of hourly overnight returns regressed on twelve lags of hourly relative signed volume. Days where the time difference between London and New York is different from 5 hours are excluded. Estimates are in basis points. t-statistics reported in parenthesis are computed from robust standard errors clustered within each month. Sample period is January 1998 – December 2020.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
SV 15:15-16:15	0.53	0.47	-0.73	-0.02	0.15	0.42	-0.49	0.31	-0.05	-1.04	-0.39	0.13
	(0.39)	(0.69)	(-2.58)	(-0.06)	(0.58)	(1.09)	(-1.67)	(0.82)	(-0.11)	(-1.58)	(-0.70)	(0.30)
NEG	1.78	-0.11	-0.32	1.18	0.44	1.01	-0.65	-0.60	2.18	-1.40	-0.94	-1.63
	(0.86)	(-0.16)	(-0.32)	(2.08)	(0.63)	(1.38)	(-0.96)	(-0.86)	(2.01)	(-1.12)	(-0.95)	(-1.31)
SV x NEG	-0.45	-1.47	-0.00	0.57	0.17	-0.18	0.02	-1.20	-1.27	1.00	1.01	-0.30
	(-0.31)	(-1.77)	(-0.00)	(0.95)	(0.39)	(-0.48)	(0.03)	(-3.42)	(-2.97)	(1.17)	(1.50)	(-0.50)
μ	-1.81	-0.52	0.00	-0.09	-0.25	-0.47	0.76	0.05	-0.36	1.18	1.13	0.93
	(-1.09)	(-0.72)	(0.01)	(-0.21)	(-0.67)	(-1.14)	(1.60)	(0.08)	(-0.83)	(1.52)	(1.73)	(1.18)
Adj. R^2(%)	0.06	0.55	0.44	0.13	0.05	0.13	0.28	0.42	1.73	0.13	0.20	0.18

A.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
SV 15:15-16:15	-2.37	-1.03	0.83	-0.18	0.48	-0.51	0.47	-0.90	1.40	1.24	0.38	-1.46
	(-1.52)	(-1.05)	(1.27)	(-0.41)	(0.87)	(-0.80)	(1.55)	(-1.19)	(3.04)	(2.28)	(0.37)	(-2.82)
VIX 16:15	-0.03	0.02	0.08	-0.00	-0.04	0.02	0.07	0.03	0.07	-0.04	-0.09	-0.07
	(-0.25)	(0.36)	(1.15)	(-0.11)	(-1.12)	(0.42)	(2.09)	(0.96)	(0.71)	(-0.71)	(-1.05)	(-0.54)
SV x VIX	0.10	0.03	-0.06	0.01	-0.01	0.03	-0.04	0.03	-0.11	-0.06	-0.00	0.08
	(1.32)	(0.63)	(-2.06)	(0.48)	(-0.50)	(0.82)	(-2.07)	(0.72)	(-4.11)	(-2.43)	(-0.02)	(2.79)
μ	-0.18	0.01	-1.70	0.16	0.61	-0.25	-1.00	0.01	0.02	0.80	1.78	1.65
	(-0.10)	(0.01)	(-1.47)	(0.29)	(1.09)	(-0.32)	(-1.69)	(0.02)	(0.01)	(0.65)	(1.29)	(0.76)
Adj. R^2(%)	0.45	0.27	0.99	-0.08	0.04	0.18	0.75	0.24	2.91	0.24	0.15	0.70

B.

Table A.11. Regression: overnight returns on closing signed volume and interactions

Panel (a) displays regression estimates of hourly overnight returns regressed on closing signed volume and an interaction term that takes a value of '1' if $SV_{t-1}^{close} < 0$ and '0' otherwise

$$r_{t,n}^{H} = \mu_n + \beta_n^{SV} SV_{t-1}^{close} + \beta_n^{NEG} \mathbb{1}_{NEG,t} + \beta_n^{SV\times NEG} SV_{t-1,close} \times \mathbb{1}_{NEG,t} + \varepsilon_{t,n} \quad n = 1, \dots, 12.$$

Panel (b) displays regression estimates of hourly overnight returns regressed on closing signed volume and on closing signed volume interacted with the level of the VIX from the close of the preceding day

$$r_{t,n}^{H} = \mu_n + \beta_n^{SV} SV_{t-1}^{close} + \beta_n^{VIX} VIX_{t-1}^{close} + \beta_n^{SV\times VIX} SV_{t-1}^{close} \times VIX_{t-1}^{close} + \epsilon_{t,n}, \quad \text{for } n = 1, ..., 12,$$

Days where the time difference between London and New York is different from 5 hours are excluded. Estimates are in basis points. t-statistics reported in parenthesis are computed from robust standard errors clustered within each month. Sample period is January 2007 – December 2020.

	18-19	19-20	20-21	21-22	22-23
SV	-0.67	-0.62	-0.96	0.42	0.40
	(-2.00)	(-3.54)	(-2.81)	(1.18)	(1.33)
DST	-1.48	0.80	-1.08	0.26	-0.04
	(-1.26)	(1.71)	(-2.07)	(1.01)	(-0.08)
$SV \times DST$	0.69	0.44	0.44	-0.53	-0.36
	(1.38)	(1.40)	(1.12)	(-1.46)	(-1.09)
μ	-0.05	-0.13	0.59	-0.23	-0.31
	(-0.04)	(-0.30)	(1.34)	(-1.68)	(-1.29)
Adj. $R^2(\%)$	0.10	0.26	0.52	0.07	0.06

A. Asia

	24-01	01-02	02-03	03-04	04-05
SV	-0.35	-0.34	-1.17	-0.15	0.24
	(-3.98)	(-1.18)	(-4.42)	(-0.57)	(1.20)
$DIFF$	3.61	0.52	1.40	2.32	-1.57
	(2.27)	(1.43)	(3.77)	(1.28)	(-1.02)
$SV \times DIFF$	-0.31	1.70	1.07	0.45	-1.86
	(-0.40)	(2.20)	(0.86)	(0.78)	(-1.39)
μ	0.39	0.57	1.46	-0.12	0.01
	(2.38)	(3.09)	(6.57)	(-0.33)	(0.03)
Adj. $R^2(\%)$	0.59	0.39	1.30	0.08	0.19

B. Europe

Table A.12. Daylight saving tests

In panel (a) hourly overnight returns are regressed on closing relative signed volume and a dummy variable for daylight savings time:

$$r^H_{t,n} = \mu_n + \beta^{SV}_n SV^{close}_{t-1} + \beta^{DST}_n \mathbb{1}_{DST,t} + \beta^{SV\times DST}_n SV_{t-1,close} \times \mathbb{1}_{DST,t} + \varepsilon_{t,n} \quad n = 1, \ldots, 12,$$

where the dummy variable takes 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 when DST is not active and at 20:00 when DST is active. Estimates are in basis points. In panel (b) hourly overnight returns are regressed on closing signed volume and time-zone difference dummy:

$$r^H_{t,n} = \mu_n + \beta^{SV}_n SV^{close}_{t-1} + \beta^{DIFF}_n \mathbb{1}_{DIFF,t} + \beta^{RSV\times DIFF}_n SV_{t-1,close} \times \mathbb{1}_{DIFF,t} + \varepsilon_{t,n} \quad n = 1, \ldots, 12,$$

where the dummy variable takes a value of '0' when the time-zone difference between London and New York is 5 hours and a value of '1' when the time-zone difference is 4 hours. t-statistics reported in parenthesis are computed from robust standard errors clustered within months. Sample period is January 2007 – December 2020.

	CTC	CTO	OTC	OD	OR
NEG	-8.10	-1.85	-6.40	1.32	-2.14
t-stat	(-1.44)	(-0.64)	(-1.43)	(1.79)	(-1.34)
POS-LOW	-0.30	-0.09	-0.21	1.53	-3.70
t-stat	(-0.07)	(-0.04)	(-0.07)	(3.45)	(-2.60)
POS-MEDIUM	1.52	-0.41	1.87	1.96	-0.64
t-stat	(0.35)	(-0.18)	(0.50)	(3.25)	(-0.43)
POS-HIGH	4.89	4.58	0.32	1.17	-1.26
t-stat	(1.19)	(2.08)	(0.09)	(2.50)	(-0.90)
No Announcements	4.57	2.11	2.34	1.38	-1.31
t-stat	(1.86)	(1.60)	(1.17)	(4.91)	(-1.64)

Table A.13. Earnings announcements

We sort evening earnings announcements into negative, positive low/medium/high days, and non-announcement days. Within each sort we compute average returns for the close-to-close (CTC), close-to-open (CTO), open-to-close (OTC), overnight drift (OD) and opening return (OP) periods. We report t-tests of the difference against the null of zero in parenthesis. Sample period is 1998.1 – 2020.12.

	18	19	20	21	22	23	24	01	02	03	04	05	06	07	08
μ	-0.68	0.29	0.22	0.03	-0.00	-0.06	0.50	0.41	1.52	0.60	-0.16	0.06	0.42	0.09	-0.07
	(-1.57)	(1.25)	(0.79)	(0.13)	(-0.01)	(-0.35)	(2.38)	(2.13)	(5.98)	(1.77)	(-0.54)	(0.22)	(1.52)	(0.30)	(-0.16)
$\mathbf{1}_{UK}$	0.66	0.29	-0.42	0.19	-0.42	0.04	-0.05	-0.69	-0.37	-1.48	0.21	0.22	-0.88	-0.18	0.89
	(1.02)	(0.43)	(-0.67)	(0.39)	(-0.85)	(0.10)	(-0.13)	(-1.36)	(-0.56)	(-1.74)	(0.24)	(0.31)	(-0.91)	(-0.22)	(0.85)
$\mathbf{1}_{EU}$	-0.38	0.18	-0.86	-0.45	-0.76	0.52	-0.78	0.25	-0.04	-1.53	0.60	0.58	-0.44	0.22	-0.67
	(-0.40)	(0.29)	(-1.37)	(-0.89)	(-1.11)	(1.16)	(-1.69)	(0.55)	(-0.06)	(-1.60)	(0.67)	(0.70)	(-0.57)	(0.28)	(-0.49)
$\mathbf{1}_{JP}$	0.12	0.66	1.22	0.66	-0.02	0.54	0.15	-0.46	0.11	0.42	0.22	0.52	1.57	-0.39	-0.99
	(0.12)	(1.07)	(1.88)	(0.99)	(-0.03)	(1.24)	(0.31)	(-0.88)	(0.16)	(0.45)	(0.24)	(0.68)	(1.73)	(-0.35)	(-0.76)
$\mathbf{1}_{US}$	1.15	-0.42	-0.61	-0.37	0.75	-0.13	0.18	0.00	-0.04	0.14	-0.16	-0.24	1.08	-1.01	3.22
	(2.01)	(-0.81)	(-1.09)	(-0.67)	(1.63)	(-0.34)	(0.40)	(2.27)	(-0.07)	(0.17)	(-0.23)	(-0.36)	(1.38)	(-1.35)	(2.29)

A. Macro

	18	19	20	21	22	23	24	01	02	03	04	05	06	07	08
μ	-0.08	0.19	-0.11	-0.13	-0.06	0.13	0.31	0.45	1.40	0.34	-0.41	0.14	0.42	0.02	0.38
	(-0.23)	(1.03)	(-0.45)	(-0.71)	(-0.35)	(0.90)	(2.02)	(2.81)	(6.52)	(1.10)	(-1.49)	(0.58)	(1.70)	(0.06)	(0.91)
$\mathbf{1}_{BoE}$	-0.81	5.52	4.19	1.58	-0.78	-0.48	0.61	-0.36	-0.49	0.50	2.21	-1.86	0.19	-2.68	-1.98
	(-0.65)	(3.18)	(2.67)	(1.38)	(-1.11)	(-0.65)	(0.73)	(-0.49)	(-0.52)	(0.30)	(1.61)	(-1.43)	(0.17)	(-1.29)	(-0.81)
$\mathbf{1}_{ECB}$	0.80	-2.38	-0.60	-0.95	1.04	-0.66	-0.77	-1.22	0.21	0.45	1.63	0.29	1.78	2.68	-3.87
	(0.89)	(-1.92)	(-0.32)	(-0.96)	(1.41)	(-1.06)	(-0.99)	(-1.73)	(0.23)	(0.28)	(1.14)	(0.23)	(1.63)	(1.34)	(-1.38)
$\mathbf{1}_{BoJ}$	-0.18	0.07	0.75	1.80	-0.13	0.83	0.51	-0.06	0.15	-0.52	0.48	-0.41	-0.10	-1.19	1.84
	(-0.11)	(0.05)	(0.85)	(2.16)	(-0.18)	(1.13)	(0.57)	(-0.07)	(0.15)	(-0.39)	(0.40)	(-0.44)	(-0.08)	(-1.23)	(0.94)
$\mathbf{1}_{FOMC}$	-3.94	-0.29	0.35	-0.74	-0.31	-0.12	-0.43	1.27	1.39	-1.51	3.19	0.30	2.78	3.02	-4.28
	(-1.57)	(-0.30)	(0.33)	(-0.71)	(-0.34)	(-0.18)	(-0.36)	(0.99)	(1.04)	(-0.84)	(2.13)	(0.23)	(1.50)	(1.07)	(-1.43)

B. Central Banks

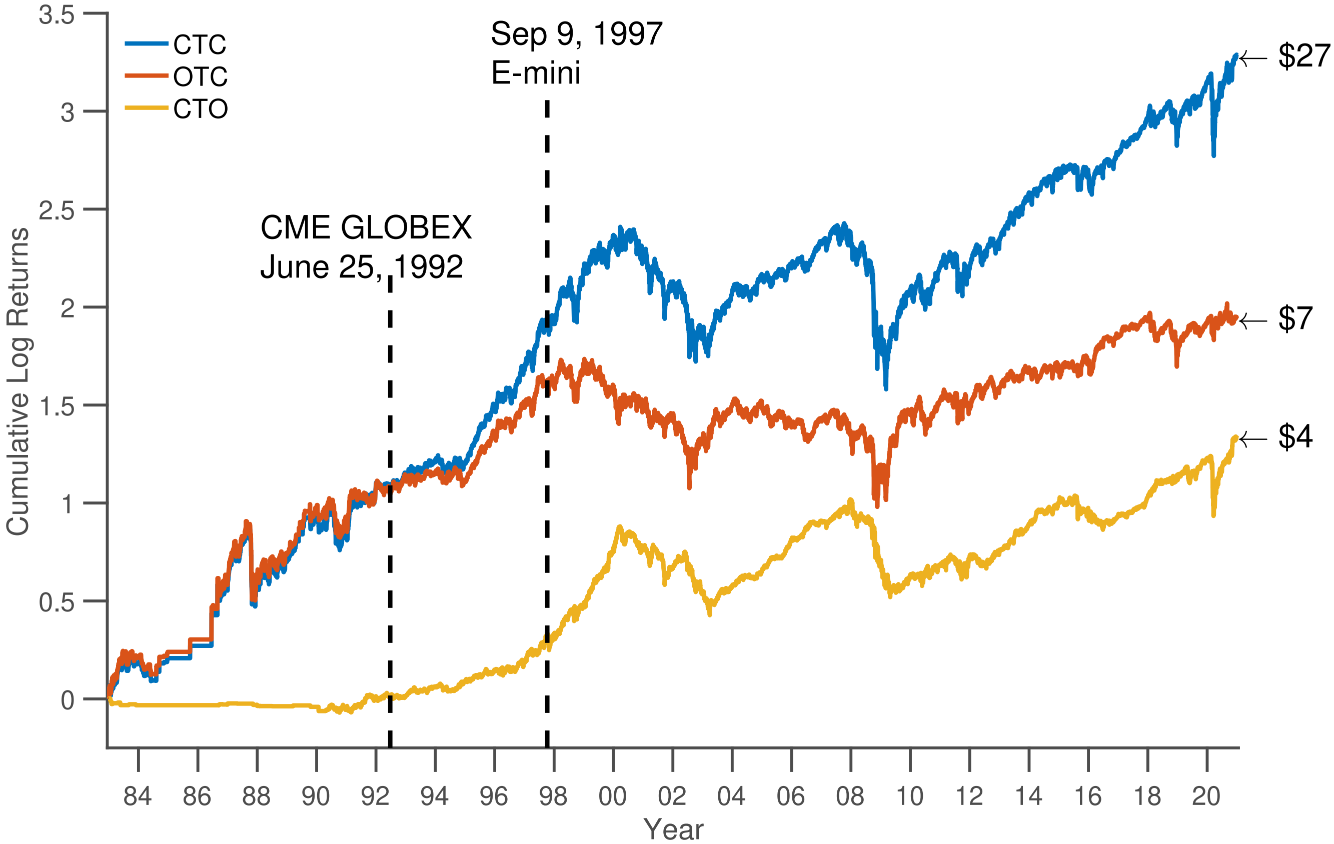
Table A.14. Announcements

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

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

where for panel (a) $\mathbb{1}_i$ is an employment, GDP or inflation announcement dummy for country i. For panel (b) $\mathbb{1}_i$ is a central bank announcement dummy for country i. t-statistics are computed from HAC robust standard errors. Sample period is 1998.1 – 2020.12.

A.6. Figures



A

Figure A.1. Time series of returns for the S&P 500 futures contract
The figure plots the time series of close-to-close, open-to-close and close-to-open log returns to the S&P 500 BIG futures contract. Opening prices are sampled at 9:30 EST and closing prices are sampled at 16:15 EST. Between 1983.1 – 1998.1 returns are computed from VWAPs sourced from the CME. Between 1998.1 – 2004.4 returns are computed from the VWAPs sourced from the Refinitiv. Beyond 2004.1 until the end of the sample in 2020.12 we computed returns from the VWAPs of the E-mini contract since it became the most liquid futures contract traded on the SPX index.

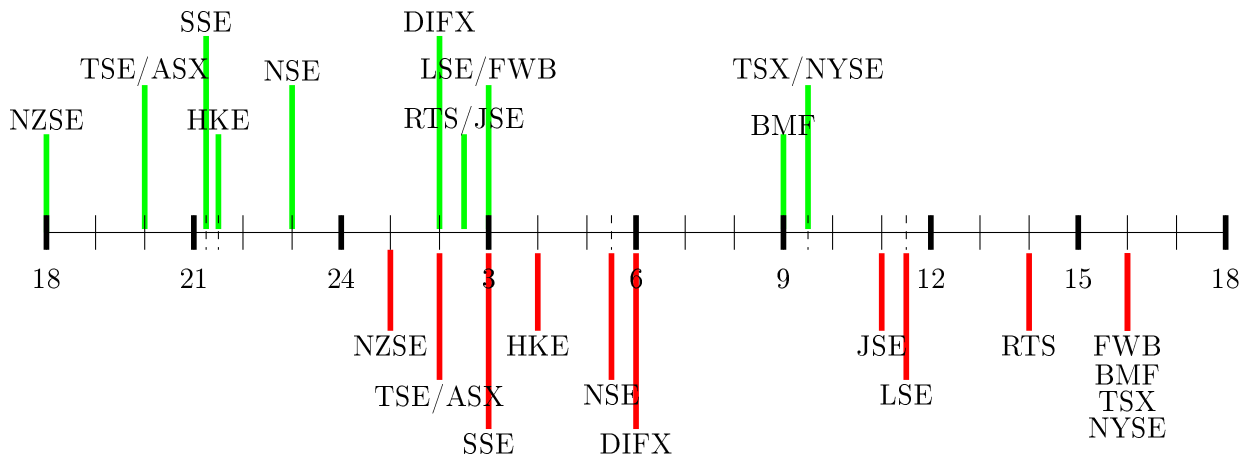


Figure A.2. Global equity market trading hours

The 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, and TSX=Toronto Stock Exchange. Opening and closing times are collected from the public websites of the exchanges and reported in Eastern Standard Time (EST). Several of the opening times shift by one or two hours when U.S. DST is not active (see table 2 for details).

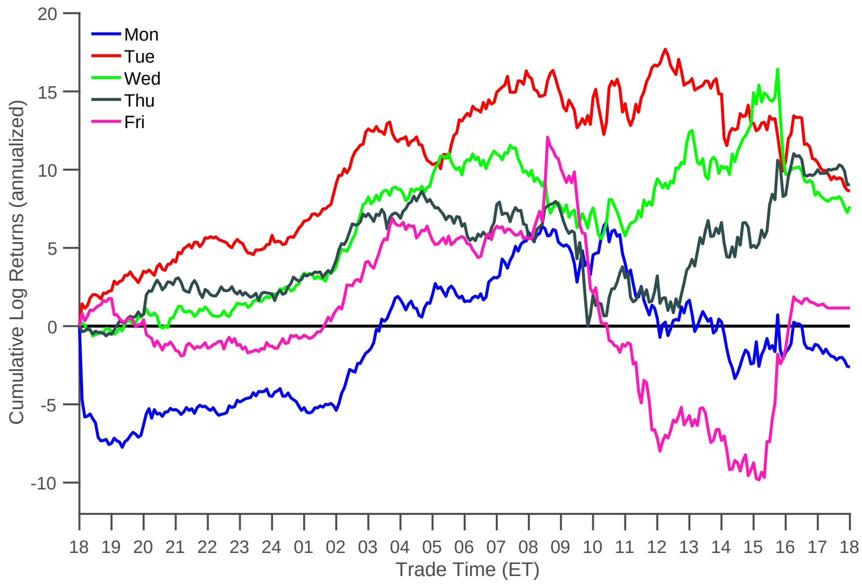


Figure A.3. Day-of-week effects

This 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. Sample period is 1998.1 – 2020.12.

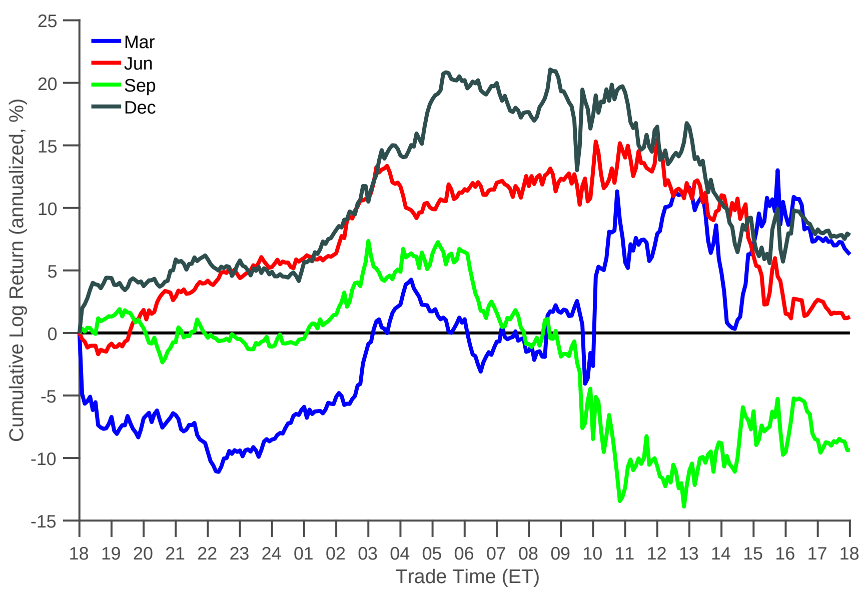


Figure A.4. Month-of-the-year effects

This figure displays the cumulative 5-minute log returns of the E-mini across the trading day, for each month in the March quarterly cycle, averaged across all trading days in our sample. Estimates are annualized and displayed in percentage points. Sample period is 1998.1 – 2020.12.

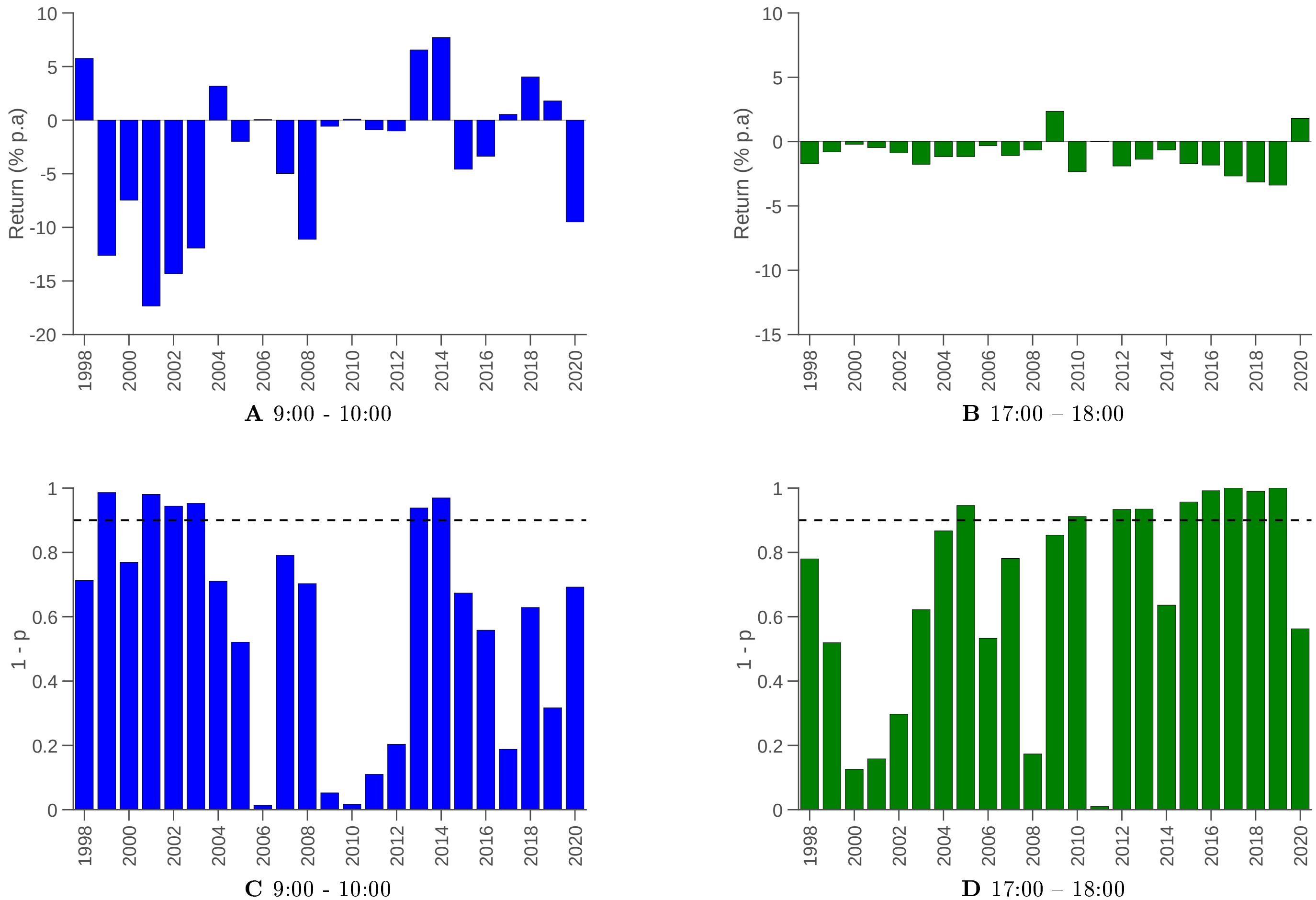
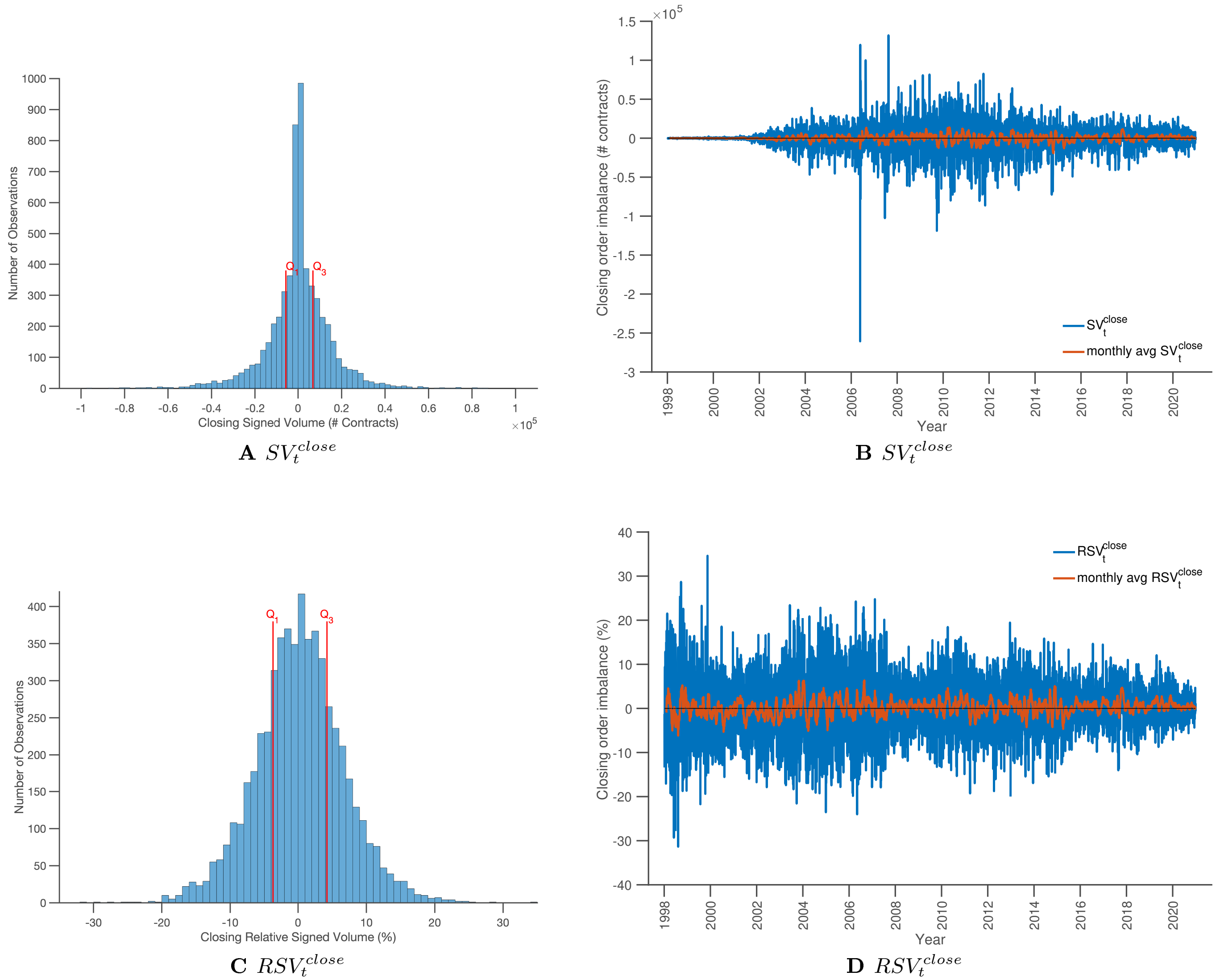


Figure A.5. Year-by-year returns: 9:00 - 10:00 & 17:00 – 18:00

This figure plots yearly average log returns (top panels) and $(1-p)$ the values from a t-test against the null hypothesis that these returns are zero (bottom panels). Sub-captions indicate the hour of the night. Sample period is January 1998 – December 2020.



A SV_t^{close} **B** SV_t^{close}

C RSV_t^{close} **D** RSV_t^{close}

Figure A.6. Distribution and time series of closing order imbalances

Distribution and time series of closing order imbalances. Order imbalances are measured both as the absolute order imbalance in number of contracts, SV and the order imbalance relative to total trading volume, RSV. The closing period is defined as 15:15–16:15 ET. The sample period is January 1998 – December 2020.

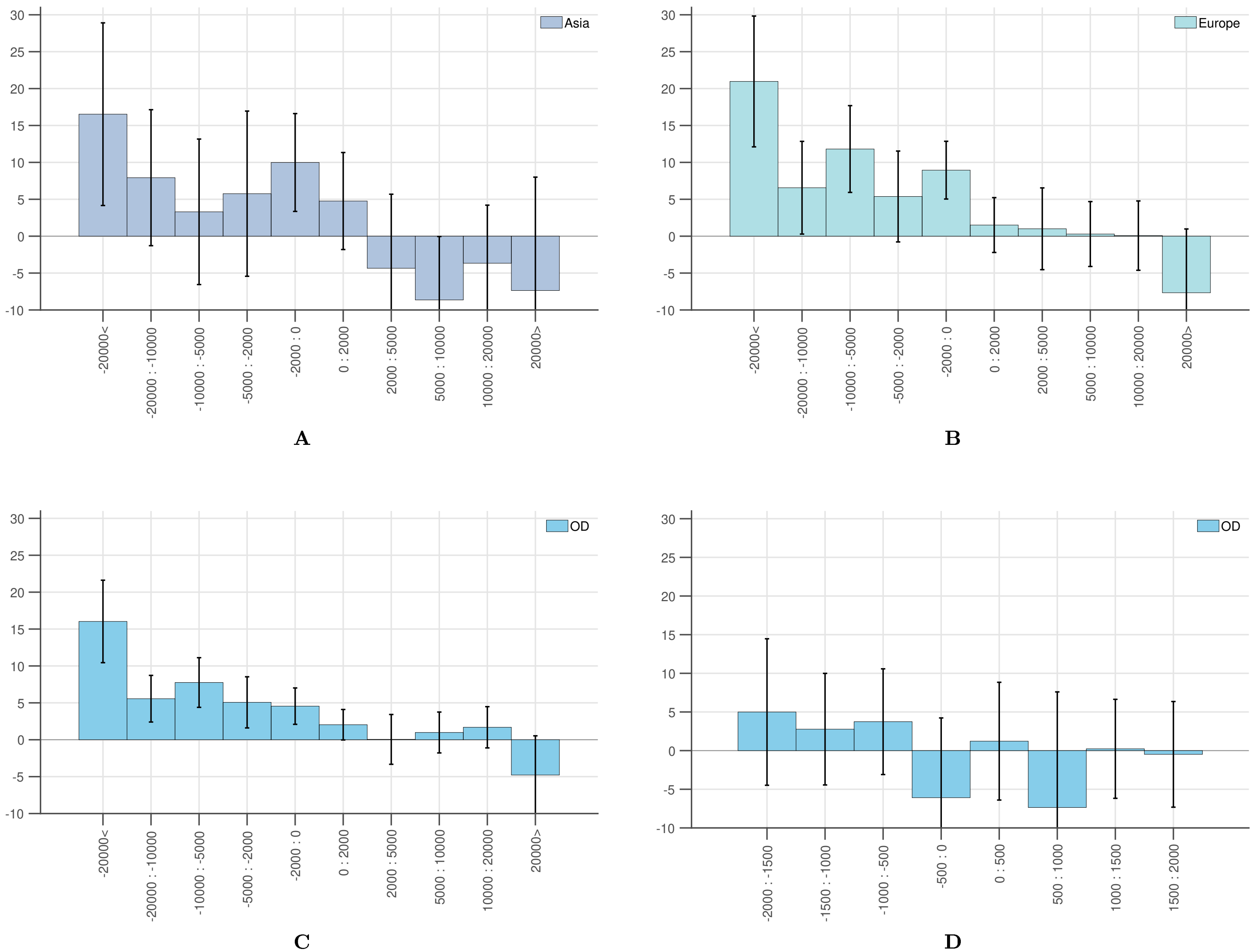


Figure A.7. Average overnight returns sorted on closing imbalance

Panels (a) - (b) sort trading days based on ten sets of absolute closing order flow of the preceding trading day, SV_t^{close}, and average annualized returns of each group are plotted for subsequent Asian trading hours (18:00 – 02:00), for returns during European trading hours (01:00-04:00), for returns during the overnight drift hour (02:00 – 03:00). Panel (d) zooms in on the overnight drift hour for closing order flow sorts straddling zero imbalances. Sample period is January 2007 – December 2020.

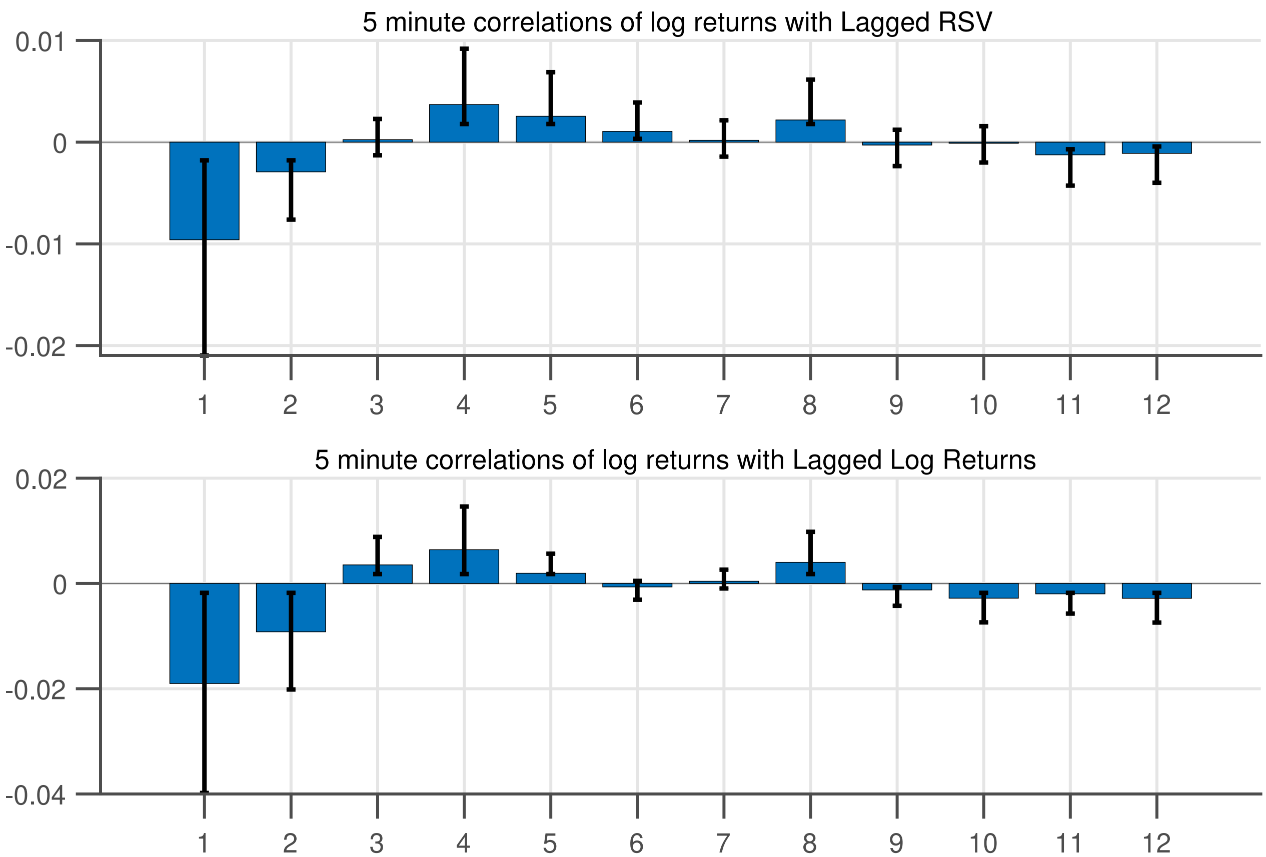


Figure A.8. Autocorrelations

The top panel reports correlation coefficients between 5-minute log returns and *lagged* 5-minute relative signed volume. The bottom panel plots correlation coefficients between 5-minute log returns and *lagged* 5-minute log returns. Black bars indicate 95% upper and lower confidence intervals. Correlations are computed using all hours of the trading day for the sample period January 1998 - December 2020.

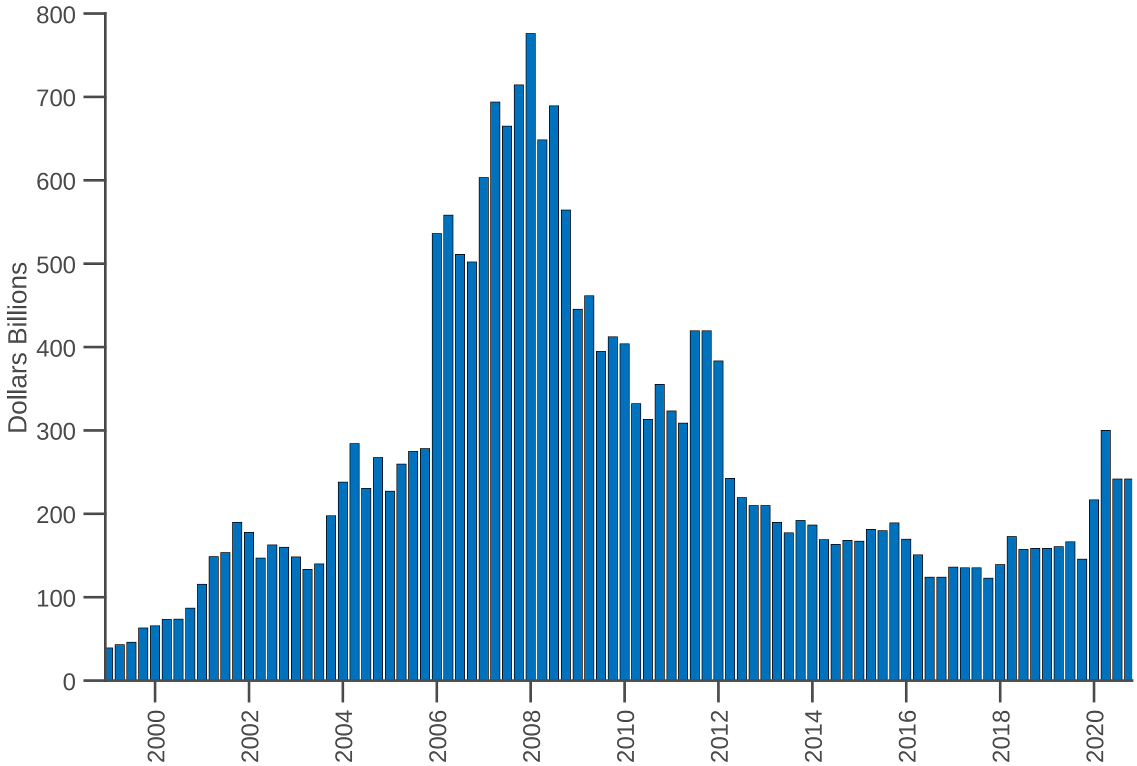
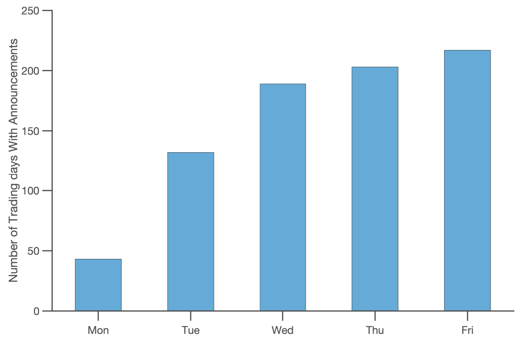
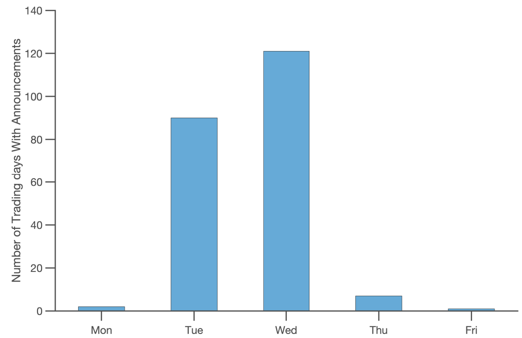


Figure A.9. Equity VaR

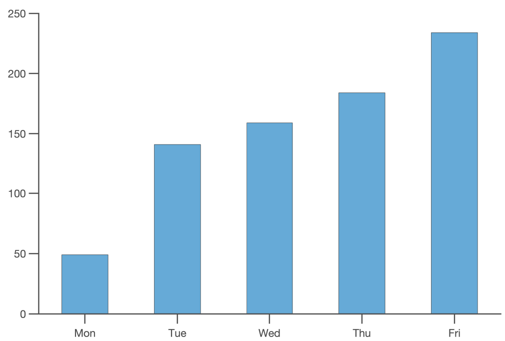
As in Adrian and Shin (2014), for firms that report VaRs at the 95% confidence level, we scale the VaR to the 99% using the Gaussian assumption. This figure displays the time series of the resulting equity VaR. Source: Bloomberg. Sample period is 1999 Q1 – 2020 Q4.



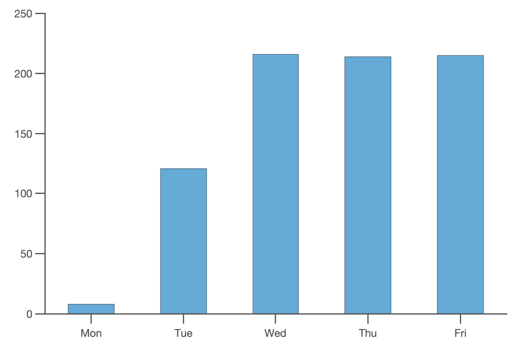
A U.S. Macro Announcements



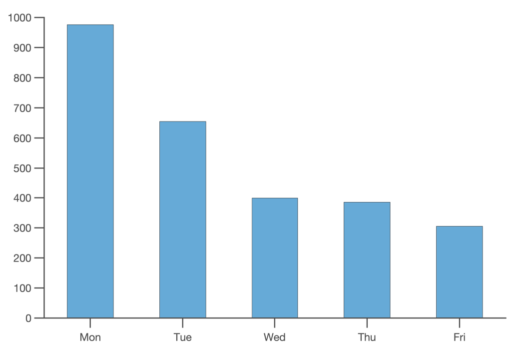
B FOMC Announcements



C Negative Earnings



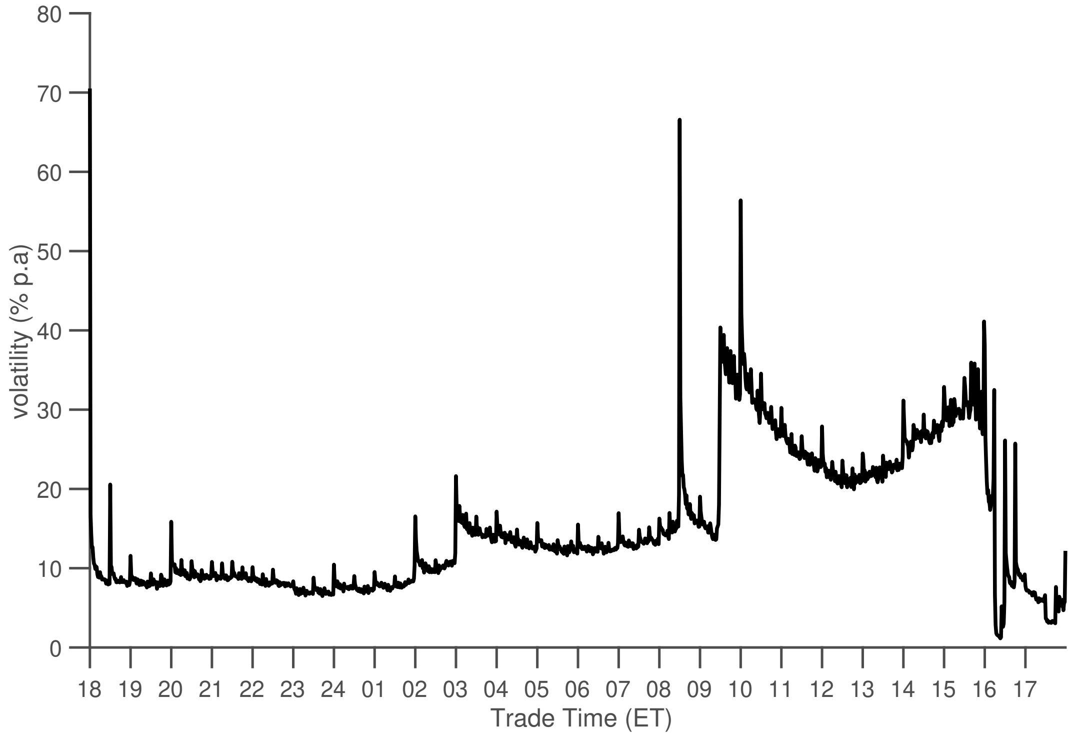
D Positive Earnings



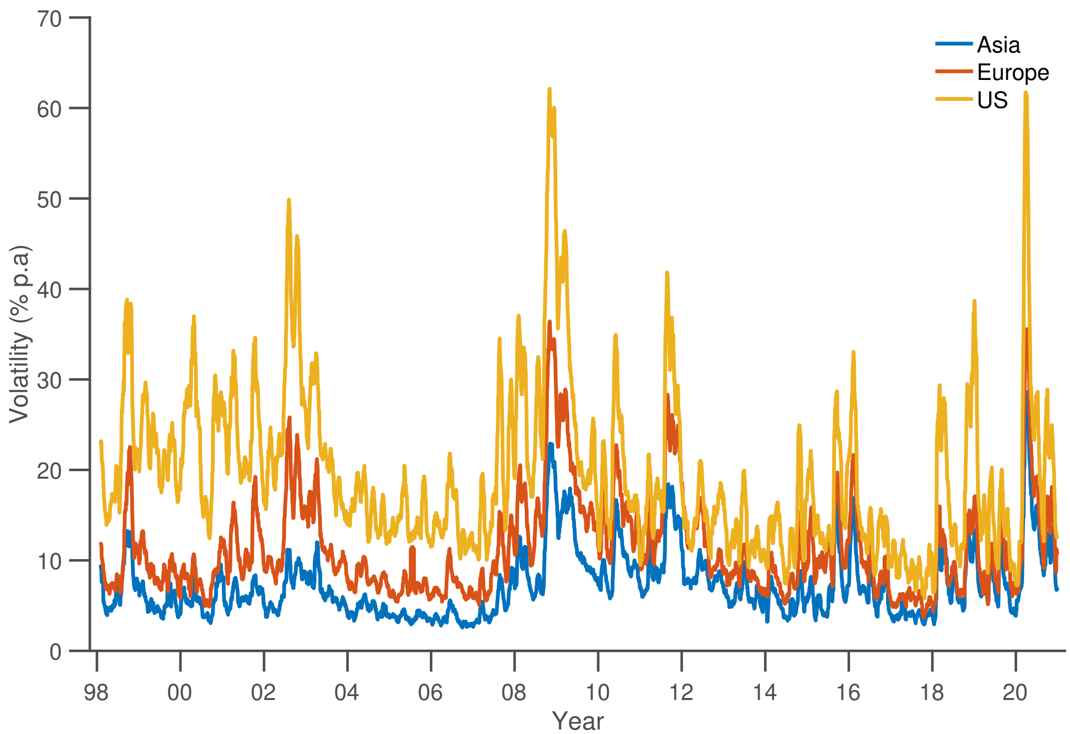
E No Earnings

Figure A.10. Announcements per weekday

The figure displays the number of trading days, for each day of the week, where U.S. macro, bank or earnings announcements are released. Sample period is 1998.1 – 2020.12.



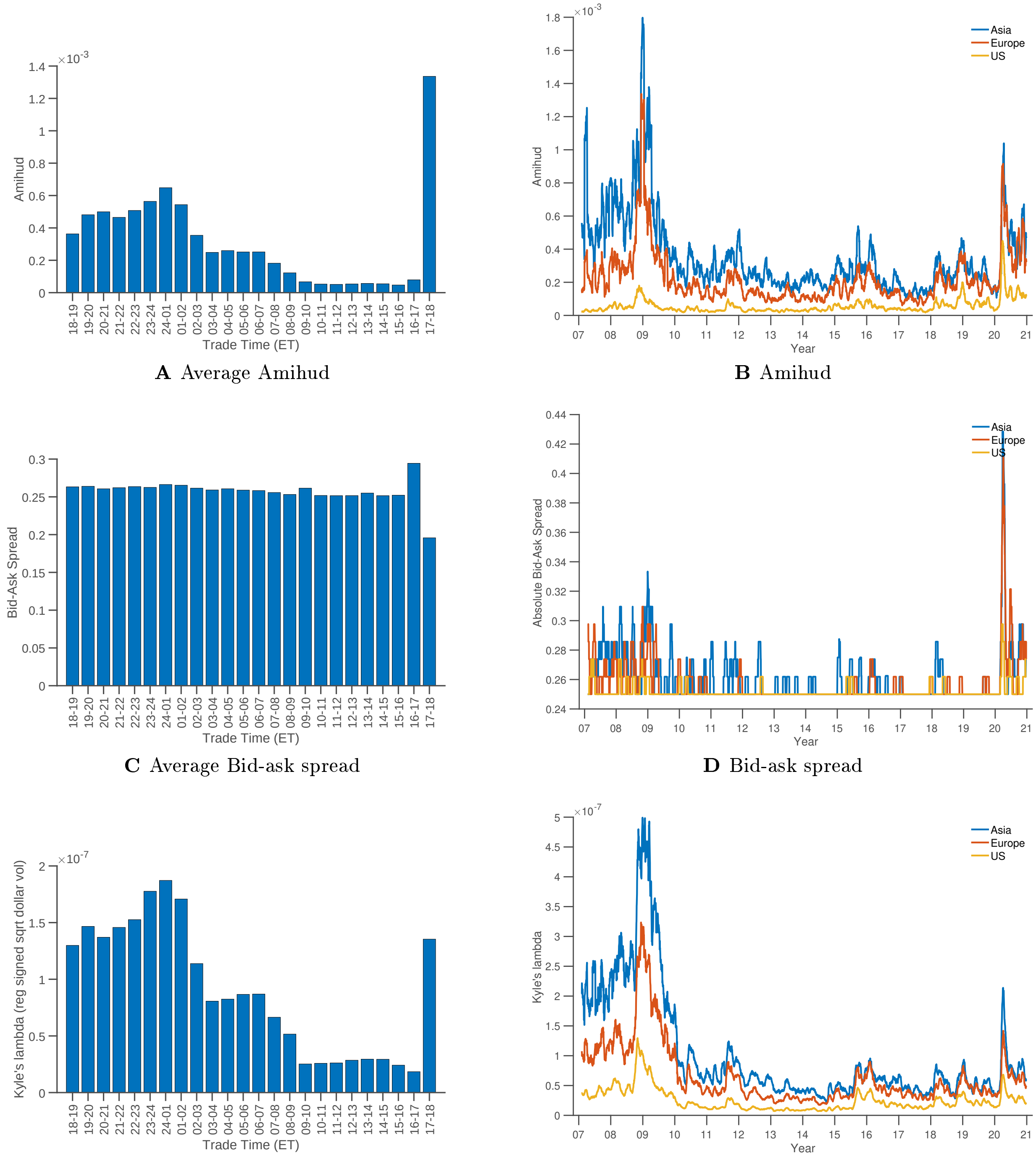
A



B

Figure A.11. Realized volatility

Panel (a) displays the average intraday realized volatility of the E-mini computed from 1-minute data. Volatility is annualized and displayed in percentage points. Panel (b) displays a time series of annualized realized volatility sampled within Asian, European, and U.S. trading hours. Sample period is 1998.1 – 2020.12



A Average Amihud

B Amihud

C Average Bid-ask spread

D Bid-ask spread

E Average Kyle's lambda

F Kyle's lambda

Figure A.12. Liquidity measures

The figure displays the intraday Amihud measure, Bid–Ask spread and Kyle's lambda of the E-mini and time series of the 3 measures for the Asian, European and U.S. trading hours. The sample period is 2007.1 – 2020.12.

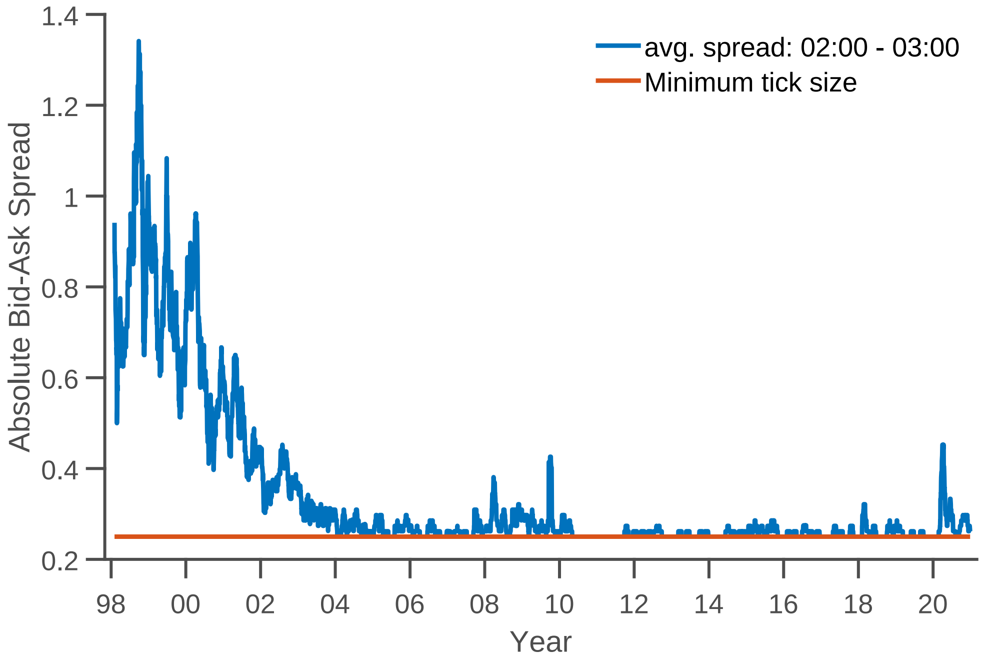


Figure A.13. Times series of the bid–ask spread during the OD hour
The figure displays the times series of the average bid–ask spread for the E-mini S&P 500 futures contract between 02:00–03:00. The sample period is 1998.1 – 2020.12.

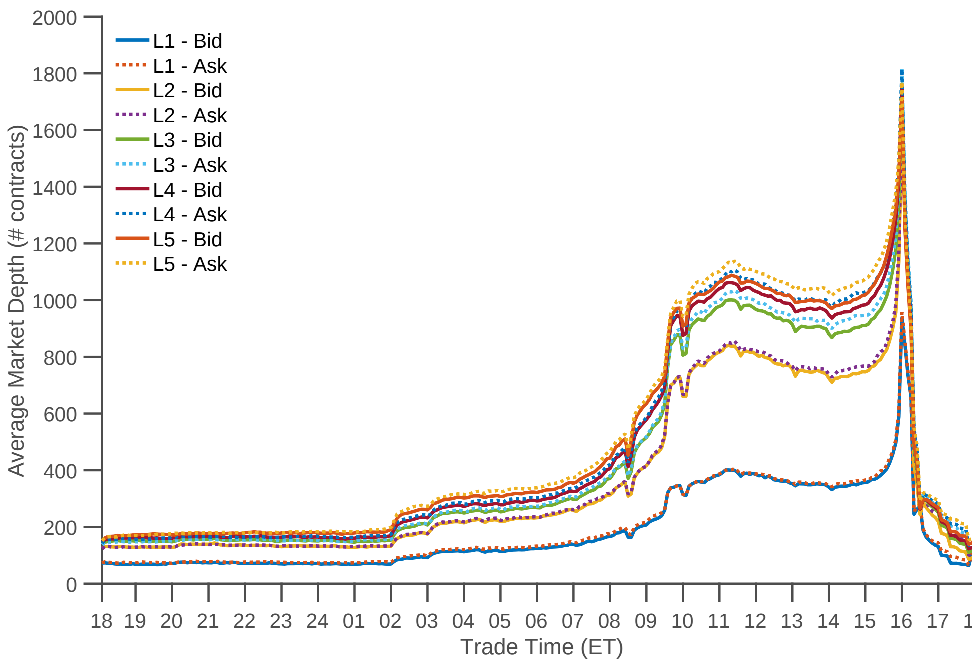


Figure A.14. Market depth
The figure displays the average market depth measured at a 5-minute frequency throughout the trading day. Market depth is measured as the number of contracts available and is reported for the first five levels on each side of the order book. The sample period is 2009.1 – 2020.12.

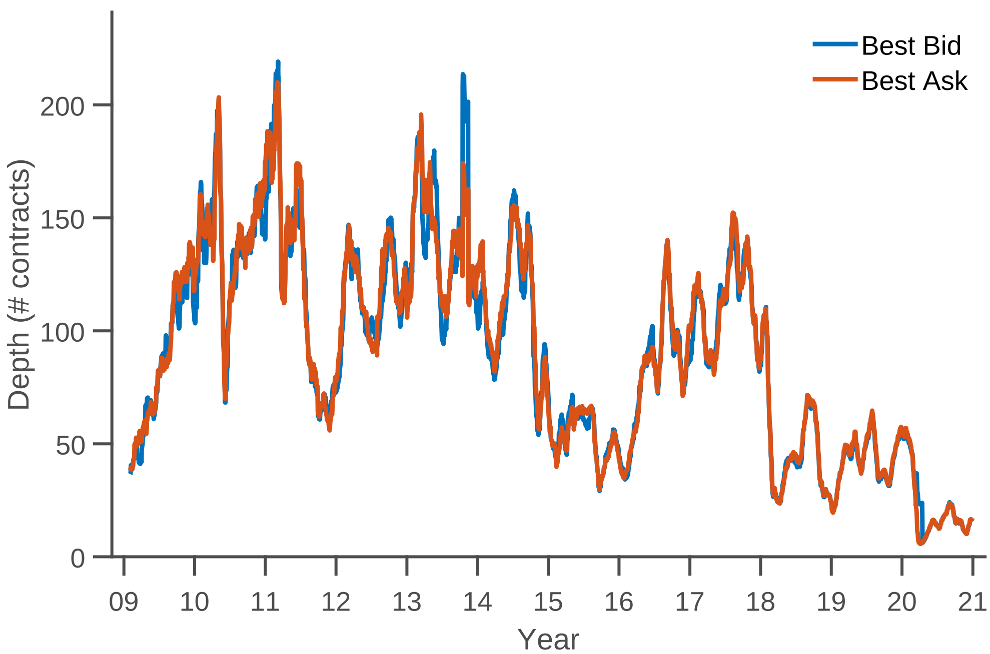


Figure A.15. Times series of market depth at the best bid and ask quote during the OD hour
The figure displays the times series of market depth at the best available bid and ask quotes for the E-mini S&P 500 futures contract between 02:00–03:00. Market depth is measured as the number of contracts available and is plotted as a rolling average over 21 business days (one month). The average depth throughout the sample period is 89.8 for the best bid and 89.1 for the best ask. The sample period is 2009.1 – 2020.12.

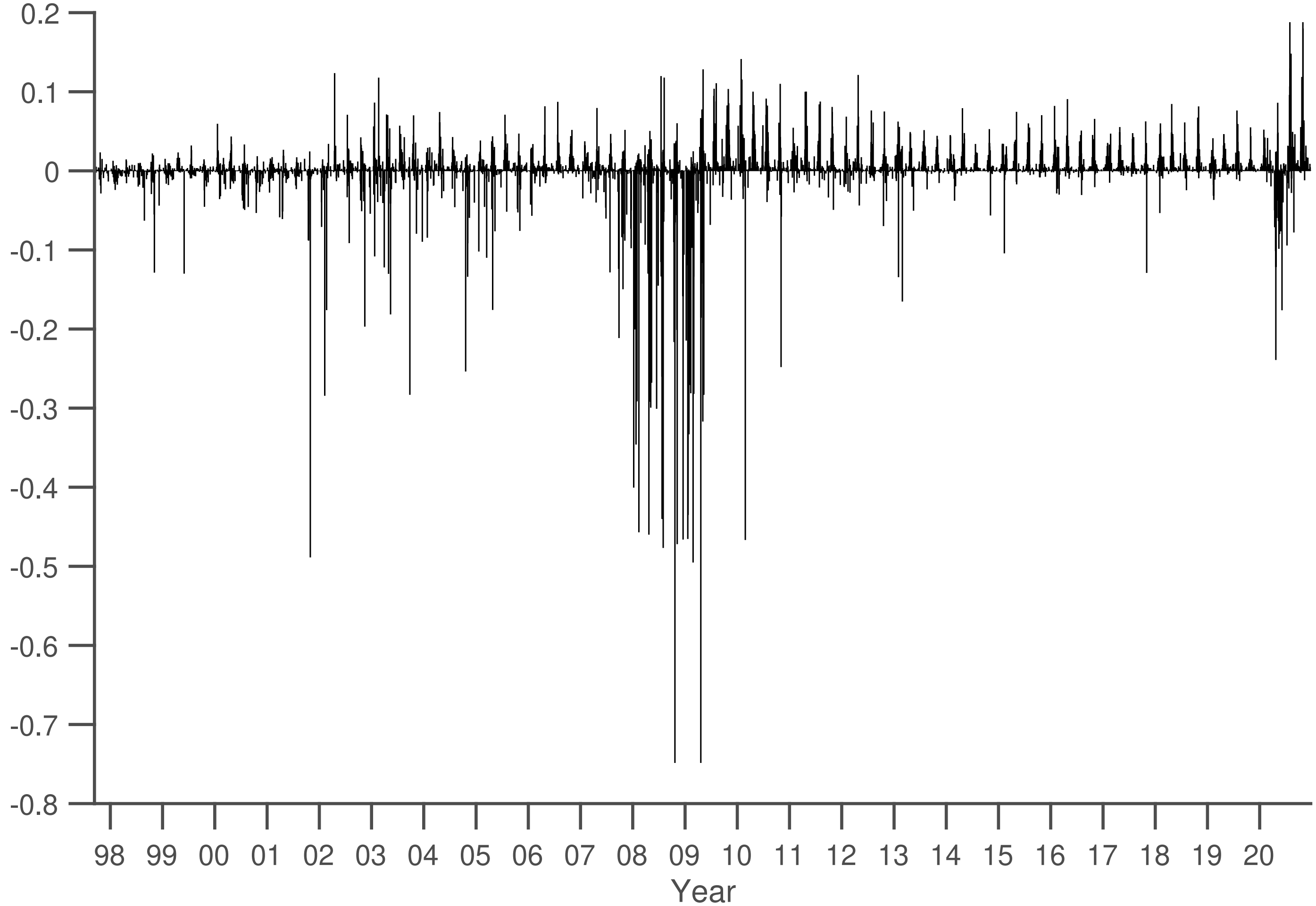


Figure A.16. SUE score

The figure displays the time series of the SUE score for the S&P 500 index. The daily earnings surprise of the S&P 500 index is defined as the daily sum of all individual firm surprises, $ES_{i,t}$. For each firm i and on day t we define the earnings surprise as $ES_{i,t} = \frac{A_{i,t} - F_{i,t-}}{P_{i,t-}}$, where A is the actual earnings per share (EPS) as reported by the firm, F is the most recent median forecast of the EPS and P is the stock price of the firm at the end of the quarter. The earnings data are obtained from I/B/E/S and Compustat. The sample period is 1998.1 – 2020.12.