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Abstract

This paper documents large positive returns to holding U.S. equity futures overnight during the opening hours of European markets. Consistent with models of inventory risk and demand for immediacy, we demonstrate a strong relationship with order imbalances arising at the close of trade from the previous U.S intraday session. Rationalizing unconditionally positive "overnight drift" returns, we uncover a strong 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 this demand shock asymmetry is consistent with time-variation in dealer risk bearing capacity.

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

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Since the advent of electronic trading in the late 1990's, U.S. S&P 500 index futures have traded close to 24 hours a day. In this paper we document that, despite the 24 hour nature of the market, returns do not accrue linearly around the clock. In fact, the largest positive returns are between 2:00 a.m. and 3:00 a.m., the opening of European markets in U.S. Eastern Time terms, averaging 3.6% on an annualized basis. Focusing on returns during this hour, we show that positive average returns are highly statistically significant, consistently present throughout the 1998 – 2020 sample, accompanied by substantial trading volume, and do not cluster on any particular day of the week or month of the year. We dub this positive average return the 'overnight drift', and argue that this pattern of returns is driven by overnight resolution of order imbalances from the end of the preceding U.S. trading day. Consistent with predictions of models of immediacy, we document that the overnight drift is larger following days with larger end-of-day sell order imbalances and even more so when occurring during periods of heightened uncertainty.

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

We conduct a number of tests to document that the relationship between the overnight drift and trading imbalances is as predicted by Grossman and Miller-style models. First, sorting days based on end-of-trading-day order imbalance, we show that positive overnight returns occur only on nights following market sell-offs (negative end-of-day order imbalances). When end-of-day sell order imbalances are large (more than 10,000 contracts), contemporaneous closing returns are, on average, -94.7% p.a.. The subsequent overnight returns average 8.95% p.a. during Asian hours

[1]The CME does not designate 'specialist' market makers in e-mini futures. Instead, effective market makers are any participant willing to post limit orders on both sides of the order book and hence supplying liquidity (immediacy) to market takers.

and 14.5% p.a. during the EU open, of which 10.78% p.a. accrues around the opening of European markets between 2:00 a.m - 3:00 a.m ET alone. Price reversals following market *rallies* are much more modest: When buy order imbalances are above 10,000 contracts, contemporaneous closing returns are on average 87.98% p.a. but the subsequent overnight returns average -8.84% p.a. during Asian hours, 0.4% p.a. during European hours, and there is no reversal effect between 2:00 a.m - 3:00 a.m ET. Thus, although market sell-offs and market rallies at U.S. close are similar in magnitude (though, naturally, of opposite sign), positive closing order imbalances lead to much smaller price reversals than negative closing imbalances, generating an unconditional positive overnight drift. We confirm the asymmetry of price reversals following positive and negative end-of-day order imbalance days more formally by estimating high frequency predictability regressions of returns on end-of-day order imbalance, and find statistically and economically significant loadings on the hours when London and Frankfurt financial markets open. Thus, high frequency returns become predictable as market makers transact with new participants arriving overnight, trading away order imbalances remaining from the previous U.S. trading day.

Second, we document that price reversals following negative closing order imbalance days are larger if order imbalances occur on days with increased uncertainty. In double sorts on end-of-day order imbalance and the end-of-day level of 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 imbalance. 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 heightened uncertainty. Moreover, the double sorts on end-of-day order imbalances and end-of-day level of the VIX reveal that the distribution of the VIX is similar across positive and negative order imbalance days, suggesting that the asymmetry in price reversals following negative and positive end-of-day order imbalances 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 time-varying risk-bearing capacity of the market makers in this market, with large market sell-offs potentially leading to fewer active market makers in the market.

Third, we conduct a natural experiment to test the relationship between the overnight price reversal 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 Japanese market opening changes exogenously from 7 p.m. in winter to 8 p.m. in summer.[2] Indeed, accounting for DST, return predictability around Tokyo open shifts forward by one hour when moving from winter to summer time, so that exogenous variation in the time of arrival of liquidity traders leads to predictable variation in the returns earned overnight. Expanding the natural experiment to also include the 3 weeks of the year when the DST is asynchronous between the U.S. and Europe, we again find that the overnight return predictability shifts to the 4-5 a.m. hour (the first hour of regular trading in London and Frankfurt when the U.S. - Europe time difference is 4 hours) though the point estimate is not significant due to the low number of observations.

A natural question is why do price reversals not happen immediately upon overnight market opening but instead take time to resolve. The answer is that, even though overnight volumes have grown steadily over our sample period, the close of regular trading at 16:15 EST marks the only time of the day when volumes jump discontinuously down. Even in recent years volumes during Asian open hours remain substantially below volumes at the U.S. close: between 2009 - 2020 trading volumes in regular Asian hours (18:00 - 2:00 a.m.) were 50 to 100 times lower than volumes during U.S. trading hours. Indeed, if we recast the trading day in *volume time* instead of clock-time, returns increase linearly in signed volume until around 60,000 contracts are traded, corresponding to the average number of contracts traded by 3 a.m. In other words, it takes market makers roughly 60,000 transactions to offset end-of-day order imbalances as of the previous day, with this re-balancing occurring earlier during the night as trading increases during Asian market hours. We show that the linearity in the relationship between signed volume and returns in volume-time terms persists even after we condition on market sell-offs, emphasizing the importance of studying inventory management motives in volume time.

We conclude by studying a set of trading strategies that exploit overnight price reversals in the post-2005 sample period. Pre-transaction costs, a trading strategy that goes long the S&P 500 futures between 2:00 a.m. and 3:00 a.m. earns large positive returns equal to 3.94% p.a. with a Sharpe ratio of 1.18, but accounting for bid-ask spreads reduces strategy returns to −0.13%

[2] The Tokyo Stock Exchange trades from 9.00 a.m. to 3.00 p.m. in Japanese Standard Time.

p.a. Extending the trading interval to the sub-period between 1:30 a.m and 3:30 a.m increases pre-transaction returns to 6.37% and post-transaction costs remains barely profitable with returns of 2.34% p.a. and a Sharpe ratio of 0.4. This is exactly what would be predicted by models of inventory risk: market makers position their limit order books to incentivize trades that bring their inventory closer to their targets, making the contrarian trade – where a *client* would earn the bid-ask spread – non-profitable. However, conditioning on date $t-1$ order imbalance, we consider a 'buy-the-dip' strategy that goes long the S&P 500 between between 1:30 a.m and 3:30 a.m only on trading days following market sell-offs. Trading approximately 50% of days, this strategy generates (post transaction cost) returns equal to 4.37% p.a with a Sharpe ratio of 1.2, which is five times larger than a passive (no transaction costs) position in the market over the same sample period. More generally, the presence of the overnight drift implies that the timing of portfolio adjustments should be an important consideration for a wide range of asset managers.

Related Literature: In the time-series, existing studies have documented that equities earn a substantial proportion of their returns during the overnight period compared to the regular U.S. trading-hours (for example, Cliff, Cooper, and Gulen, 2008 or Kelly and Clark, 2011). In work subsequent to ours, Bondarenko and Muravyev (2020) replicate our finding that the lion's share of CTC equity futures returns are earned around the opening hours of European markets.

In the cross-section, Heston, Korajczyk, and Sadka (2010) study high frequency periodicity in firm level returns documenting persistent intraday return reversals, which the authors argue arise because investors have predictable demand for immediacy at certain points within the day. Lou, Polk, and Skouras (2017) document firm level reversal patterns between intraday and overnight returns: overnight (intraday) returns predict subsequent overnight (intraday) returns positively, while overnight (intraday) returns predict subsequent intraday (overnight) negatively. The authors link this pattern to a 'tug of war' between retail investors trading at the beginning of the day and institutional investors who trade at the end of the day. Bogousslavsky (2018), on the other hand, studies institutional constraints and overnight risk in the cross-section of intraday pricing anomalies. Consistent with limits to arbitrage theory, a mis-pricing factor earns positive returns throughout the day but negative returns on market close when arbitragers are forced to close their positions. Hendershott, Livdan, and Rösch (2018) also study intraday versus overnight return components in the cross-section and present evidence that the CAPM holds overnight. These authors argue their findings are consistent with short lived beta-related price effects at market open and close.

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

Theoretical models on intraday patterns have focused on price discovery and learning at market openings (Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990; Biais, Hillion, and Spatt, 1999; Hong and Wang, 2000). In contrast, we motivate our empirical design from a literature that studies demand for immediacy and inventory risk (Ho and Stoll, 1981; Grossman and Miller, 1988; Vayanos, 1999, 2001; Rostek and Weretka, 2015). A common prediction of these models links price reversals to temporary order imbalances absorbed by liquidity providers.[3] Indeed, the Duffie (2010) presidential address reviews price dynamics with 'slow-moving' capital and highlights that *'Even in markets that are extremely active, price dynamics reflect slow capital when viewed from a high-frequency perspective.'*

The nature of our data set enables us to measure liquidity demand (order imbalance) at the market close and study variation in high frequency demand for liquidity faced by dealers. Our empirical findings complement the literature on the investors' demand for liquidity such as, the return to liquidity-providing trading strategies (Nagel, 2012), liquidity demand by mutual funds (Coval and Stafford, 2007; Da, Gao, and Jagannathan, 2011; Rinne and Suominen, 2016) or by hedge funds (Jylhä, Rinne, and Suominen, 2014; Choi, Shachar, and Shin, 2019).

The rest of the paper is organized as follows. We describe the high-frequency futures data in Section I. We present the our main contribution in Section II. Section III describes a motivating framework and tests predictions arising from inventory risk models linking order imbalances to returns. We recast the predictions from models of immediacy in high frequency predictability terms in Section IV. We examine the profitability of a trading strategy based on the overnight

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

drift in Section V. Section VI concludes.

I. Data

Our primary focus is data on intraday trades and quotes for S&P 500 futures contracts 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 U.S. regular trading hours concurrently with the cash market.[4] 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.[5] In September 1993, the SP contract began trading electronically outside regular hours via the CME GLOBEX electronic trading platform. The S&P 500 e-mini futures contract (henceforth ES) was introduced on September 9, 1997 and is quoted at fifty times the index, i.e. one-fifth of the big SP contract. The 'e' in e-mini is for electronic as trading takes place only on the CME GLOBEX platform which facilitates global trade for (almost) 24-hours a day, 5-days a week. The two futures contracts have quarterly expiries on the third Thursday in March, June, September and December. The most traded contract is almost always the front contract (the contract closest to expiry). Only when the front contract is close to expiry is the back contract (the contract second closest to expiry) more traded. This is because market participants roll their positions in advance of the expiry. We always use the most traded contract.

Exact trading times on CME platforms have changed over time but today trades are executed continuously from Sunday (18:00; 6 p.m.) – Friday (17:00; 5 p.m.), with a daily maintenance break between 16:15 – 16:30 (4:15 p.m. – 4:30 p.m.).[6]

Our primary data source exploits tick-by-tick data on trades and quotes for the ES contract

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

[5]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.

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

from Refinitiv Datascope Select, which we complement with data obtained directly from the CME.[7] The trades dataset includes the trade price, trade size and trade time. The quotes dataset includes quote price, quote size and quote time, with the first five levels of the order book available at all times. All trades and quotes are time-stamped to the millisecond, using Universal Time (UT). We convert the UT timestamps to U.S. Eastern Time (ET), 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 must 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 5 levels of the order book is available since 2009.

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

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

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

II. 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 - December 31, 2020.

A. Main result

The n-th 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 $n = N$ corresponds to 18:00 ET when a new trading day begins as defined by the CME. We work interchangeably with hourly returns ($N = 24$), 15-minute returns ($N = 96$), 5-minute returns ($N = 288$), and 1-minute returns ($N = 1440$).[8]

The grey bars in panel (a) of figure 2 display hour-by-hour returns averaged across all trading days in our sample. Estimates are annualized and displayed in percentage points. During our 23 year sample period, ON returns were positive, on average, between the hours of 12 a.m. (midnight in New York) and 4 a.m. Thirty minutes prior to the opening of the cash market in the U.S. at 9:30 a.m., equity returns were initially large and negative, then became smaller in magnitude but remained persistently negative until 12 p.m. The ID period was then characterized by a flat return profile until 3:00 p.m. followed by a sequence of large positive returns until the closing bell at 4:15 p.m.[9]

This return pattern is surprising. The red line in figure 2 plots the cumulative average return profile one would expect if information arrived continuously and returns followed linearly, while the black line plots the actual average realized cumulative returns. The gross CTC return was 5.7%, which is very close to the average yearly return on the S&P 500 index cash over this sample

[8]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.

[9]We note that the first 5-minute return between 18:00-18:05 is negative and large, which is largely driven by the final year of our sample.

period. More than half of this return was generated during the ON session: from 16:15 p.m. to 9:30 a.m. equity returns average 3.5% p.a. More striking than this, the average return during the hour from 2 a.m. to 3 a.m. ET was 3.7% p.a. We dub the return sequence of this hour the *'overnight drift'* (OD), which is indicated by the first blue shaded bar. Panel (b) of figure 2 displays a more granular view of returns around the OD. We see a persistent sequence of positive returns which are clearly visible in almost every interval between 1:30 a.m. and 3:00 a.m., showing that the positive average return between 2 a.m. and 3 a.m. was not driven by within-the-hour outliers but instead represent a continuous 'drift' over this interval of the overnight trading session.

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

From figure 2 (a) we also note that between the hours of 9:00 a.m. and 10:00 a.m., we observe a sequence of negative returns averaging -3.0% p.a.; we dub this the *'opening returns'* (OP) sequence, which is indicated by the second blue shaded bar and discuss its properties further below.

[Insert figure 2 here]

B. *Summary statistics*

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

Consider first panel (a) of table I which collects ON return statistics. Average returns for the hours {24-01, 01-02, 02-03} were equal to {0.46, 0.43, 1.48} basis points per hour per day, respectively, with corresponding t-statistics equal to {2.77, 2.75, 7.13}, respectively. Due to 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 basis points per day.[10] Median returns are lower than mean returns, implying that the return distribution in this hour is positively skewed. Indeed, return skewness during the OD hour equal to 1.20, which compares to daily CTC return skewness of -0.30.

Consider now panel (b) I which collects ID return statistics. The OP returns are strongly negative, equal to -1.24 basis points per hour per day with a t-statistic of 2.60. The remaining ID returns are flat and statistically indistinguishable from zero.

[Insert table I here]

C. Time-series evidence

Panel (a) of Figure 3 displays the cumulative log returns to a $1 initial investment that trades either the OD, OP or close-to-close (CTC) sub-periods of the day, for each day in our sample. A $1 investment in e-mini futures CTC would have returned $3.8 by December 2020. This investment bears considerable 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 pandemic. 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 significantly less return variation. A $1 investment trading the OP period would have lost more than 50% of its value returning $0.4 by the end of the sample.[11]

Panel (b) of Figure 3 examines average returns year-by-year for OD versus OP sub periods. The OD is positive in 20 out of 23 years. The OD is slightly negative in the recessionary years of 2002 and 2008, and again in 2019. Panel (c) of reports $(1-p)$ values from a t-test of OD or OP returns versus the null hypothesis of zero. At the 10% level, the OD is significant in 17 out of 23 years. Interestingly, the largest yearly average OD return (10.7% p.a) occurred in 2020, during the initial year of the pandemic, and the cumulative log return profile from panel (a) suggests this

[10]The OA reports findings for returns computed from volume weighted average prices (VWAPs) which are very close to returns computed from quotes. However, median returns computed from VWAPs are positive for the hours {24-01,01-02, 02-03} and equal to {0.17, 0.44, 0.77} basis points per day

[11]A detailed analysis of investment returns with and without transaction costs is delayed until section V.

was negatively correlated with the market. Testing this observation, we estimate a daily regression of OD returns on the CTC return from previous trading session

$$r_t^{OD} = \underbrace{3.83}_{(7.33)} - \underbrace{0.02}_{(-3.73)} r_{t-1}^{CTC} \quad , \quad R^2 = 2.11\%. \tag{2}$$

Point estimates are reported above HAC robust t-statistics in parenthesis. Strikingly, we find that the OD is strongly *negatively* forecasted by the previous days CTC return, which provides a second clue towards a potential explanation.

Turning now to the OP returns, we see that these can be very large but are only statically different from zero in 6 years. Moreover, OP returns are concentrated in recessionary years and, in particular, around the bust of the dot-com bubble. Splitting the sample year-by-year highlights the consistency of the OD returns compared to alternative intraday trends observed from figure 2.

Section D in the OA studies the robustness of these findings along different dimensions and demonstrates that positive average returns around the opening of European markets are a systematic feature of the data, and do not cluster on any particular day of the week or month of the year. In contrast, OP returns are only present on Thursdays and Fridays. Furthermore, estimating a daily regression of OP returns on OD returns of the same night session and CTC of the preceding trading session

$$r_t^{OP} = -\underbrace{3.99}_{(-2.90)} + \underbrace{0.10}_{(1.19)} r_t^{OD} - \underbrace{0.01}_{(-0.47)} r_{t-1}^{CTC} \quad , \quad R^2 = 0.01\% \tag{3}$$

we observe a weak *positive* relationship to the OD, so the OP is not a price reversal from the OD, and has no detectable relationship to preceding CTC returns. Thus, the OD and the OP are distinct phenomena. We focus here on the more systematic OD.

III. Inventory management and price reversals

In this section, we propose an explanation for the overnight drift based on demand for immediacy and liquidity provision. To highlight the channel we have in mind, consider the following stylized example. Assume bad news is announced during the U.S. intraday trading session, resulting in selling pressure at market close. These orders transact at the best available bids and, consequently, execute at successively lower prices down the order book. As the sell-off unfolds, prices drop below fundamental values because risk-averse market makers bear inventory risk.[12] The risk-averse market makers are compensated for bearing that extra risk through high expected returns, earned when they offload their extra inventory to new customers arriving overnight.

Grossman and Miller (1988) (GM) provide a framework that models such 'liquidity events' through the supply and demand for immediacy.[13] In GM, there are three periods $t = 0, 1, 2$ and two trading dates $t = 1, 2$. We think about $t = 0$ representing the intraday trading session, $t = 1$ representing the closing of intraday markets, and $t = 2$ being the opening of Asian or European markets. At $t = 0$, a representative intraday liquidity trader (LT^{ID}) arrives with demands to sell. A second overnight liquidity trader (LT^{ON}) arrives at $t = 2$ and will enter an offsetting trade. However, due to the asynchronous arrival of LT^{ID} and LT^{ON} end-of-day demand for immediacy arises, which is supplied by market makers (MMs) who are continuously present.[14]

In particular, MMs 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, i.e., 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 Asian or European timezones. 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

$$E\left[R_{ON}|\mathcal{F}_1\right] = \substack{\text{Dollar Order}\\ \text{Imbalance}} \times \substack{\text{Return}\\ \text{Variance}} \times \binom{\text{Risk Bearing}}{\text{Capacity}}^{-1} \tag{4}$$

Models of the GM type provide an intuitive link between liquidity provision, demand for immediacy and price formation.[15] The basic prediction of GM-type models is that the expected returns to providing immediacy are higher when (1) the order imbalance is bigger; (2) when payoffs are more uncertain; (3) when the total risk bearing capacity of the MMs in the market is lower. In the

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

[13] Important related contributions include Stoll (1978), Ho and Stoll (1981, 1983), Biais (1993), and more recently Brunnermeier and Pedersen (2009). There also exists a related literature studying price formation with large risk averse investors; for example see Vayanos (1999, 2001) or Rostek and Weretka (2015).

[14] We use the terms market makers, liquidity providers or arbitrageurs interchangeably. For the readers convenience, Section A.2 in the OA provides a review of the GM equations and an interpretation for our setting.

[15] A wealth of empirical evidence exists on return reversals that arise as a result of order imbalance. See, for example, Hendershott and Menkveld (2014) and the references therein.

following, we test the plausibility of the demand for immediacy and liquidity provision explanation for the overnight drift by studying the relationship between the overnight drift and measures of order imbalance and conditional return uncertainty.

A. *End-of-day Volumes*

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

Quantifying the intraday magnitudes in the recent sample, panels (c) plots average volumes for all hours of the day during 2020. With the index level at 3000 (late May / early June) closing volume in the interval 16:10 - 16:15 averaged $85000 \times 50 \times 3000 \sim 13$ billion USD. By comparison, panel (d) zooms in on the overnight hours showing that volumes are an order of magnitude smaller. Cumulative volumes between 18:00 and 3:00 a.m total $13500 \times 50 \times 3000 \sim 2$ billion USD 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 take-away from figure 4 is that there is an economically large downward jump in intraday volume at U.S. 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 U.S. close at 16.15 ET can generate large inventory imbalances. Such imbalances cannot be immediately traded away when the overnight session starts at 18:00 ET because the overnight trading activity is much lower. Moreover, even in recent years, it is likely that order imbalances last most of the overnight period and cannot be resolved until European trading begins.

[Insert figure 4 here]

B. *End-of-day Order Imbalance*

We begin by testing the basic prediction of inventory management models: the return to providing immediacy should be higher when order imbalances are larger. We measure end-of-day (EOD) order imbalances in terms of signed volume defined as

$$SV_t = \#buy\ orders - \#sell\ orders, \tag{5}$$

where # of orders is defined as of number of contracts. All results in this section are for the sample period is 2007–2020 since total volume was relatively stationary in this period (see figure 1).[16] In the OA, we present counterparts to the results of this section, but using an alternative measure that takes into account the historic changes in total volume, which we denote $RSV_t = \frac{SV_t}{Total\ Volume_t} \in [-1, 1]$. The results using the RSV are qualitatively similar.

Table III 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) zoom in on the signed volume during the closing hour of U.S. trading. In the following, we use the last hour preceding the maintenance to measure *closing* order imbalances. Thus, SV_t^{close} denotes the order imbalance based on all trades sampled during the hour 15:15 – 16:15 (3:15 p.m. – 4:15 p.m.).

[Insert table III here]

Table IV sorts all trading days into four groups based on the closing order imbalance. For each group panel (a) reports contemporaneous return averages and return averages during Asian

[16] Using SV_t to measure order imbalance across our entire sample period is problematic as volumes has increased by more than a factor 1000. For example, an order imbalance of 1000 contracts was massive in 1998 when the E-mini had just started trading but today it would be considered as a small imbalance.

hours (18:00 - 01:00), EU open (01:00 - 04:00), the OD hour (02:00 - 03:00), and the subsequent close-to-close return. Two groups have a negative closing order imbalance and two groups have a positive order imbalance. The sorting is performed such that the groups are approximately equal in size. Panel (b) reports overnight trading patterns (imbalances) conditional on our four sets of SV_t^{close}.

Consider first panel (a). The first group reports return averages for all days with closing sell imbalances of more than 10,000 contracts. We observe 801 of such days and the average SV_t^{close} is -23,009 contracts, which with the index level at 3000 corresponds to an imbalance of $\sim$ 3.5 billion USD. The fourth group shows the effect of market rallies with positive SV_t^{close}, which are close in magnitude but opposite in sign to the SV_t^{close} during sell-offs.[17] The middle groups with mild imbalances are also symmetric. Considering the first group (market sells-offs), the contemporaneous closing return is -94.70 % p.a. The return in the subsequent overnight period is 8.95 % during Asian hours, 14.50 % during EU open and 10.78 % during the OD hour. Considering the fourth group (market rallies), the contemporaneous closing return is 87.98 % p.a. Asian returns are close in size to their equivalent value in the first group, equal to -8.84 %, as one would expected from an inventory risk explanation. However, returns during EU open and OD hour, while negative, are an order of magnitude smaller than their corresponding values in group 1.[18]

Turn next to panel (b). In the first group, following market sell-offs, the average SV_t is 435 during Asian hours, 1,094 during EU opening hours, and 538 in the OD hour. In the bottom group, following market rallies, we find the opposite result, consistent with the idea that market makers adjust quotes to induce mean reversion in their inventories: return patterns in panel (a) are mirrored by quantities of trade in panel (b). Moreover, as we see with returns, we also observe a strong asymmetry in overnight imbalances during EU hours and the OD hour: reversion in inventories is stronger following market sell-offs than market rallies.

Summarizing, table IV shows that: (i) order imbalances at U.S. close are followed by overnight price reversals as predicted by inventory models; (ii) price reversals are much stronger follow-

[17]Note that SV_t^{close} is defined as buys minus sells so that a negative imbalance implies dealers are long and from equation 4 overnight expected returns should therefore be positive.

[18]We also note that, on average, market sell-offs do not fully revert consistent with the idea that large negative intraday returns are partly due to bad news, from which investors update their beliefs, and partly is due to the risk aversion of market markets.

ing market sell-offs giving rise to an unconditional positive overnight drift; (*iii*) as predicted by inventory models, price reversal overnight are accompanied by trading flow reversals.

[Insert table IV here]

Figure 5 provides a more granular dissection of order flow by sorting on ten sets of closing order flow of the preceding trading day. Black bars indicate 95% confidence intervals. The results are consistent with panel (a) of table III, displaying an almost monotonic link between closing order imbalances and subsequent overnight returns. The figure also displays an asymmetry in that a negative SV_t^{close} induce a strong positive return while positive SV_t^{close} induce a small negative return.

Equation 4 contains an additional intuitive prediction that close to zero order imbalances should have little price impact. Indeed, market makers should not require liquidity premium for holding zero inventory. Panel (d) examines this prediction by zooming in on OD returns based on SV_t^{close} straddling zero. Consistent with an inventory channel, when closing imbalances are approximately zero we find reversal returns which are economically small and statistically indistinguishable from zero.

[Insert figure 5 here]

C. Volume Time

From table IV we see that returns earned during the OD hour account for a substantial proportion of the total CTC reversal. This result is in line with the basic idea of Grossman and Miller (1988)-style models, which imply that, conditional on an order imbalance, prices revert as new participants 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 if trading activity is zero. Indeed, when trading activity is high, markets markers can quickly revert inventories to zero.

In this context a natural alternative to *clock time* is to measure time elapsed in terms of the trading volume. Specifically, we consider *volume time* which advances one increment for every single contract traded and thus equals the 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 time.

Figure 6 displays the cumulative log returns (computed from VWAPS) and the cumulative signed volume in both clock time and volume time, sorted by SV_t^{close}. The sample period is again 2007.1 – 2020.12. Panel (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 ET) 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. Panel (b) and (d) are in volume time. Following negative (positive) closing order imbalance, both signed volume and returns increase (decrease) essentially monotonically. Following market sell-offs, most of the close-to-close return is earned by the time 60,000 contracts are traded, or in other words, around the time when European markets open: On average, for 2007-2020, 48,000 contracts were traded by 2:00 a.m., 57,000 contracts were traded by 3:00 a.m. and 200,000 contracts (the last observation in the plots) were traded by 8:33 a.m.

Corresponding positive closing order imbalance generate a smaller price impact than negative closing order imbalance, 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 demand shock asymmetry in prices throughout Asian and European hours.

Summarizing, in addition to the evidence presented in table IV, as one would expect in a standard inventory model, returns and signed volume accrue in an approximately linear fashion when plotted in volume time. Thus, recast in volume-time terms, the return pattern is no longer abnormal around Tokyo open and EU open. Instead, the clock-time pattern reflects the trading volume spikes at Tokyo open and EU open.

[Insert figure 6 here]

D. Volatility risk

The second prediction of equation 4 is that expected overnight returns are increasing in the return variance of the risky asset. This arises because risk averse market makers demand a higher premium for holding larger price risk. Testing this prediction, and motivated by the demand shock asymmetry above, we split the sample into positive and negative closing order imbalance days. Panel a (panel b) of table V then reports double sorts conditional on negative (positive) SV_t^{close} days for the sample period January 2007 – December 2020. Double sorted return averages are reported based on terciles of SV_t^{close} and the closing level of the VIX sampled at 16:15 each day.[19] Within each set we also report average SV_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 EOD VIX appears quite symmetric conditional on positive versus negative SV_t^{close} days. Thus, it is unlikely that the asymmetric price impact is due to a correlation between order imbalance and the level of asset return variance.[20] Considering panel (a) (positive SV_t^{close}) there is really no clear pattern is 3×3 sorted OD return averages. Panel (b) (negative SV_t^{close}) on the other hand is consistent with our priors from equation 4: (i) Conditional on the level of the VIX, moving from low to high SV_t^{close} states, the OD return averages are increasing. (ii) Conditional on the level of the SV_t^{close}, moving from low to high SV_t^{close} states, the OD return averages are also increasing. The only exception is in high VIX states where the impact of SV_t^{close} is large but flat. Moreover, the high-minus-low return spreads are in the anticipated direction and statistically significant in 5 out 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 V here]

E. 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 and inventory management in response to positive vs. negative demand shocks. This strong asymmetry generates a positive

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

[20] 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 mild.

unconditional overnight return which in *clock* time is concentrated in the hour from 2:00-3:00 (the OD). In Section III.C we then showed that re-cast in *volume* time, that 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 4 that the conditional expected return to providing immediacy is the product of three terms: the end-of-day order imbalance, conditional variance of returns, and the inverse of the risk-bearing capacity of the MMs. Table V 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 0 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 MMs in this market. This may arise through two different channels.

First, since there are no designated market makers for e-mini contracts, there is no obligation on the part of institutions that normally act as market makers 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 number of market makers present and thus 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. Brunnermeier and Pedersen (2009), which builds on Grossman and Miller (1988), argue that such decreases in market maker risk-bearing capacity may 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. In contrast, large market rallies are unlikely to precipitate entry of new market makers into the market, at least at the horizons over which return reversals occur overnight. We leave the investigation of this possible source of price reversal asymmetry for future research.

F. Economic Magnitudes

We conclude this section by evaluating the *quantitative* plausibility of the inventory risk hypothesis in explaining overnight reversals of the magnitude documented in section II. From the data, we can easily observe three of the four terms that enter into the predicted relationship 4 between order imbalances and subsequent price reversals: the expected overnight returns $E\left[R_{ON}|\mathcal{F}_1\right]$, the end-of-day dollar order imbalance, and the (conditional) return variance. The final component – the risk-bearing capacity of the market makers in the market is harder to observe directly. Instead, we note that the risk bearing capacity can be expressed as $\begin{pmatrix}\text{Risk Bearing}\\ \text{Capacity}\end{pmatrix} = \frac{N+1}{ARA}$ 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 re-cast equation 4 as a prediction for the RRA of the market makers in this market

$$\text{RRA} = \frac{E\left[R_{ON}|\mathcal{F}_1\right]}{\substack{\text{Dollar Order}\\ \text{Imbalance}} \times \substack{\text{Return}\\ \text{Variance}}} \times \overline{\text{Wealth}} \tag{6}$$

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 intermediaries (see e.g. Adrian and Shin, 2014) and proxy for $\overline{\text{Wealth}}$ with the equity value-at-risk (VaR) of large dealers.[21] 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.

We obtain the quarterly time series of average broker-dealer equity VaR from Bloomberg in order to perform a proxy calculation of implied market maker RRA. Figure A.6 in the OA shows the time-series of equity VaR varies between 50 and 750 billion USD 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 300 billion USD, which we take as our proxy for $\overline{\text{Wealth}}$. Then, from panel (b) of figure 6 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 6 we obtain the corresponding resolved overnight market maker imbalance of ~ 1500 contracts that, with the index level at 2000, equates

[21] 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), firms report VaRs at the 95% confidence level, which we scale the VaR to the 99% using the Gaussian assumption.

to a dollar imbalance of $1500 \times 50 \times 2000 = 150$ billion USD. We measure $\left(\frac{\text{Return}}{\text{Variance}}\right)$ as the unconditional level of the VIX^2 through our sample which was $20\%^2$. The implied market maker relative risk aversion is therefore

$$RRA = \frac{0.17}{150 \times 0.04} \times 300 = 8.5 \tag{7}$$

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. Malkhozov, Mueller, Vedolin, and Venter (2016) perform a a similar calculation for mortgage backed security arbitrageurs coming up with an estimate of 88. This back-of-the-envelope calculation thus suggests that, not only is the inventory risk explanation plausible from a qualitative perspective but also from from a quantitative one.

IV. High frequency return predictability

Section II documented our central empirical finding and section III 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.

A. Order Imbalance, Demand Asymmetry, and Volatility Risk

Panel (a) of table VI reports point estimates from univariate regressions of hourly returns within the overnight session (18:00 – 6:00 a.m) on closing imbalances:

$$r^H_{t,n} = \mu_n + \beta^{SV}_n SV^{\text{close}}_{t-1} + \epsilon_{t,n}, \quad \text{for } n = 1, \ldots, 12, \tag{8}$$

together with t-statistics computed from robust standard errors clustered within each month. Returns are measured in basis points, and SV^{close}_{t-1} is divided by 10,000 for readability. Thus, a point estimate equal to 1 implies a 1 basis point return response to a closing imbalance of 10,000 contracts.

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 a.m. – 3 a.m. The estimates are both economically and statistically significant. A 1-standard deviation (18,000 contracts) decrease in SV_{t-1}^{close} (a sell-off) induces a 2.12 basis point increase in returns between 2 a.m. – 3 a.m. We also observe a statistically significant negative relationship between 20 p.m. – 21 p.m. which is the opening of Japanese (TSE) and Australian (ASX) markets, and between 24 a.m. – 1 a.m. which is the opening of Indian markets (NSE). The point estimates imply a 1-standard deviation decrease in SV_{t-1}^{close} generate positive overnight returns during these opening times of 1.2 (TSE & ASX) and 0.6 basis points (NSE).

Panel (b) of Table VI conducts a falsification test by including as separate regressors imbalances measured in the final three hours of the trading day (13:15–14:15, 14:15 – 15:15, and 15:15 – 16:15) in a multivariate extension to equation A.27. 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 have no impact on overnight returns. This is indeed what is suggested by the estimates in Table VI. For example, focusing on the 2 a.m. – 3 a.m. interval, the point estimates monotonically decline the earlier in the day the order imbalance is measured and are insignificant beyond 15:15.

[Insert table VI here]

The sorting based approach of the previous section revealed a strong asymmetry in price impact in response to positive vs. negative demand shocks, which generates an unconditional positive overnight drift return (reversal) . Panel (a) of table VII explores the asymmetry in a regression design that interacts SV_t^{close} with a dummy variable that takes on a value of '1' if $SV_{t-1}^{close} < 0$ and '0' otherwise

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

Consider first the estimates around the opening times of the TSE and ASX. The point estimates imply no asymmetry. At 20:00 p.m., the estimate of $\beta_n^{SV \times NEG}$ is virtually zero and in the hours around here there are no significant interaction effects. This finding is consistent with the return averages in Asian time reported in table IV which display a symmetric response to demand shocks, as one would expect in a simple inventory model. Consider now the overnight drift hour. The point estimate on the negative closing imbalance dummy is equal to -1.27 with a t-statistic of

-2.97, showing that almost all of the predictability in this hour, as reported in table VI, is coming from negative as opposed to positive demand shocks.

We also investigate the standard inventory risk prediction that price reversals should be amplified in states of high volatility. Testing this, we interact SV_t^{close} with the level of the VIX index sampled at 16:15 p.m ET

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

for $n = 1, ..., 12$. Panel (b) of Table VII reports the estimates, showing that ex-ante volatility has a strong amplification effect on the relationship between order imbalance and overnight returns between 2 a.m. – 4 a.m. A 1-standard deviation decrease in SV_{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 $1.4 \times (-1) - 0.11 \times (-1) \times 20 = 0.8$ basis points. With the VIX at its 90th percentile (30%) the return response is 1.9 basis points and with the VIX at its 10th percentile (12 %) there close to zero effect.

[Insert table VII here]

B. Daylight savings tests

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

Figure 7 shows that, during the second half of our sample (January 2007 – December 2020), when the trading volume during Asian opening hours is non-negligible, there is a spike in e-mini trading volume at 7 p.m. ET when DST is not active (red line) which is exactly at the opening of the Tokyo stock exchange (TSE). When DST is active, the increase in volume occurs instead at 8 p.m. ET, which again corresponds to the opening of TSE in the U.S. summer. Notice, also, a secondary spike in trading volume at 22:30 (10:30 p.m.) ET when the TSE re-opens after its lunch break during U.S. winter months and at 23:30 (11:30 p.m.) ET when the TSE re-opens after the lunch break during the U.S. summer months.[22]

[Insert figure 7 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 VIII reports the estimated coefficients from a regression of hourly overnight returns between 18:00 – 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

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

for $n = 1, \ldots, 12$, where the dummy variable takes on a value of 1 in summer time (DST active) and 0 in winter time (DST not active), with daylight savings seen from a U.S. perspective. The sample period is 2007.1 – 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 SV 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 0. Here, Australia opens at 18 ET, TSE opens at 19 ET, and Singapore opens at 20 ET (also, Shanghai opens at 20:15 and Hong Kong opens at 20:30). As expected, the effect of SV negative in hours with market openings where new agents arrive. specifically, $\beta_n^{SV} = \{-0.67; -0.62; -0.96\}$ for the hours 18-19, 19-20 and 20-21.

Next, in U.S. summer time, where the DST dummy equals 1, there are no major market openings at 18 ET, TSE opens at 20, Australia opens at 19 or 20[23], and Singapore opens at 21.

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

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

Now, we find the effect of SV by summing $\beta_n^{SV} + \beta_n^{SV \times DST} = \{0.02; -0.18; -0.52\}$ and, indeed, we see that the effect of SV shifts in accordance with DST.

We can likewise exploit the fact that DST is observed both in Europe and the U.S. The standard time difference between New York and London is five hours but throughout our sample period the U.S. and Europe have switched to DST at different times, typically 1 week apart. For the sample period 2007.1 – 2020.12 this gives us 240 trading days where the time difference was four hours and 3282 trading days where the time difference was five hours. Panel (b) of table VIII reports estimates of hourly overnight returns between 24:00 – 05 a.m. regressed on closing signed volume and a time difference dummy:

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

where the dummy variable takes on a value of '0' when the time difference between London and New York is 5 hours and a value of '1' when the time difference is 4 hours. We find that the predictability of SV disappear in the hour 2-3 am on days where the U.S. - EU time difference only is four hours. Predictability due to an overnight return reversal actually shifts by two hours to 4-5 a.m., which is the first hour of regular trading in London and Frankfurt when the U.S. - EU time difference is 4 hours. We note that there are only 240 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 idea that liquidity traders are no longer entering the market at this time, predictability disappears.

[Insert table VIII here]

V. Trading overnight reversals

We conclude the paper by considering a set of trading strategies designed to exploit overnight price reversals, with-and-without transaction costs, and in doing so implicitly study how market makers 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 sub-period of each trading day compared to passively holding the ES contract. Returns on trading day j earned on a strategy that goes long the ES contract in the sub-period $[t_1, t_2]$ are computed as

$$r^L_{j,[t_1,t_2]} = \frac{P_{j,t_2} - P_{j,t_1}}{P_{j,t_1}}, \tag{11}$$

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

$$r^L_{j,[t_1,t_2]} = \frac{P^{\text{bid}}_{j,t_2} - P^{\text{ask}}_{j,t_1}}{P^{\text{ask}}_{j,t_1}} \quad , \quad r^S_{j,[t_1,t_2]} = -1 \times \frac{P^{\text{ask}}_{j,t_2} - P^{\text{bid}}_{j,t_1}}{P^{\text{bid}}_{j,t_1}}. \tag{12}$$

We consider the following strategies:

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

We also consider a conditional trading strategy that "buy-the-dip", denoted BtD, which holds the e-mini during the $OD+$ period but only on trading days following a negative order flow at market close ($SV^{close}_{t-1} < 0$). We report findings for the sample period 2007.1 — 2020.12 since as after this point the bid-ask spread during the overnight period reached its effective minimum of one tick size (=0.25 index points) around 2007.

Table IX (a) reports summary statistics of the trading strategies when transaction costs are excluded. Holding the ES contract continuously (the CTC strategy) since 2007 has yielded an average yearly log return of 5.95% with a Sharpe ratio of 0.26.[24] The beta is equal to 1 by definition as we use the CTC return as a proxy for the market return. OTC returns have contributed a larger proportion to the total return earned by a passive investor holding the index than CTO returns: On an annualized basis, OTC returns averaged 3.30% and CTO returns averaged 2.66%. A dissection of this magnitude is not particularly surprising in itself. However, it is surprising that the average CTO return is below the OD return component which averaged 3.94%. The

[24]Sharpe ratios are computed from daily risk free rates implied by 4 week U.S. Treasury bills obtained from CRSP.

OD strategy has a Sharpe ratio of 1.18, which outperforms the market Sharpe ratio, and arises from a combination of high excess returns and low volatility during the overnight drift period. The best performing strategy is the conditional versions of $OD+$ which holds the e-mini on $\sim$ 50% of trading days. Returns from trading the BtD strategy are considerable larger than $OD+$ returns, which we interpret as additional evidence in support of the inventory risk prediction that past SV should predict subsequently higher expected returns, as new agents arrive to market and liquidity suppliers offload their long positions. In addition to larger returns, the BtD strategy return variance is significantly lower and thereby the Sharpe ratio higher. Specifically, $SV_{t-1}^{close} < 0$ has a Sharpe ratio of 1.79 compared to 1.30 of $OD+$[25].

Table IX (b) reports summary statistics post transaction costs. Returns on all strategies are significantly lower and none of the simple trading strategies are profitable over the full sample period. However, the BtD strategy remains profitable because it only pays the bid-ask spread on half the trading days when returns are higher. This is exactly what we would expect from an inventory management perspective. Market makers earn the bid-ask spread, buying at the bid at the end of the trading day on negative closing SV days 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.

It is important to highlight that small yet persistent intraday return seasonalities can have large low frequency effects. To illustrate this point, figure 8 depicts the cumulative returns of the CTC, OD,$OD+$ and BtD strategies for a one dollar investment in January 2007. The overnight strategies have performed exceptionally well in the sense that they never experience large negative returns. Remarkably, the BtD strategy has large positive returns during the financial crises even though the strategy never shorts the market. Panel (a) displays returns for a hypothetical investor who trades without costs. Trading the OD ($OD+$), a one dollar initial investment in 2007 generated a portfolio value of \$1.60 (\$2.25) in December 2020. Panel (b) of figure 8 displays cumulative returns including transaction costs. The CTC return remains unchanged as it is a passive strategy (we only have to roll the contract at a quarterly basis and pay for the spread between the initial buy in

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

2007 and final sell in 2020). With transaction costs, the OD is not profitable in practice. However, the BtD strategy earns large positive returns and while it does not beat a passive position in the market, it has a significantly higher Sharpe ratio and does not experience large losses related to the business cycle.

[Insert table IX and figure 8 here]

VI. 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 European market regular trading hours.

We argue that the large positive drift in returns is consistent with standard theories of demand 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 negative and positive order imbalance days is what generates the unconditionally positive returns around European opening times. We conjecture that the asymmetry in return reversals arise due to 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 is not only 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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VII. 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
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
Sdev	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	CTC
Mean	−1.24	−0.25	−0.23	0.41	−0.15	−0.06	0.61	0.00	−0.43	2.32
t-stat	−2.60	−0.45	−0.52	1.07	−0.37	−0.12	0.99	0.01	−3.62	1.46
Median	0.00	0.85	1.20	1.12	0.96	0.00	1.20	1.10	0.00	6.88
Sdev	36.11	42.28	32.96	29.17	30.52	36.80	50.79	20.91	9.16	127.40
Skew	−0.99	−0.07	−0.36	−0.48	0.51	0.31	1.25	−1.88	−0.56	−0.30
Kurt	19.40	11.10	10.40	24.56	21.12	14.26	30.65	21.09	61.82	14.43

(b) Intraday

Table I. Summary statistics: hourly returns around the clock

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 point terms. t-statistics testing again the null of zero returns are computed from HAC robust standard errors. Sample period is January 1998 — December 2020.

Abbreviation	Name	Open	Close	Time difference	ET open	ET close
NZSX**	New Zealand	10:00	17:00	16	18:00	01:00
TSE*	Tokyo	09:00	15:00	13	20:00	02:00
ASX**	Australia	10:00	16:00	14	20:00	02:00
SGX*	Singapore	09:00	17:00	12	21:00	05:00
SSE*	Shanghai	09:15	15:00	12	21:15	03:00
HKE*	Hong Kong	09:30	16:00	12	21:30	04:00
NSE*	India	09:15	15:30	9.5	23:45	06:00
DIFX*	Dubai	10:00	14:00	8	02:00	06:00
RTS*	Russia	09:30	19:00	7	02:30	14:00
FWB	Frankfurt	08:00	20:00	6	02:00	14:00
JSE*	South Africa	08:30	17:00	6	02:30	11:00
LSE	London	08:00	16:30	5	03:00	11:30
BMF**	Sao Paulo	10:00	17:00	1	09:00	16:00
NYSE	New York	09:30	16:00	0	09:30	16:00
TSX	Toronto	09:30	16:00	0	09:30	16:00

Table II. Open and Closing Times of Global Equity Cash Indices

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

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 III. 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.

SV_t^{close}	$\#Obs$	$Avg\ SV_t^{close}$	r_t^{close} (%)	r_{t+1}^{Asia} (%)	r_{t+1}^{EU} (%)	r_{t+1}^{OD} (%)	r_{t+1}^{CTC} (%)
$< -10,000$	801.00	$-23,009.00$	-94.70	8.95	14.50	10.78	34.61
$\in [-10,000, 0)$	829.00	$-4,596.00$	-23.05	4.51	7.23	6.88	16.48
$\in [0, 10,000]$	1,030.00	4,562.00	25.33	-7.41	1.80	-0.07	-2.98
$> 10,000$	860.00	21,045.00	87.98	-8.84	0.40	-0.52	-5.31

(a)

SV_t^{close}	$\#Obs$	SV_t^{close}	SV_{t+1}^{Asia}	SV_{t+1}^{EU}	SV_{t+1}^{OD}	SV_{t+1}^{CTC}
$< -10,000$	801.00	$-23,009.00$	435.02	1,094.32	538.50	$-2,942.02$
$\in [-10,000, 0)$	829.00	$-4,596.00$	169.15	179.18	186.60	$-2,712.07$
$\in [0, 10,000]$	1,030.00	4,562.00	-352.23	-71.40	4.10	-847.55
$> 10,000$	860.00	21,045.00	-539.38	-471.00	-177.62	$-2,359.69$

(b)

Table IV. Sorting on Closing Order Imbalance

We sort trading days into four sets, each with approximately equal number of observations, based on the closing order flow of the preceding trading day. Panel (a) reports average annualized returns of each group are reported for the contemporaneous *CTC* returns and closing returns, for returns during Asian trading hours (18:00 – 02:00), for returns during European trading hours (01:00-04:00), for returns during the overnight drift hour (02:00 – 03:00) and for the subsequent close-to-close return. Panel (b) reports corresponding average signed volumes computed within each trading period. 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 V. Double Sorts on Closing Order Imbalance and Closing VIX

We split the sample into positive (panel a) and negative (panel b) closing order imbalance. Within each set we double-sort trading days into terciles of closing order imbalance SV and the closing level of the VIX. Within each set we report average SVs 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 VI. Regression: overnight returns on closing signed volume

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

$$r_{t,n}^{H} = \mu_n + \beta_n^{SV} SV_{t-1}^{close} + \varepsilon_{t,n} \quad n = 1, \ldots, 12.$$

Panel (b) estimates a multivariate extension to this regression that includes 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 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	0.53	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 VII. 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 on a value of '1' if $SV_{t-1}^{close} < 0$ and '0' otherwise

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

Panel (b) displays regression estimates of hourly overnight returns regressed on closing signed volume and an 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 VIII. Daylight Saving Tests

In panel (a) hourly overnight returns are regressed on closing 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 on a value of '0' in winter time (DST not active) and '1' in summer time (DST active) and daylight savings is seen from a U.S. perspective. The Tokyo Stock Exchange (TSE) opens at 19:00 (7 p.m.) ES when DST is not active and at 20:00 (8 p.m.) when DST is active. Estimates are in basis points. In panel (b) hourly overnight returns are regressed on closing signed volume and time-zone difference dummy:

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

where the dummy variable takes on a value of '0' when the time-zone difference between London and New York is 5 hours (3282 observations) and a value of '1' when the time-zone difference is 4 hours (240 observations). 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	$OD+$	$SV_{t-1}^{close} < 0$
Mean	5.95	2.66	3.30	3.94	6.37	6.26
Sdev	20.50	12.15	15.74	2.88	4.47	3.18
Sharpe ratio	0.26	0.17	0.17	1.18	1.30	1.79
beta	1.00	0.38	0.62	0.02	0.04	0.03
Skew	−0.66	−0.97	−0.65	1.01	1.91	4.47
Kurt	15.32	18.37	12.78	28.36	35.38	84.00

(a) Without Transaction Costs

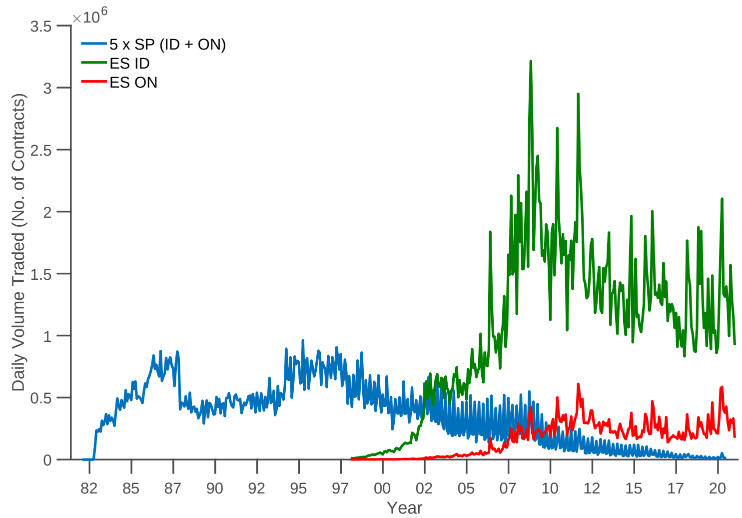
	CTC	CTO	OTC	OD	$OD+$	$SV_{t-1}^{close} < 0$
Mean	5.95	−1.36	−0.72	−0.13	2.34	4.37
Sdev	20.50	12.15	15.74	2.88	4.47	3.16
Sharpe ratio	0.26	−0.16	−0.08	−0.24	0.40	1.21
beta	1.00	0.38	0.62	0.02	0.04	0.03
Skew	−0.66	−0.99	−0.67	0.92	1.85	4.34
Kurt	15.32	18.36	12.82	28.31	35.15	84.87

(b) With Transaction Costs

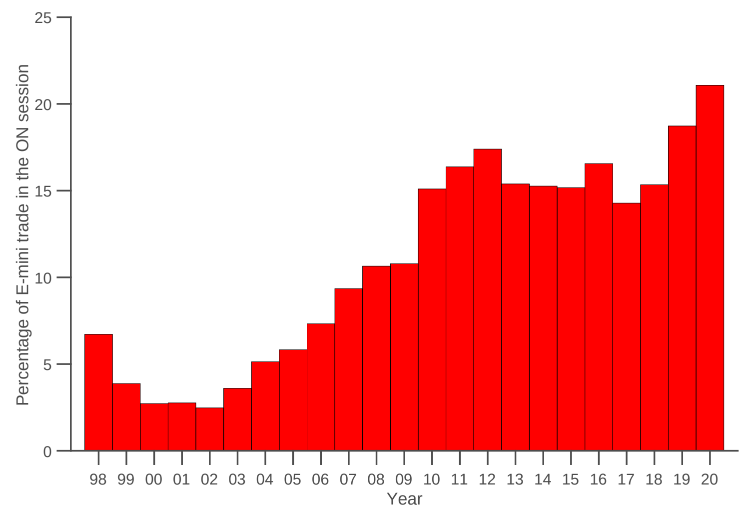
Table IX. Trading Strategies

Summary statistics for returns of intraday trading strategies excluding (panel (a)) and including (panel (b)) transaction costs. CTC is continuously holding the E-mini contract. CTO is holding the contract from 16:15 (4:15 p.m.) to 8:30; OTC is from 9:30 to 16:15 (4:15 p.m.); $-OR$ is shortening the opening returns from 8:30 to 10:00; OD is the overnight drift from 02:00 to 03:00; $OD+$ is from 1:30 to 3:30. $SV_{t-1}^{close} < 0$ is a buy the dip strategy that goes long from 1:30 to 3:30 only on days following a negative closing order flow. Means and standard deviations are in annualized percentages. The Sharpe ratios uses the 4 week U.S. Treasury bill as the risk-free rate. Betas are computed using the CTC return as the market return. Returns excluding transaction cost are computed from mid quotes and returns including transaction costs are computed from the best bid and ask prices quotes. The sample period is 2007.1 — 2020.12

VIII. Figures



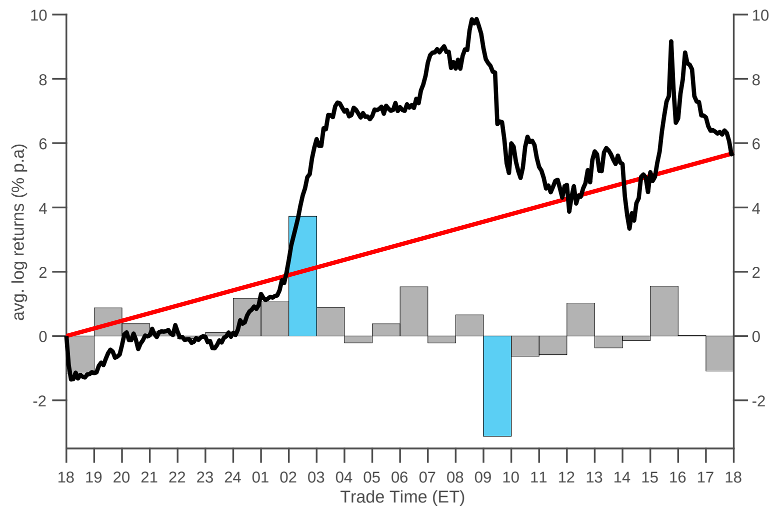
(a)



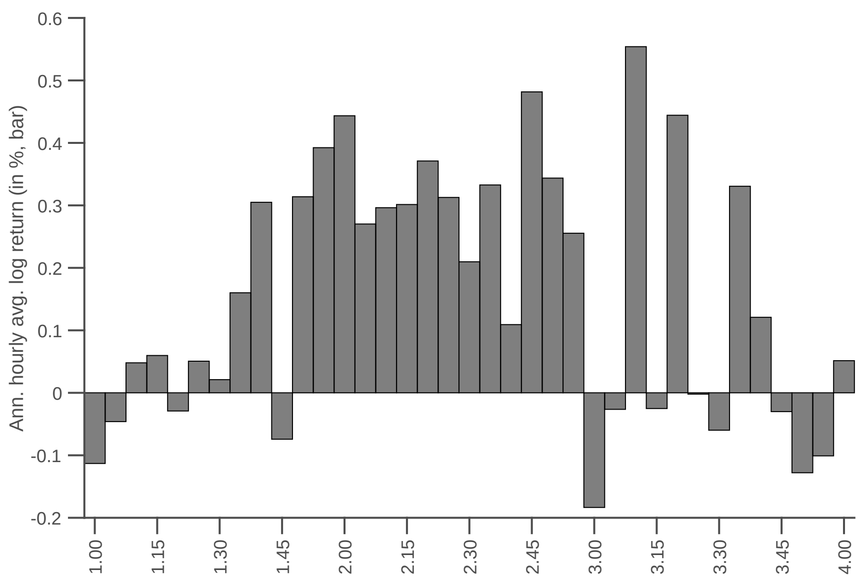
(b)

Figure 1. Overnight vs Intraday e-mini Volume Split

Panel (a) plots average daily trading volumes in the *SP* and *ES* contracts with the *ES* split by overnight versus intraday trading sessions. Panel (b) plots year-by-year average percentages of overnight volume relative to total volume for the ES contract. Volumes are measured as the total number of contracts traded. The sample period for overnight trading is January 1998 - December 2020.



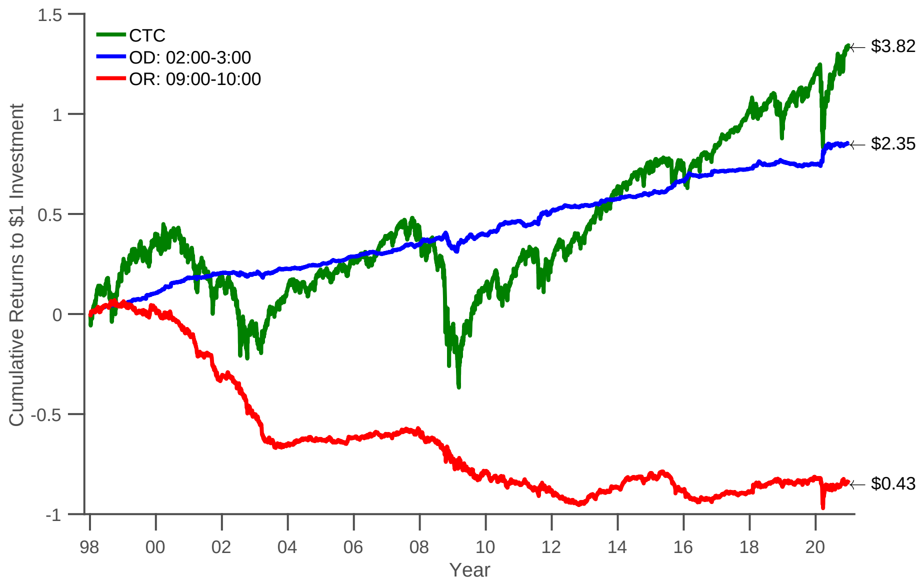
(a)



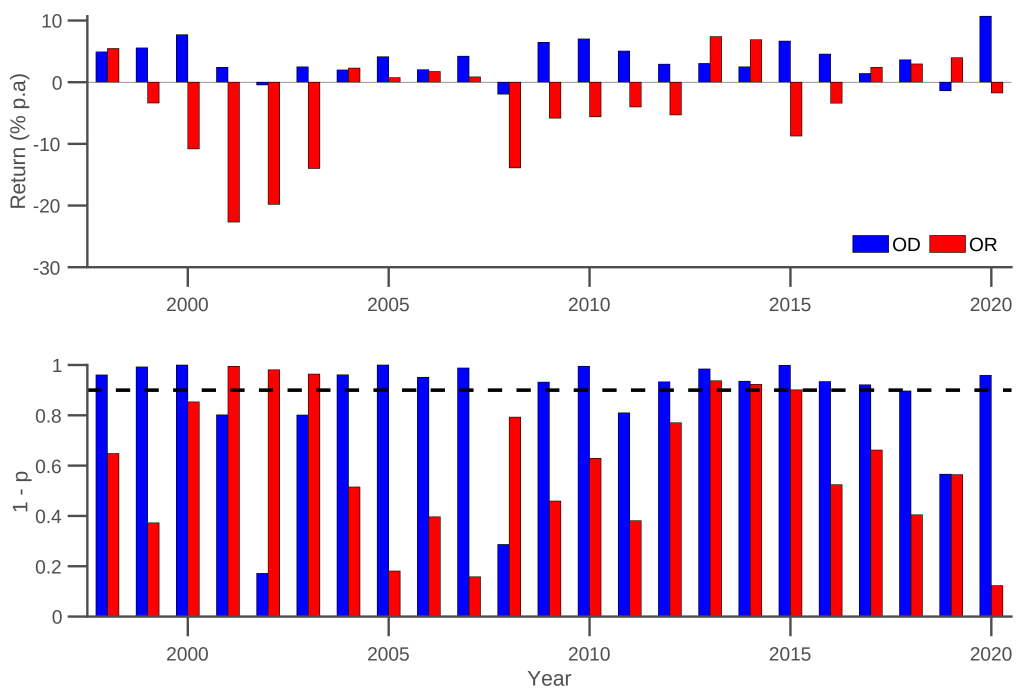
(b)

Figure 2. Intraday Return Averages

Panel (a) displays the average hourly log returns (bars) and average cumulative 5-minute log returns (solid black line) of the e-mini contract (first close-to-open and then open-to-close). Panel (b) plots average 5 minute returns for the hours 1.00-3.00 a.m. Sample period is January 1998 - December 2020.



(a)



(b)

Figure 3. Time-Series Evidence

Panel (a) displays the cumulative log returns to a $1 initial investment that trades either the OD, OR or CTC sub-periods of the day. Panel (b) plots yearly average log returns for the OD and OR periods along with $(1-p)$ the values from a t-test against the null hypothesis that these returns are zero. Sample period is January 1998 – December 2020.

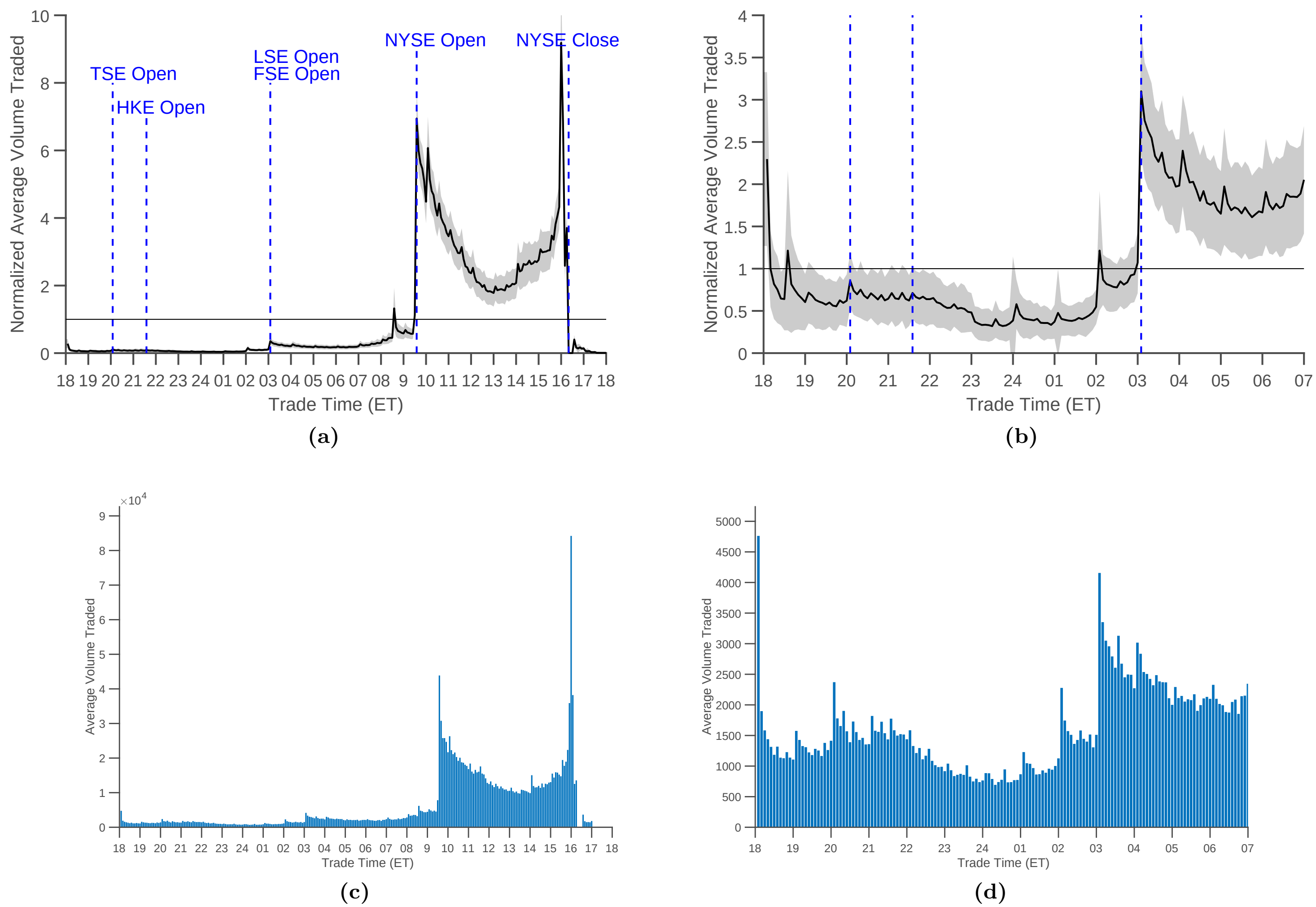


Figure 4. Intraday Equity Volumes

Panel (a) plots the average 5 minute trading volume of the e-mini for the entire trading day, showing the full intraday pattern of volume. Panel (b) focuses only on volume outside U.S. open hours. Volumes are normalised by dividing each 5-minute volume by its daily volume, and then averaging normalised 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.

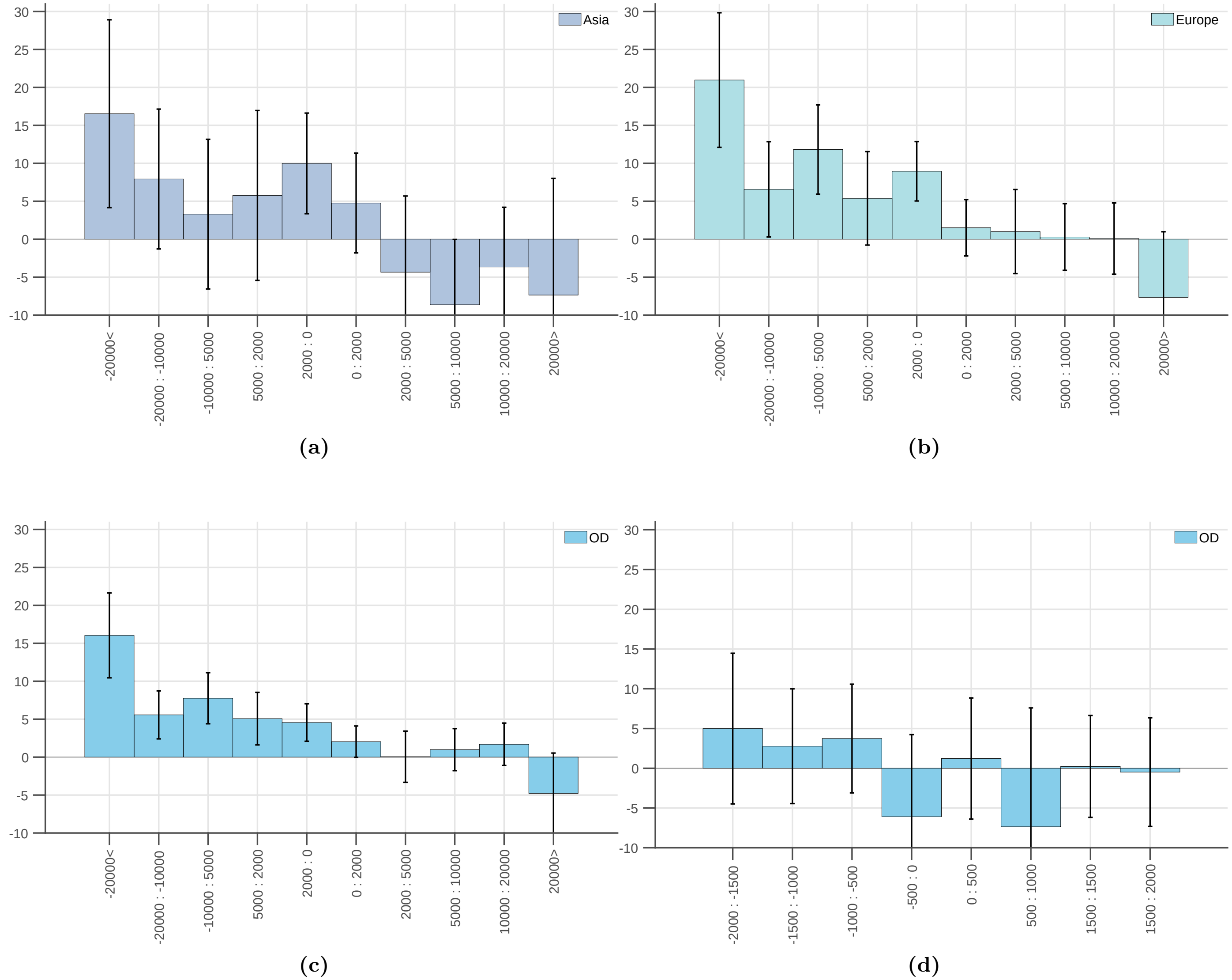
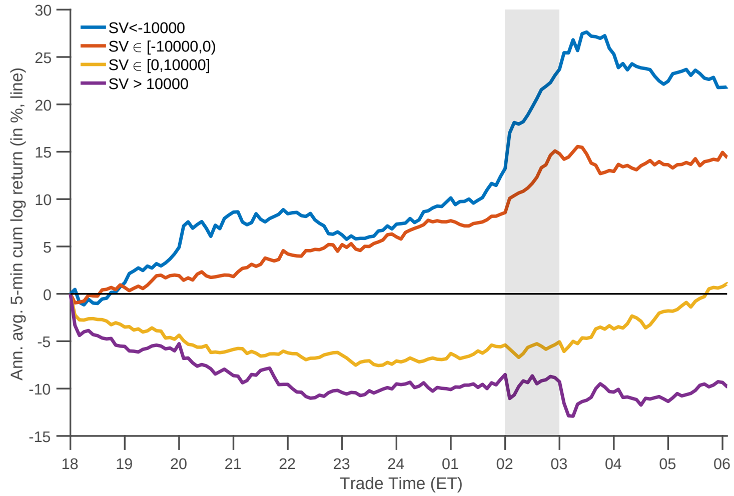
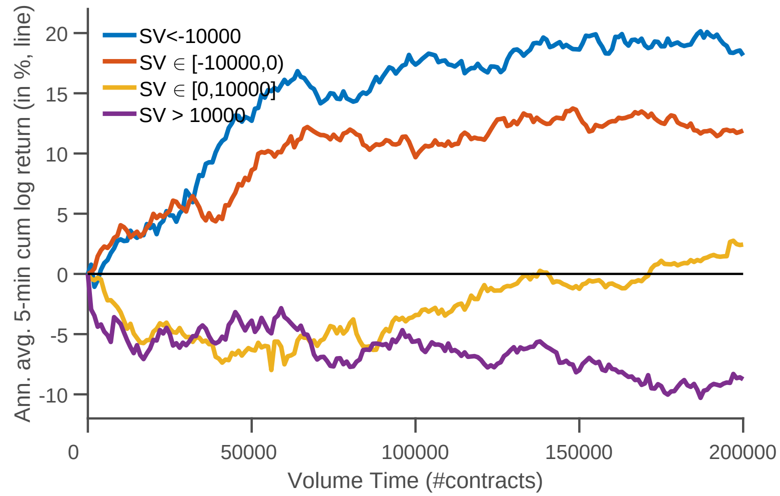


Figure 5. Average overnight returns sorted on closing imbalance

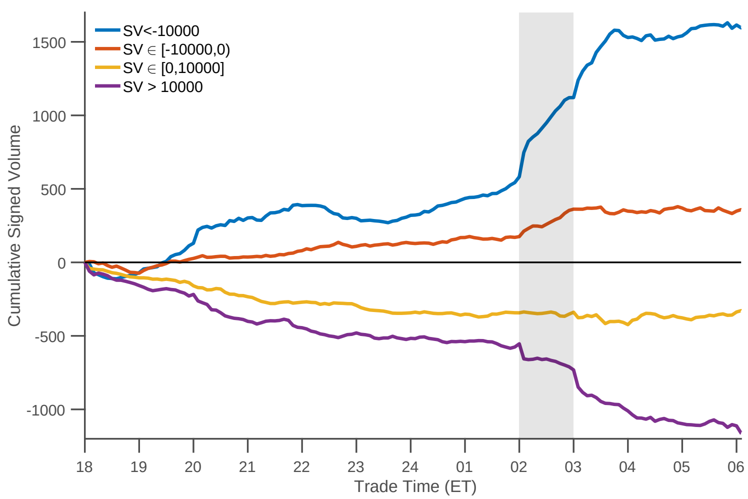
Panels (a) - (b) sort trading days based on ten sets of closing order flow of the preceding trading day and average annualized returns of each group are plotted subsequent Asian trading hours (18:00 – 02:00), for returns during European trading hours (01:00-04:00), for returns during the overnight drift 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.



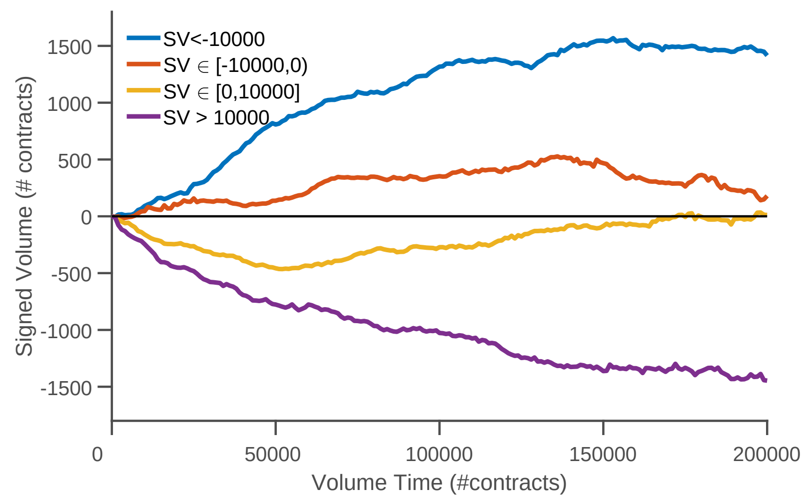
(a) Cumulative returns in clock time



(b) Cumulative returns in volume time



(c) Cumulative signed volume in clock time



(d) Cumulative signed volume in volume time

Figure 6. Volume Time

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

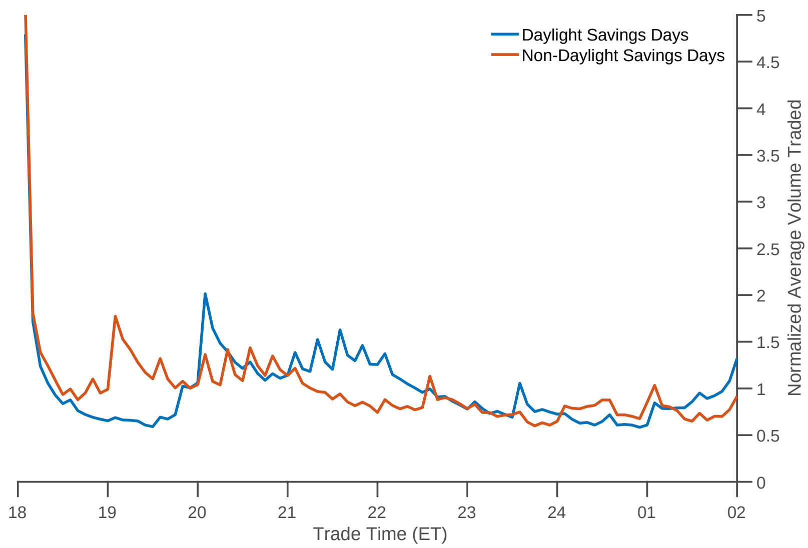
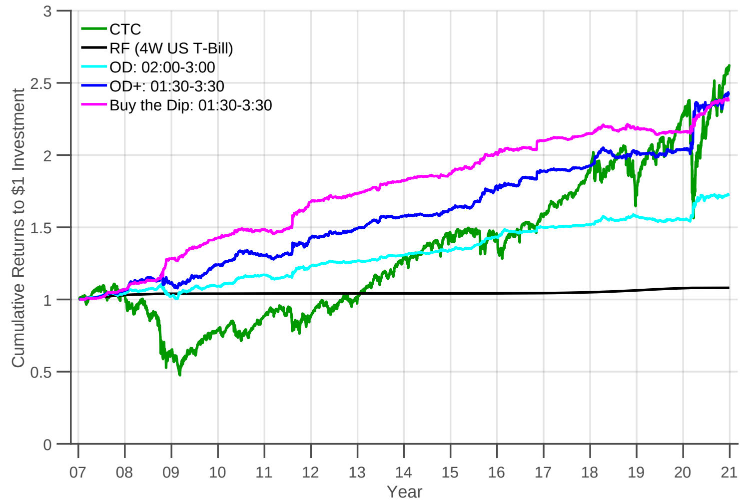
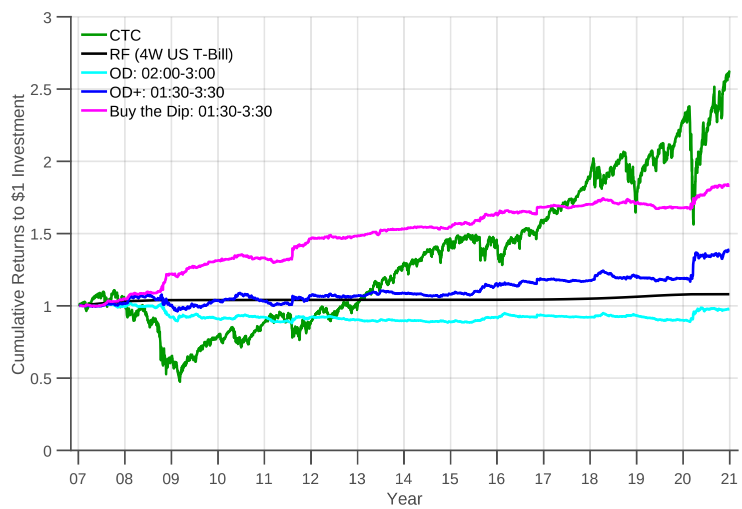


Figure 7. E-mini Trading Volume: Asian Hours

Figure displays average trading volume in the e-mini contract for the Asian trading hours. Volumes are normalised by dividing each 5-minute volume by its daily volume, and then averaging normalised 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 (7 p.m.) ET when U.S. DST is not active and at 20:00 (8 p.m.) when U.S. DST is active. TSE reopens at 22:30; 10:30 p.m. (23:30; 11:30 p.m.) after its lunch break when U.S. DST is not active (active). All volumes are computed as averages of the 5 minute volume relative to the total daily volume. The sample period is January 2007 – December 2020.



(a) Without Transaction Costs



(b) With Transaction Costs

Figure 8. 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 2007 when the overnight spread reached its effective minimum of one tick (0.25 index points). Panel a (b) is excluding (including) transaction costs. *CTC* is continuously holding the e-mini contract. *OD* is the strongest part of the overnight drift from 02:00 to 03:00, *OD+* is from 1:30 to 3:30 and buy the dip goes long from 1:30 to 3:30 only on day following a negative closing order flow. The black line shows the cumulative risk-free return measured as the return of a 4 week U.S. Treasury bill. Returns excluding transaction cost are computed from the mid quotes and returns including transaction costs are computed from the best bid and best ask price.

The Overnight Drift

Internet Appendix

Nina Boyarchenko, Lars C. Larsen and Paul Whelan

Sections 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 provides a survey of Grossman and Miller (1988) (GM) interpreting the results of that paper in the context of our setting. Section A.3 reports robustness tests related to our market making explanation. This section repeats our main inventory risk tests with an alternative measure of order imbalance and provides a falsification test that asks whether the high frequency predictability documented in the main body is special or whether our finding is an artefact of more general negative serial correlation in returns. The conclusion here is that predictability at the open of European markets due to U.S closing imbalances is unique. 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. 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.[26]. We note here that earning a substantial overnight returns 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 continuous 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.

$\Big[$ Insert figure A.1 here $\Big]$

[26] 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

B. Special Hours

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

$\Big[$ Insert figure A.2 and A.3 here $\Big]$

C. Non-Parametric Tests

Table A.3 considers a non-parametric dissection focusing on overnight returns. We report two sets of statistics: one with hourly returns sampled daily and another using hourly returns aggregated within the calendar trading month. For each set, we report the percentage of positive and negative returns together with the p-value from a two-sided test of observing this many more returns in one direction than the other, under the null hypothesis of a driftless random walk (binomial test with a probability of success equal to $\frac{1}{2}$).

Considering first returns computed from trades (panel a), for daily and monthly sampling we reject the random walk hypothesis at the 6% level or lower between the hours of 24 a.m. and 3 a.m. During the OD hour, at the monthly frequency, 64% of the months in our sample are positive, compared to 58% for close-to-close returns (not shown in the table). Outside the hours of 12 a.m. and 3 a.m., we generally cannot reject the hypothesis that overnight returns follow a random walk. Computing returns from quotes gives consistent but stronger results [27]. We observe several hours during the intraday period where we can reject the random walk hypothesis when using daily sampling. However, except for the hour 12-13, we cannot reject the hypothesis when using monthly sampling.

$\Big[$ Insert table A.3 here $\Big]$

D. Calendar Effects

D.1. Day of the week

Panel (a) of figure A.4 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.4 tests this claim formally using a regression dummy framework as above. In all

[27] For the hour 23–24 we observe a return of zero around 15% of the time. This is because the market was closed during this hour on Tuesday to Fridays from October 1998 to September 2003.

days of the week, the 2 a.m. - 3 a.m. return is positive and significant at the 1% level and the magnitude of the returns is also quite similar.

Panel (b) of Table A.4, on the other hand, shows that the OP returns are always negative but only statistically significant on Thursdays and Fridays with mean returns equal to -2.10 and -3.03 basis points per hour per day, with t-statistics equal to -2.02 and -2.76, respectively. Figure A.7 reports three pieces of suggestive evidence as to why the OP occurs only on Thursdays and Fridays: Firstly, we observe more U.S. macro announcements released at 8:30 a.m. on Thursdays and Fridays. Generally, we experience large positive returns leading up to announcements, as has been documented in the literature (Savor and Wilson (2013)). We conjecture that (short-lived) price-reversals following the macro announcements partly explain the negative opening returns. Secondly, we do not observe many FOMC announcements on Thursdays and Fridays and we also know that returns typically are positive in the hours leading up to FOMC announcements which subsequently do not revert Lucca and Moench (2015). Thirdly, we observe most negative earnings announcements days are Thursdays and Fridays. In summary, while OP returns is concentrated in the final days of the week, OD returns are systematically positive and significant in each day of the week.

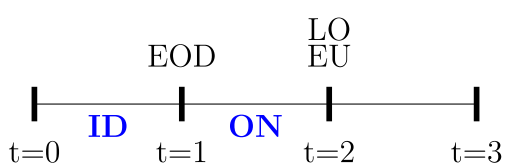
[Insert figure A.4 and A.7 and table A.4 here]

D.2. Month of the year

Panel (b) of figure A.5 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 OP are 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.5 reports the statistical significance within each calendar month. Consistent with Figure A.5, 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.5 and table A.5 here]

A.2. 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 at date $t = 1$. Dealers provide immediacy at $t = 1$ by trading with the ID agent and next at date $t = 2$ dealers meets a representative overnight liquidity trader (ON) who trades an offsetting amount. Denote the initial endowments of the ID and ON trader as $q_0^{ID} = \mathcal{I} = -q_0^{ON}$

The problem of determining equilibrium quantities and prices is solved backwards in time. At $t = 2$ agent i maximizes their expected utility subject to their 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 realised at date $t = 2$. Eliminating the cash position from the problem is equivalent to maximising

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

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

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

We now make clear why demand for immediacy arises. The demand for immediacy by the ID trader at date 1 cannot be offset at date 1 because the ON trader who holds the opposite demand does not arrive until one period later when markets clear across agents $i \in \{MM_1, \ldots MM_n, ID, ON\}$. 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 markets who start with zero inventory but are willing to carry some inventory in exchange for a liquidity premium (expected transaction return). At date 2 the market clears:

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

Moving backwards 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 maximising

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

The first order condition in excess demand terms is given by

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

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 his entire initial position to the MM. Substituting the equilibrium price back into the optimal *demands* we see

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

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 $t = 1 \to t = 2$. Noting that $S_2 = \mu + \epsilon_2$, the period $t = 1$ conditional expected return of the market makers is given by

$$E_1[R_{ON}] = S_1\mathcal{I} \times \sigma^2_{R,t} \times \frac{\alpha}{N+1} \tag{A.22}$$

$$= \begin{matrix}\text{Dollar Order}\\ \text{Imbalance}\end{matrix} \times \begin{matrix}\text{Return}\\ \text{Variance}\end{matrix} \times \begin{pmatrix}\text{Risk Bearing}\\ \text{Capacity}\end{pmatrix}^{-1}. \tag{A.23}$$

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 date $t = 0$ such that $S_1\mathcal{I}$ is random):

$$\text{cov}_0[S_1\mathcal{I}, R_{ON}] = -\text{var}_0\left(S_1\mathcal{I}\right)\sigma^2_{R,t} \times \frac{\alpha}{N+1}, \tag{A.24}$$

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.

A.3. Supplementary Results: Inventory Risk Tests

A. Relative Signed Volume

Sections III and IV conducted a number of tests of the relationship between the overnight drift and trading imbalances as predicted by by inventory risk models along the lines of Grossman and Miller. In these sections, we measured measured end-of-day (EOD) order imbalances in terms of signed volume defined as

$$SV_t = \#\textit{buy orders} - \#\textit{sell orders}, \tag{A.25}$$

where # of orders is defined as of number of contracts. In the main body of the paper tests were conducted for the sample period is 2007–2020 since total volumes were relatively stationary over this period. Using this measure in the early sample period, however, would be problematic since volumes has increased by more than a factor 1000 since the early 2000's; thus, an order imbalance of 1000 contracts would be huge in 1998 when the e-mini had just started trading but today would be quite normal. In this part of the OA we present counterparts to the results of the main body using relative signed volume, which is an alternative measure of imbalance that takes into account the historic changes in total volume

$$RSV_t = \frac{SV_t}{Total\ Volume_t} \in [-1, 1]. \tag{A.26}$$

We measure closing relative signed volume RSV_t^{close} between 15:15 and 16:15. All tests are conducted over the sample period January 1998 – December 2020.

Consistent with the findings for the sample period January 2007 – December 2020 using SV_t^{close}, table A.6 shows that sorting days based on RSV_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.7 reports double sorts on RSV_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.8 confirms high frequency return predictability arising at the opening of European financial markets via projections onto RSV_t^{close}.

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

B. Falsification Test

Microstructure theory predicts a fundamental link between order imbalance and returns both contemporaneously and at lagged intervals. Indeed, in an inventory risk context, high-frequency predictability arises as market makers manage their positions to resolve imbalances. However, one should expect 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 corporate bonds predictability can last over several hours or days. Microstructure theory also predicts negative autocorrelation in returns due to market frictions. For the e-mini, we do, in fact observe negatively autocorrelated returns. However, because of the generally large liquidity, autocorrelation coefficients are are only significant for, at most, a few minutes. 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. This implies that order imbalances at U.S close take longer time to trade away (in clock time not in volume time) and thus, the predictability of returns due to inventory management lasts longer in the period of trade post U.S close. Our claim is the relationship between closing order imbalance and the returns around European open are special.

Table A.9 provides a 'falsification' test for this claim. Focusing on the overnight hours, panel (a) estimates univariate regressions of hourly returns on one hour lagged SV_t. There is only one significant hour between 23-24 and the sign is positive not negative.

Panel (b) extends the regression to include the previous 12 lagged hours of SV_t for the night hours. Almost no point estimate is significant in the table, except some clusters highlighted in purple. Remarkably, controlling for all the intermediate order flows, focusing on the 2-3 a.m return, the 10 and 11 hour lagged order flows are *significantly negative*, which correspond to imbalances between 14:00–15:00 and 15:00–16:00. The diagonal pattern of purple highlighted estimates between 24 – 04 a.m means that these hours are all (and only) predicted by closing imbalances and not subsequent overnight imbalances. Considering now the highlighted purple estimates between 20:00 – 22:00, these hours correspond to the opening of Asian markets and *again* the lagged predicting variable corresponds to closing U.S imbalances.

Panel (c) repeats the univariate predictability regression from section IV

$$r^H_{t,n} = \mu_n + \beta^{SV}_n SV^{\text{close}}_{t-1} + \epsilon_{t,n}, \quad \text{for } n = 1, \ldots, 12, \tag{A.27}$$

but instead sampling SV^{close}_{t-1} on the hour between 15:00 – 16:00 to demonstrate univariate estimates comparable to panel (b). Taken together, these results show that in general, for a liquid asset such as the e-mini, order flow does not generally predict subsequent returns. However, as claimed, overnight predictability due to end-of-day imbalances is truly special in both economic and statistical terms.

[Insert table A.9 here]

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 CBOE.

A. Volatility Risk

Figure A.8 (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 US trading hours where volatility is high at the beginning and at the end of each trading period Andersen, Bondarenko, Kyle, and Obizhaeva (2018). Across trading periods, the level of volatility is lowest during Asian trading hours and highest during US trading hours, relative to the average trading volume across the 3 periods. Comparing average levels for each session, we find that US hours volatility is more than twice as large as Asian hours volatility and therefore considerably larger than estimates of return volatility using close-to-close prices. The large spike in volatility at 8:30 is caused by the spike in volume observed just after US macro announcements. Figure A.8(b) plots time series of the realized volatility for each of the three trading periods. The volatility is always lowest during Asian hours and highest during US hours but the difference has diminished over time as trading volume in the overnight session has picked up. The 3 time series are highly positively correlated, indicating that volatility increases on the same days for all three trading periods. More importantly, we do not observe an obvious link between realised quantities of risk and returns.

[Insert figure A.8 here]

B. Overnight Liquidity

To measure liquidity risk we construct hourly estimates of 1) Kyle (1985) lambda (based on returns sampled at the 1-min frequency), 2) the Amihud price impact measure and 3) the bid-ask spread. Figure A.9 depicts the average intraday patterns of these measures as well as their time series for the Asian, European and U.S. trading hours. As expected, intraday illiquidity is lowest during U.S. trading hours where the trading activity is highest and illiquidity is highest during Asian hours when the trading activity is at its lowest. The bid-ask spread is very close to the minimum tick size (0.25 index points) at all times during the trading day. All liquidity measures experience large changes throughout the sample period. Most notably, the overnight illiquidity (Asian and European hours) has decreased strongly as overnight trading activity has picked up, and today is much closer to the illiquidity level in regular U.S. trading hours. Secondly, the illiquidity increases during times of crises, as one would expect.

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

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

[Insert figures A.9 and A.10 here]

C. Overnight News

We now consider if overnight news released after the U.S. cash market close are not immediately incorporated into prices during Asian hours but instead accumulate and are resolved at European open when trading volumes increase. Indeed, a large fraction of U.S. corporate earnings announcements are released after U.S. market close. Furthermore, Asian and European macro or central bank information released during the U.S. overnight session may signal news about U.S. growth prospects. Explanations for the overnight drift along these lines are related to a literature that shows conditional risk premia are higher on days prior to and on days of macroeconomic announcements.[28] We study this conjecture by examining hour-by-hour returns conditional on U.S. earnings announcements., and U.S., Japanese or European macro- and central bank announcements.

C.1. Earnings Announcements

We test if firm-specific announcements predict intraday returns. Previous literature (see e.g. Bernard and Thomas, 1989; Sadka, 2006, and the subsequent literature) has documented a positive (negative) drift in stock prices of individual firms following a positive (negative) earnings announcement surprise. The earnings data is obtained from I/B/E/S and Compustat. Following Hirshleifer, Lim, and Teoh (2009), for each firm i and on day t we define the earnings surprise as

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

where A is the actual earnings per share (EPS) as reported by the firm, F is the most recent median forecast of the EPS and P is the stock price of the firm at the end of the quarter. As I/B/E/S updates the professional forecasters' expectations on a monthly basis, the shock is the difference between the actual earnings and forecasters expected earnings approximately 1 month prior to the announcement date. Scaling the shock $A - F$ by the stock price implies that firm shocks are equally weighted.[29] We define the daily earnings surprise of the S&P 500 index, ES_t, as the daily sum of all ES_i.[30]

Figure A.11 plots the time series of ES_t. The shocks are periodic on a quarterly basis and generally positive ($\sim 75\%$ of all shocks are positive). Notably, we see large negative shocks during the financial crisis and almost exclusively positive shocks following the crisis.

To test this conjecture formally, we sort all trading days based on ES_t. We choose only announcements that are published after U.S. close (4 p.m. ET). This is because the effect of announcements published early in the day should be incorporated into the price on that day, while announcements that occur after CTO hours could affect returns in these hours. Table A.10 reports the average returns for day $t+1$ after sorting on ES_t. We sort all trading days into 5 groups based on ES_t. In group 1, $ES_t < 0$. For group 2-4, ES_t is positive and increasing by group. Group 5 is for days where ES_t is zero, i.e. not a single firm announced their earnings prior to these days (this was $\sim 46\%$ of all trading days. The table contains a number of interesting findings. First, we see a strong monotonic positive relation between earnings shocks and CTC returns across groups. Second, no news days have the highest CTC return, equal to 4.57 % 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 as it is positive and significantly different from zero for all 5 set of days.

[Insert figure A.11 and table A.10 here]

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

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

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

C.2. Macro and Central Banks

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

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

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

For central banks, we collect announcement dates and times from the websites of the following central banks: (*i*) FOMC; (*ii*) the ECB; (*iii*) the BoE; (*iv*) the BoJ. FOMC target rate announcements are released at or very close to 2:15 p.m. ET. ECB target announcements are at 6:45 a.m. ET, followed by a press conference at 7:30 a.m. ET. BoE announcement days often coincide with ECB days and the announcements are at 7:00 a.m. ET. Finally, BoJ announcements do not occur at a regular time but target rate decisions are generally announced between 22.00 and 1.00 a.m. ET. Our sample period is January 1998 to December 2020.

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

$$r_{t,n}^{H} = a^n + b_1^n \mathbb{1}_{\text{U.K.}} + b_2^n \mathbb{1}_{\text{EU}} + b_3^n \mathbb{1}_{\text{JP}} + b_4^n \mathbb{1}_{\text{U.S.}} + \varepsilon_t^n, \tag{A.28}$$

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

Panel (a) of table A.11 reports estimates for macro announcements. The intercept during the OD hour (2-3 a.m) 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 significant *negative* at the 10% level at 3 a.m (which is 8 a.m in London). More generally, we fail to detect an announcement effect in any of the overnight hours. U.S. announcements occur at 8:30 and indeed we see a large positive return of 3.22 bps with a t-statistics of 2.29. Panel (b) of table A.11 reports estimates for central bank announcements. Again, the intercept is unaffected at 2-3 a.m 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 a.m - 5 a.m consistent with central bank announcement premium. The FOMC dummy is large but insignificant.

[Insert table A.11 here]

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

C.3. Resolution of Uncertainty

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

To investigate this hypothesis, we consider *changes* in volatility by computing intraday and overnight VIX futures (VX) returns. Indeed, investors wanting to manage volatility risks around the clock can now trade VIX futures (VX) contracts in all time zones. VX futures are open nearly 23 hours a day, 5 days a week, trading electronically on the CBOE futures exchange. VX is closed daily from 4:15 to 4:30 PM and from 5:00 to 6:00 PM ET time. On Sundays, they start at 6:00 PM ET time. VX futures trade with a dollar value of \$1000× the level of the VIX Index. Regular expirations are on the Wednesday 30 days before the corresponding S&P 500 option expiration. Due to holidays the option expiration date may be irregular and settle on the preceding Tuesday. VX futures contracts trade with monthly expirations and we consider a position that trades the front month contract and rolls into the next-to-delivery contract on the Monday preceding expiration Wednesdays and thus avoiding settlement returns.

Panel (a) of figure A.12 displays the average cumulative 5-minute log returns for the front month VX contract. The intraday VX returns are relatively flat during the U.S. hours. At the close of regular U.S. trading hours, in the run up to the maintenance break, VX returns are strongly negative, exceeding -80% p.a.[31] During regular Asian trading hours VX returns rebound, generating annualized returns of 50% between 18:00 and 1:00 am. At the opening of European markets VX returns are negative, equal to 50% p.a between 2:00a.m. and 4:00 am. Panel (a) of table A.12 reports average overnight hourly VX returns, measured in basis points, which are highly statistically significant around European open.

Focusing on VX returns at European open, one can easily rationalize a contemporaneous negative co-movement with ES returns (absent a resolution of uncertainty conjecture) in terms of the 'leverage effect', which is the well known empirical fact that equity volatility tends to fall (rise) when equity returns are positive (negative). A common explanation for this phenomenon is due to Black (1976) and Christie (1982) who argue that companies become mechanically more leveraged as equity prices decline relative value of their debt and, as a result, their equity values become more volatile as in Merton (1974). Panel (b) of figure A.12 demonstrates the leverage effect in intraday data by computing the intraday 1-minute correlations between ES and VX futures returns ($r_t^{ES} \times r_t^{VX}$) for intervals where we observe quote updates and averaging these over all days in our sample. During both overnight and intraday periods the correlation is close to -80% which demonstrates that economic interpretations of resolution of uncertainty based on a contemporaneous VIX relationship is limited: "correlation does not imply causation".

[Insert figure A.12 here]

[31] Volumes between 16:15 and 18:00 are very low and we do not report returns or correlations for this period of the day.

More interesting, is the question of whether end-of-day order imbalances in one futures contract predict overnight returns in the other contract. Table A.12 answers this question by estimating two sets of high frequency predictability regressions. Panel (a) reports multivariate regressions with e-mini returns on the left and EOD ES and VX order imbalances on the right hand side

$$ES\ r^H_{t,n} = \mu_n + \beta^{ESSV}_n ES\ SV^{close}_{t-1} + \beta^{VXSV}_n VX\ SV^{close}_{t-1} + \epsilon_{t,n}, \quad \text{for } n = 1, ..., 12,$$

while panel (b) replaces the left hand sides with VX returns

$$VX\ r^H_{t,n} = \mu_n + \beta^{VXSV}_n VX\ SV^{close}_{t-1} + \beta^{ESSV}_n ES\ SV^{close}_{t-1} + \epsilon_{t,n}, \quad \text{for } n = 1, ..., 12.$$

Summarizing the table, while ES imbalances at U.S. close predict subsequent overnight returns in both the ES and the VX contracts, VX imbalances only predict overnight VX returns. Overnight ES returns between 2:00 a.m. and 3:00 a.m. are forecastable by closing ES order imbalance after controlling for VX order imbalances. VX returns, on the other hand, are predicted by ES order imbalances between 2:00 a.m. and 3:00 a.m. and then subsequently we observe some marginally significant predictability by VX order imbalances between 4:00 a.m. and 6:00 am, albeit with positive and negative signs.

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

[Insert tables A.12 here]

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
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	CTC
Mean	−1.33	−0.08	−0.27	0.48	−0.11	−0.13	0.52	−2.65	−0.61	2.64
t-stat	−2.96	−0.15	−0.61	1.28	−0.27	−0.29	0.87	−0.96	−1.08	1.71
Median	−0.57	1.36	1.12	0.87	1.18	0.78	1.41	0.78	−0.63	7.17
Sdev	34.05	41.83	32.95	28.48	30.40	35.83	49.42	24.97	14.84	122.70
Skew	−0.28	−0.04	−0.38	−0.09	0.33	0.28	1.27	−3.95	1.19	−0.17
Kurt	11.97	9.78	10.44	20.56	20.74	13.32	30.95	26.23	14.10	11.00

(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 point terms. 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
daily % POS	49.77	50.89	50.52	50.61	51.24	50.92	51.16	52.80	53.91	50.15	51.18	51.11	51.75	52.18	49.24
daily % NEG	47.76	48.58	49.03	49.05	48.42	48.42	48.16	46.60	45.77	49.73	48.72	48.71	48.14	47.75	50.67
daily p-val	0.52	0.13	0.34	0.32	0.07	0.13	0.06	0.00	0.00	0.78	0.08	0.09	0.01	0.00	0.28
monthly % POS	27.54	54.35	50.72	50.36	50.36	39.86	51.81	50.36	63.77	53.26	48.55	53.26	50.72	55.07	51.09
monthly % NEG	20.65	44.20	46.74	47.10	46.01	46.01	36.96	37.32	29.71	43.48	49.28	44.57	48.55	44.93	48.91
monthly p-val	0.12	0.10	0.54	0.63	0.50	0.30	0.01	0.02	0.00	0.11	0.95	0.16	0.76	0.10	0.76

(a) Overnight hourly returns: Trades

Hour	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09
daily % POS	47.35	45.59	44.58	45.32	45.92	40.20	45.46	47.05	50.11	47.72	47.88	48.21	48.09	49.21	47.05
daily % NEG	46.27	42.50	44.54	43.54	41.81	37.91	41.70	41.34	41.39	46.81	46.17	45.06	44.63	44.68	48.05
daily p-val	0.41	0.01	0.99	0.15	0.00	0.05	0.00	0.00	0.00	0.48	0.18	0.01	0.01	0.00	0.44
monthly % POS	52.17	55.43	53.99	55.43	54.35	50.72	57.61	59.06	70.65	54.35	52.17	54.71	55.07	56.52	52.90
monthly % NEG	47.83	44.57	46.01	44.57	45.65	49.28	42.39	40.94	29.35	45.65	47.83	45.29	44.93	43.48	47.10
monthly p-val	0.51	0.08	0.21	0.08	0.17	0.86	0.01	0.00	0.00	0.17	0.51	0.13	0.10	0.03	0.37

(b) Overnight hourly returns: Quotes

Table A.2. Non-Parametric Tests

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

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	CTC
daily % POS	48.99	52.03	52.45	52.32	52.72	51.67	52.27	55.26	47.01	54.17
daily % NEG	51.01	47.97	47.55	47.68	47.28	48.33	47.73	44.74	52.70	45.83
daily p-val	0.13	0.00	0.00	0.00	0.00	0.01	0.00	0.42	0.15	0.00
monthly % POS	44.93	48.19	51.81	59.06	50.00	48.55	52.90	3.99	10.87	60.51
monthly % NEG	55.07	51.81	48.19	40.94	50.00	51.45	47.10	4.35	13.41	39.49
monthly p-val	0.10	0.59	0.59	0.00	1.00	0.67	0.37	0.00	0.46	0.00

(a) Intraday hourly returns: Trades

Hour	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	CTC
daily % POS	48.23	50.08	50.55	50.68	50.42	49.44	50.70	51.10	34.61	54.03
daily % NEG	49.13	47.38	45.84	44.89	45.72	46.15	45.37	42.69	43.02	45.52
daily p-val	0.50	0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
monthly % POS	45.65	51.09	52.90	57.25	48.91	50.36	52.17	53.99	38.04	61.59
monthly % NEG	54.35	48.91	47.10	42.75	51.09	49.64	47.83	46.01	61.96	38.41
monthly p-val	0.17	0.76	0.37	0.02	0.76	0.95	0.51	0.21	0.00	0.00

(b) Intraday hourly returns: Quotes

Table A.3. Non-Parametric Tests

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

Hour	18-19	19-20	20-21	21-22	22-23	23-24	24-01	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09
Monday	-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.4. 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.5. 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.

RSV_t^{close}	obs	r_t^{CTC} (%)	r_t^{close} (%)	r_{t+1}^{Asia}(%)	r_{t+1}^{EU} (%)	r_{t+1}^{OD} (%)	r_{t+1}^{CTC} (%)
$[-100\%, -4\%)$	$1,340.00$	-122.30	-92.14	9.91	11.77	6.96	24.31
$[-4\%, 0\%)$	$1,391.00$	-52.28	-27.95	6.75	8.66	7.44	13.79
$[0\%, 4\%)$	$1,469.00$	60.29	36.51	-7.26	0.85	1.50	-8.78
$[4\%, 100\%]$	$1,488.00$	133.65	85.73	0.08	-2.22	-0.60	10.38

(a)

Table A.6. Sorting on Relative Signed Volume

We sort trading days into four sets, each with approximately equal number of observations, based on the closing relative signed volume of the preceding trading day. Table reports average annualized returns of each group are reported for the contemporaneous *CTC* returns and closing returns, for returns during Asian trading hours (18:00 – 02:00), for returns during European trading hours (01:00-04:00), for returns during the overnight drift hour (02:00 – 03:00) and for the subsequent close-to-close return. Sample period is January 1998 — December 2020.

	VIX Low	VIX Med	VIX High	VIX Low	VIX Med	VIX High
	Panel A1: Positive SV			Panel 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
			Panel A3: OD Average Returns			
	VIX Low	VIX Med	VIX High	High - Low	p-value	
RSV Low	0.59	0.80	2.33	1.74	0.54	
RSV Med	-2.41	1.96	6.02	8.43	0.00	
RSV High	-0.12	-0.11	-1.96	-1.84	0.44	
High-Low	0.71	0.91	4.30			
p-value	0.59	0.67	0.22			
	Panel B1: Negative SV			Panel 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
			Panel B3: OD Average Returns			
	VIX Low	VIX Med	VIX High	High - Low	p-value	
RSV Low	0.88	4.93	12.66	11.78	0.00	
RSV Med	3.23	6.33	13.03	9.80	0.00	
RSV High	4.42	8.93	7.01	2.60	0.31	
High-Low	3.54	3.99	-5.64			
p-value	0.02	0.09	0.12			

Table A.7. 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. 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
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. $R^2(\%)$	0.00	0.07	0.07	0.01	0.02	0.00	0.01	0.11	0.57	0.31	0.03	0.00

Table A.8. Regression: overnight returns on closing relative signed volume

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

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

Days where the time difference between London and New York is different from 5 hours are excluded. Estimates are in basis points. t-statistics reported in parenthesis are computed from 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)

	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 3:00-4:00	0.20	-0.19	-0.62	-0.19	0.11	0.23	-0.36	-0.23	-0.92	-0.56	0.32	0.35
	(0.63)	(-0.89)	(-3.63)	(-1.49)	(1.01)	(1.39)	(-3.44)	(-1.01)	(-3.59)	(-2.23)	(1.38)	(1.51)
μ	-0.18	0.36	0.12	0.15	0.08	0.05	0.32	0.39	1.39	0.26	-0.03	0.04
	(-0.44)	(2.96)	(0.99)	(1.39)	(0.68)	(0.43)	(2.01)	(2.62)	(6.88)	(1.04)	(-0.10)	(0.19)
Adj. R^2(%)	0.02	0.04	0.32	0.05	0.02	0.13	0.25	0.10	0.85	0.16	0.07	0.10

(c)

Table A.9. 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 signed volume. Panel (c) displays regression estimates of hourly overnight returns regressed on closing relative signed volume measured between 15:00 and 16:00. 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.

	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.10. 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.11. Announcements

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

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

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.

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
μ	2.39	0.68	0.18	4.37	2.73	0.88	-0.58	-0.27	-11.41	-6.27	2.77	-2.01
	(1.16)	(0.82)	(0.09)	(2.15)	(1.24)	(0.84)	(-0.36)	(-0.14)	(-7.58)	(-1.57)	(0.97)	(-0.96)
N. obs	1403	1403	1403	1403	1403	1403	1403	1403	1403	1403	1403	1403

(a) average VX return

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
VX SV 3:15-4:15	4.85	-0.83	1.50	-1.61	0.76	1.29	-2.14	1.54	-0.73	-2.71	2.52	0.51
	(2.25)	(-0.80)	(0.48)	(-1.23)	(0.67)	(1.33)	(-1.17)	(1.68)	(-0.53)	(-1.22)	(1.66)	(0.40)
ES SV 3:15-4:15	-0.66	0.05	-0.64	-0.62	-0.12	-0.37	-0.40	0.13	-1.36	0.74	0.17	0.30
	(-0.96)	(0.13)	(-1.29)	(-1.41)	(-0.23)	(-1.00)	(-1.17)	(0.48)	(-3.18)	(1.32)	(0.35)	(0.74)
μ	-0.62	0.34	0.16	0.30	0.04	0.20	0.41	0.27	1.61	-0.09	-0.07	0.62
	(-0.95)	(0.96)	(0.32)	(0.68)	(0.10)	(0.68)	(1.35)	(0.82)	(3.72)	(-0.17)	(-0.15)	(1.48)
Adj. R^2(%)	0.31	-0.11	0.10	0.06	-0.11	0.14	0.21	-0.03	0.67	0.19	0.01	-0.10

(b) ES return predictability

	18-19	19-20	20-21	21-22	22-22	23-24	24-01	01-02	02-03	03-04	04-05	05-06
VX SV 3:15-4:15	14.46	-4.80	-4.16	0.85	-11.18	-5.31	4.36	-13.13	1.69	32.74	-26.06	-11.13
	(1.07)	(-0.60)	(-0.49)	(0.10)	(-1.64)	(-0.75)	(0.59)	(-1.60)	(0.26)	(1.75)	(-1.87)	(-1.51)
ES SV 3:15-4:15	3.12	1.39	5.42	5.14	2.07	3.97	1.43	-0.88	4.83	1.09	-3.46	-0.44
	(1.51)	(0.81)	(2.12)	(2.39)	(0.64)	(1.61)	(0.82)	(-0.58)	(2.27)	(0.28)	(-1.38)	(-0.21)
μ	2.20	0.61	-0.03	4.12	2.70	0.71	-0.66	-0.16	-11.58	-6.62	3.09	-1.92
	(0.94)	(0.37)	(-0.02)	(1.71)	(1.29)	(0.45)	(-0.44)	(-0.09)	(-5.68)	(-2.02)	(1.21)	(-0.89)
Adj. R^2(%)	0.16	-0.01	0.45	0.24	0.13	0.49	-0.04	0.19	0.33	0.40	0.49	0.00

(c) VX return predictability

Table A.12. Regression: overnight returns on closing signed volume: VX

Panel (a) displays regression estimates of hourly overnight VX returns regressed on a const which measured the unconditional mean during this hour. Panel (b) displays regression estimates of hourly overnight ES returns regressed on ES and & VX closing signed volume leading up to the U.S. close period of the previous trading day:

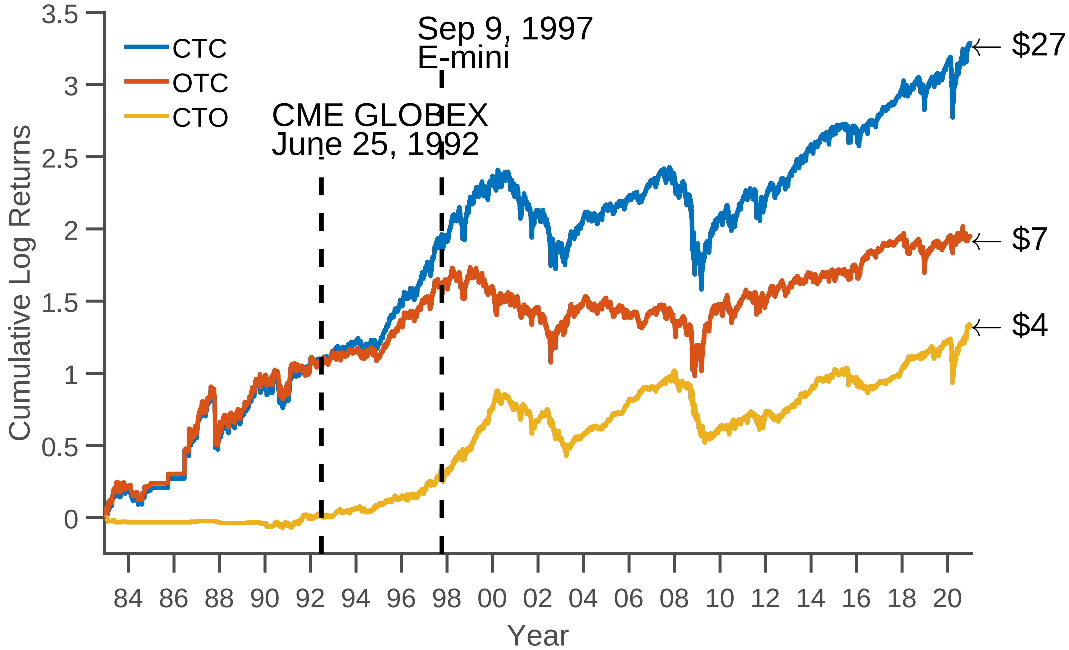
$$ES\ r^H_{t,n} = \mu_n + \beta^{ESSV}_n ES\ SV^{close}_{t-1} + \beta^{VXSV}_n VX\ SV^{close}_{t-1} + \epsilon_{t,n}, \quad \text{for } n = 1, ..., 12,$$

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

$$VX\ r^H_{t,n} = \mu_n + \beta^{VXSV}_n VX\ SV^{close}_{t-1} + \beta^{ESSV}_n ES\ SV^{close}_{t-1} + \epsilon_{t,n}, \quad \text{for } n = 1, ..., 12,$$

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 2015.1 – 2020.12

A.6. Figures



(a)

Figure A.1. Time series of Returns for the S&P 500 futures contract
Figure plots the time series of close-to-close, open-to-close and close-to-open log returns 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 on the e-mini contracts since this became the most liquidity futures contract traded on the SPX index.

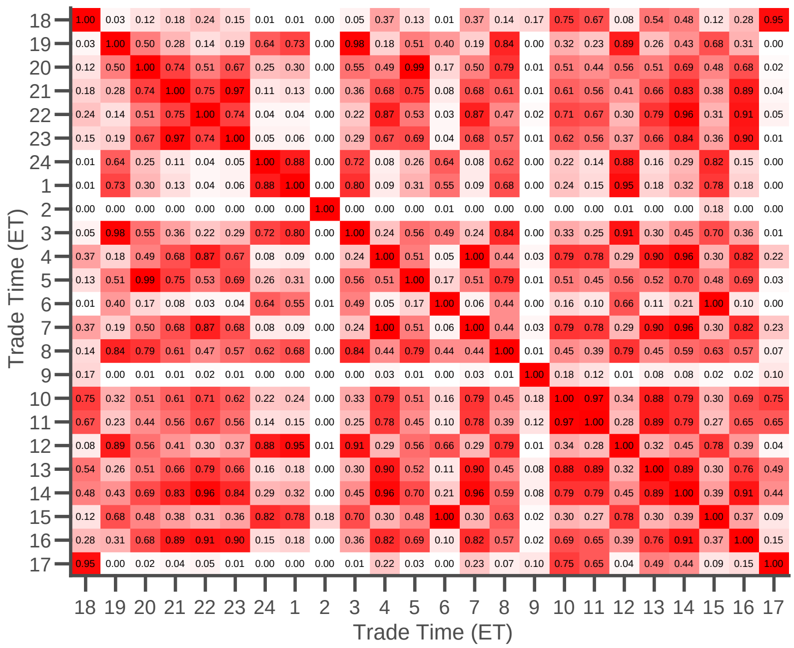


Figure A.2. p-value heat map of hourly differences test

This figure displays a heat map visualising the p-values from a test of equality of hourly returns. White values indicate a p-value of zero, i.e., a rejection that the average hourly return in two intervals is the samee. Dark red values indicate p-values close to 1, indicating we cannot reject the null of equality. x and y labels indicate the hourly return intervals. Sample period is 1998.1 – 2020.12.

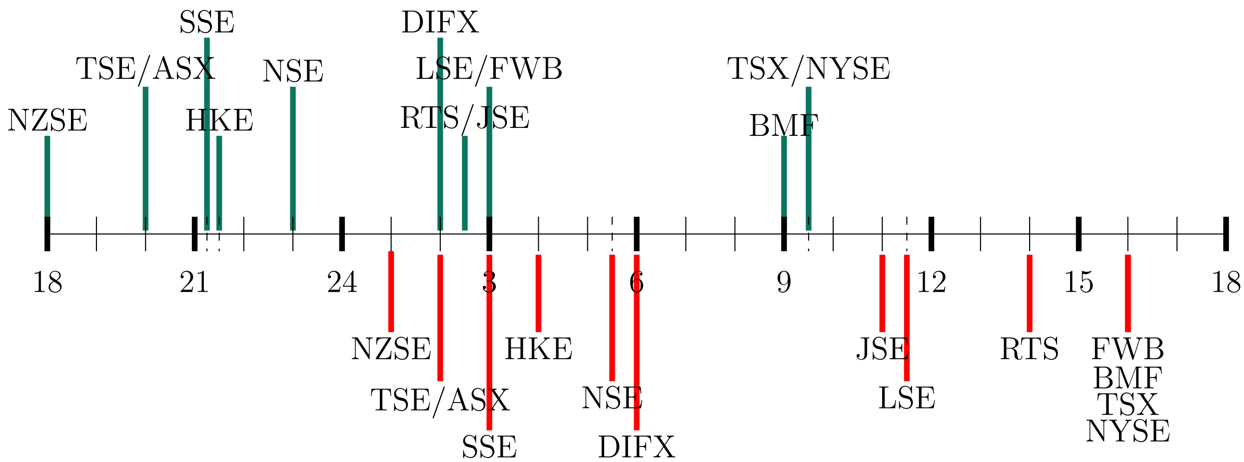


Figure A.3. Global Equity Market Trading Hours

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

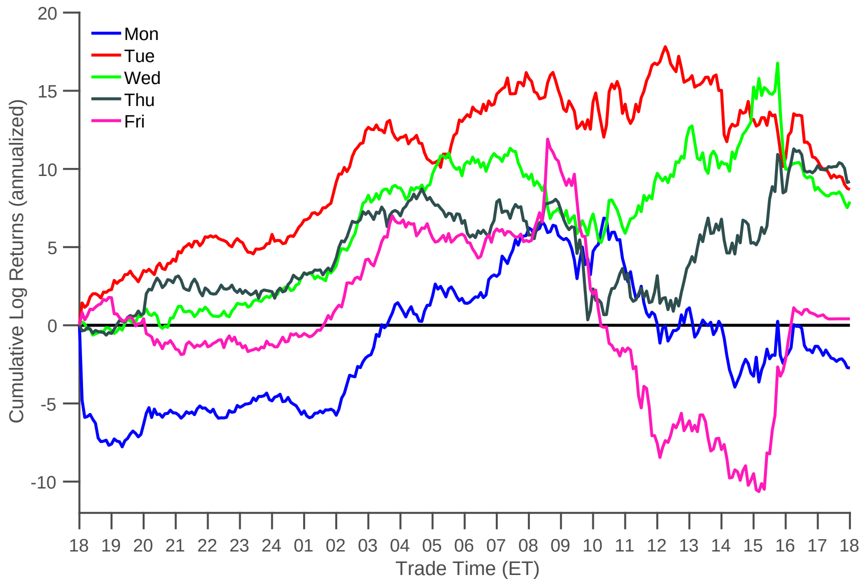


Figure A.4. Day-of-week effects

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.

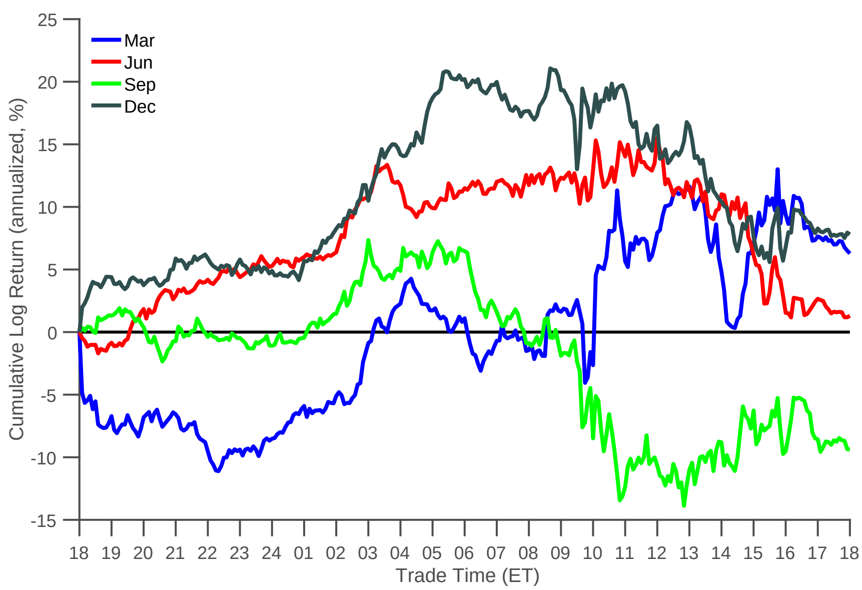


Figure A.5. Month-of-the-year effects

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.

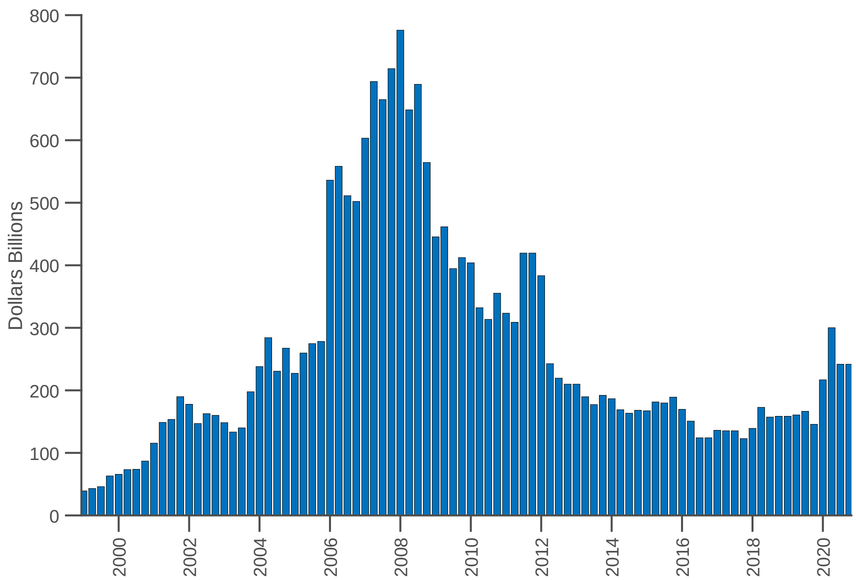
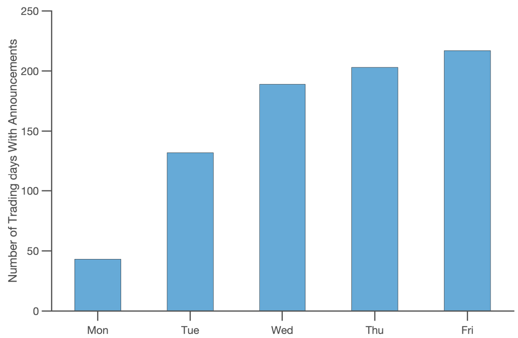
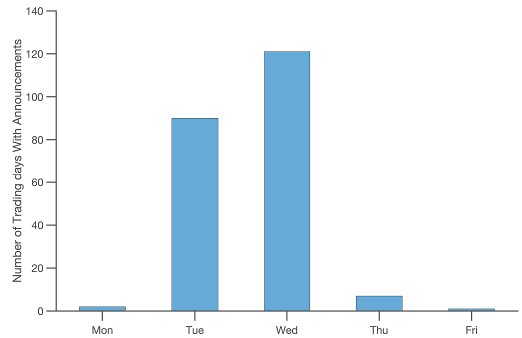


Figure A.6. Equity VaR

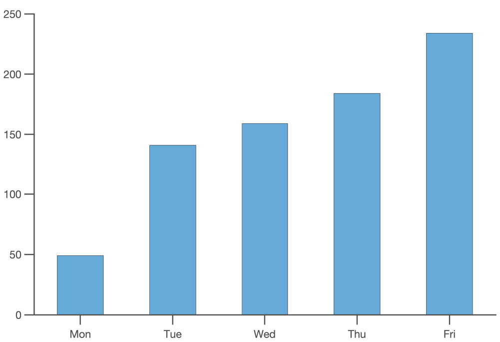
This figure displays the 95% equity VaR for reporting firms as in Adrian and Shin (2014). Source: Bloomberg. Sample period is 1999 Q1 – 2020 Q4.



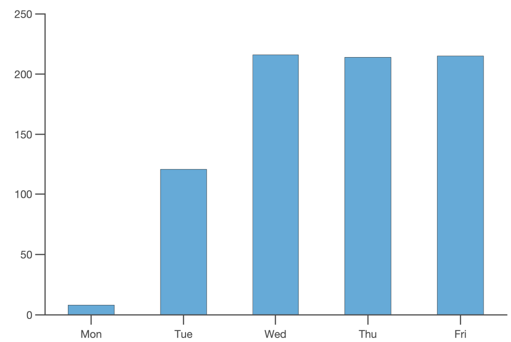
(a) U.S. Macro Announcements



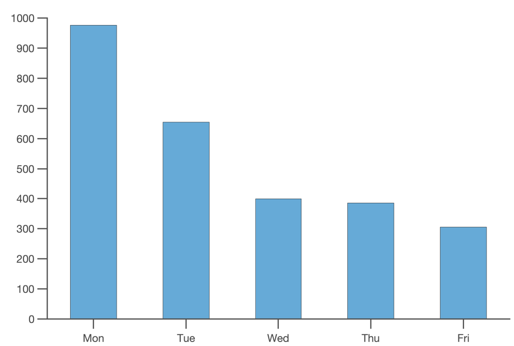
(b) FOMC Announcements



(c) Negative Earnings



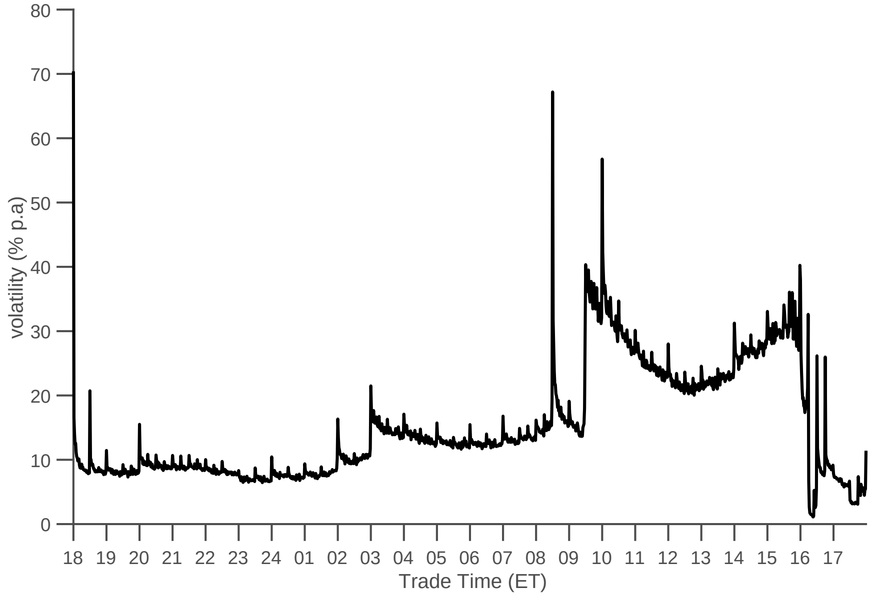
(d) Positive Earnings



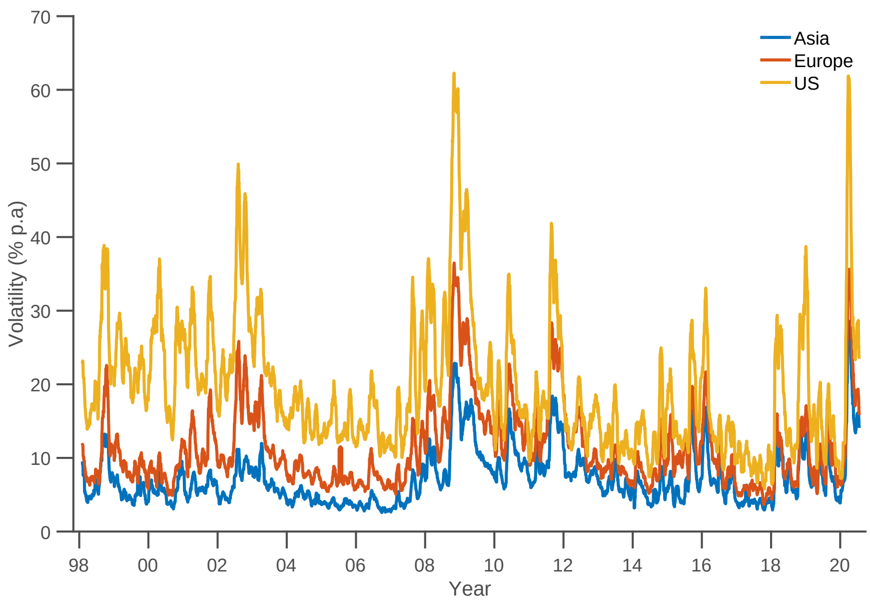
(e) No Earnings

Figure A.7. Announcements per Weekday

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



(a)



(b)

Figure A.8. 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 annualised realised 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.9. Liquidity Measures

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

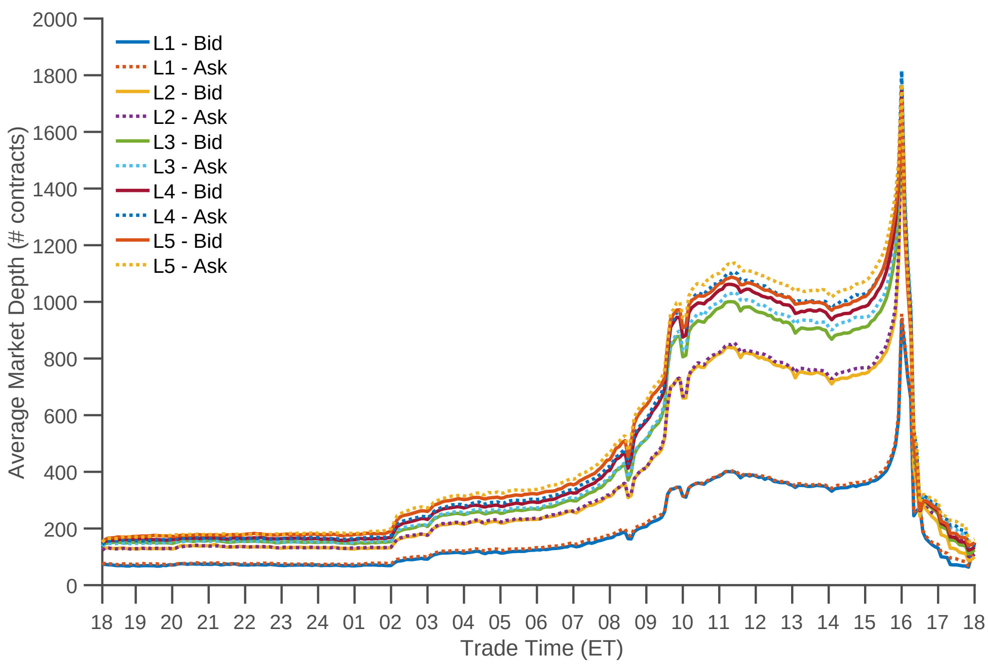


Figure A.10. Market Depth

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

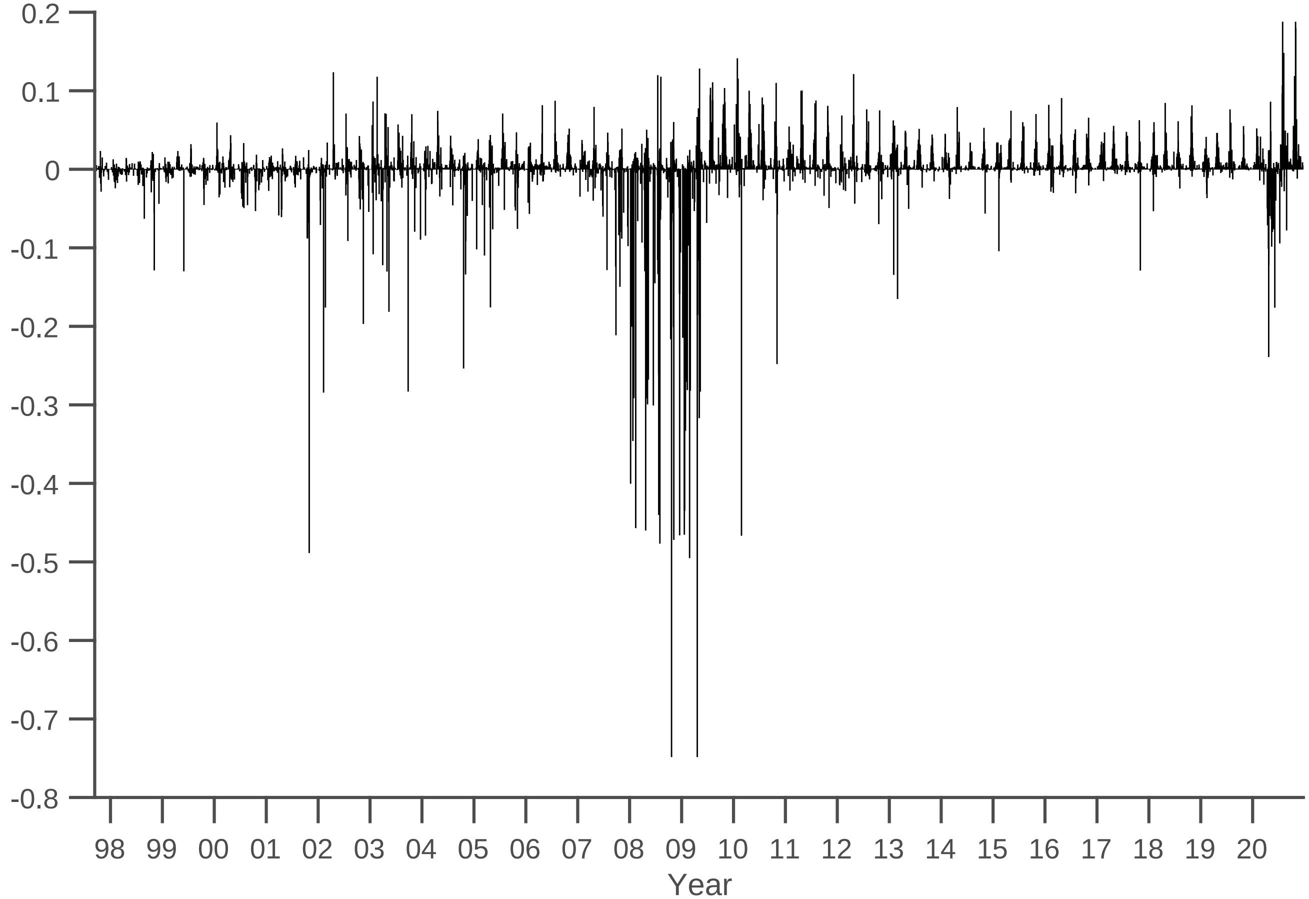
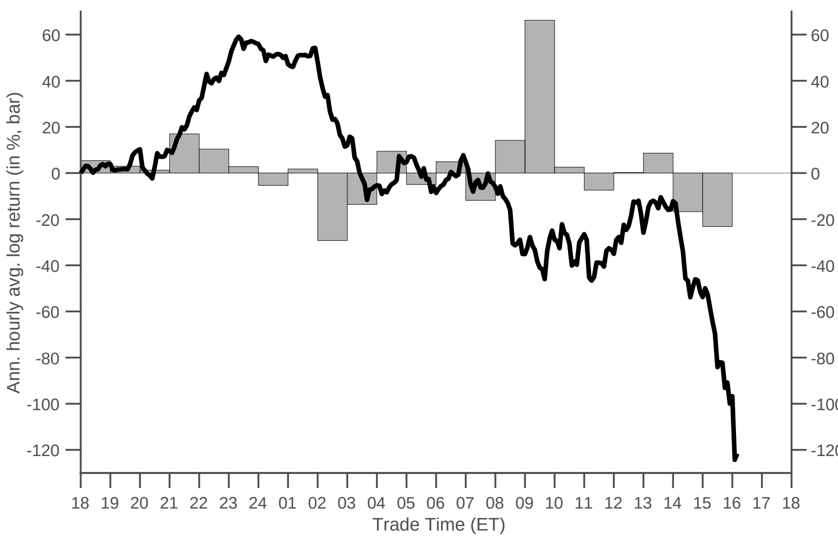
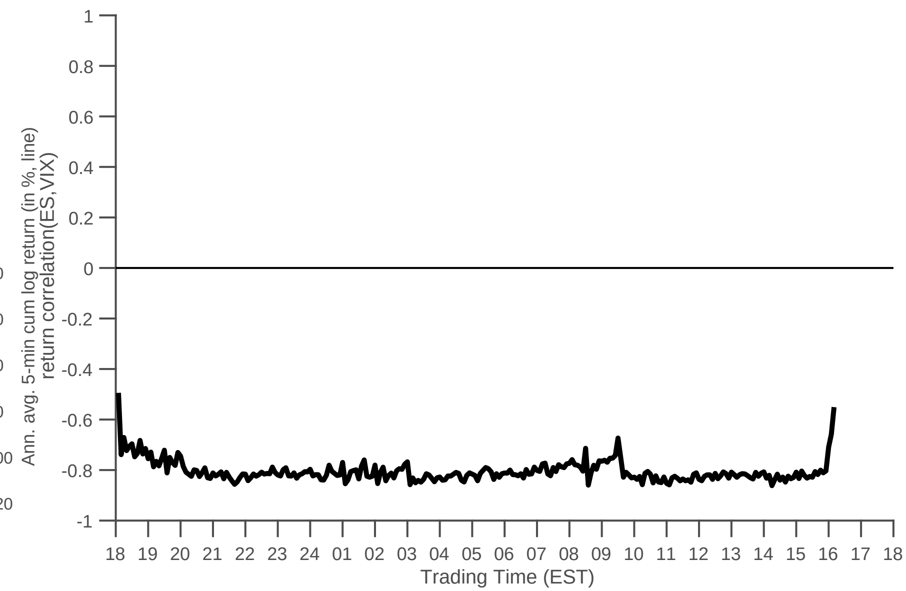


Figure A.11. SUE score

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



(a) Average Intraday Cumulative Returns



(b) Correlation(r_{ES}, r_{VX})

Figure A.12. VIX Futures

Panel (a) displays the average hourly log returns (bars) and average cumulative 5-minute log returns (solid black line) of the VIX Futures contract (first close-to-open and then open-to-close). Panel (b) plots intraday 1-minute correlations between ES and VX futures returns ($r_t^{ES} \times r_t^{VX}$) for intervals where we observe quote updates and averaging these over all days in our sample. The sample period is 2015.1 – 2020.12.