Intraday Option Return: A Tale of Two Momentum

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Abstract

Intraday returns on option straddles display the same persistent seasonality pattern as its underlying stock, even though straddles are delta-neutral. Specifically, straddle return in a given half-hour interval today positively predicts the return in the same intraday interval tomorrow. Such a continuation pattern is most prominent at the market open and close, which we label as morning and afternoon momentum, respectively. We find that morning momentum reflects investors' underreaction to volatility shocks, while afternoon momentum is driven by persistent inventory management by option market makers.

1 Introduction

A recent literature has examined stock return predictability at the intraday frequency. For example, Heston et al. (2010) document that a stock's return during a particular trading interval today positively predicts its returns during the same interval in subsequent days. Such an intraday return continuation pattern can reveal important new insights regarding the behavior of investors and market makers. Indeed, Bogousslavsky (2016) attributes the pattern to infrequent rebalancing by institutional investors. Yet, to our best knowledge, no such intraday analysis has been done in the option market. Our paper fills in the gap.

Ex-ante, it is not clear whether one should find any intraday return patterns among stock option straddles. Straddles are delta-neutral and therefore should be insensitive to the underlying stock price movement. Surprisingly, we find that the intraday periodicity documented by Heston et al. (2010) for individual stocks also extends to their option straddles. Specifically, a straddle's return during a particular 30-minute trading interval today positively predicts its returns during the same 30-minute interval in subsequent days. Examining this pattern for each of the thirteen intervals during a trading day, we find such a periodicity is driven by momentum of straddle return at the market open, and before the market close. Put differently, open return (the first 30 minute) on a straddle today positively predicts its open return tomorrow; close return (last 30 minutes before close) today positively predicts close return tomorrow. We label these two continuation patterns as morning and afternoon momentum, respectively.

Both morning and afternoon momentum are sizable. For example, a daily rebalanced trading strategy based on the morning momentum generates a return of 41 bps per day or 103.3% per year (with a t-value abve 29). Aggregating these daily returns to monthly and applying risk-adjustment model produces a monthly alpha of 9.3% (t-value = 7.53). The economic magnitude of afternoon momentum is smaller. Yet it still implies a daily return of 8 bps (or 20% per year with a t-value of almost 16) and a monthly alpha of 1.7%.

The two momentum effects are distinct from each other. First, 4pm returns revert the next morning. Second, 10am and 4pm returns on the same day are uncorrelated. Investigating their underlying economic forces reveals a tale of two momentum.

We find afternoon momentum to reflect persistent price pressure arising from inventory management by option market makers (OMM). Large end-user purchase (sale) of options towards the end of the day results in negative (positive) OMM inventory and exerts large positive (negative) price pressure. A persistent demand / inventory shock will therefore introduce end-of-day price pressure in the same direction from one day to the next, and result in afternoon momentum. We confirm this pattern by sorting on the option inventory level at the end day t. The negative-inventory portfolio indeed has higher afternoon returns on both day t and $t+1$ than the positive-inventory portfolio does.

Relatedly, we confirm that afternoon winners on day t indeed have lower OMM inventory levels than afternoon losers do on both day t and day $+1$. We do not observe such patterns for morning winners and losers. This is because inventory shocks are less likely to result in price pressure in the morning since the inventory can be managed and may partially reversed during the day.

In sharp contrast, we find morning momentum to reflect continuing under-reaction to overnight volatility news. Since straddles are delta-neural, extreme straddle returns must reflect shocks to implied volatility. We confirm that morning winners and losers on day t indeed experienced large positive and negative implied volatility shocks during that trading day. They experience abnormal amount of morning trading on both days t and $t+1$, consistent with continuing reaction to the volatility news.

The distinctive economic forces that drive the morning and the afternoon momentum also predict different future return patterns. Specifically, if under-reaction to volatility news drives the morning momentum, then the return continuation in the morning should not be reverted, since it reflects delayed incorporation of fundamental volatility news. In sharp contrast, if the afternoon momentum reflects persistent price pressure, we should observe subsequent reversal since price pressure is transitory. We confirm this contrast in the data.

Unlike the stock market, where intraday volume pattern is almost symmetrically U-shaped, the intraday pattern of option trading volume has asymmetric U-shape. For both call and put options we observe the highest trading dollar volume in the early morning after the open, and the second highest volume in the late afternoon before the close. The explanation offered in the stock market for high morning volume is investors' portfolio re-balancing due to most recent news-releases after the previous day close and overnight. The high volume in the afternoon before the close is normally attributed to institutional, mutual funds, trading.

Just as the high trading volume in the stock market during the morning reflects the incorporation of overnight news into prices, the morning momentum in options shortly after the market opens is consistent with incorporating volatility news released after the previous day's trading hours or overnight.

Our results for the afternoon momentum echo those reported in the stock market literature. Hendershott and Menkveld (2014), Hendershott et al. (2022) show that stock prices are also distorted by price pressures. Hendershott et al. (2022) argue that these distortions can lasts for weeks or even months. Market makers use these price pressures to mean revert their inventories which results in return reversals. We are the first to document that the end-of-day inventory management by OMM causes large price pressure in the option market.

While intraday seasonality in stock return has been well studied, intraday seasonality in option return is not. Jones and Shemesh (2018) and Muravyev and Ni (2020) separate intraday vs. overnight option returns and find intraday returns to be higher. More recently, Heston et al. (2023) document option return momentum at monthly frequency and Heston et al. (2022) document a new quarterly cross-sectional continuation pattern in both realized variance and implied variance of individual stocks. To our best knowledge, we are the first to examine intraday seasonality in option returns.

2 Data and Variable Construction

In this section, we describe our data sources, sample and variable construction. We also provide the summary statistics of our sample.

2.1 Data source and sample construction

The main options data are from Chicago Board Options Exchange (CBOE)/LiveVol. They include two data sets: trades data with all intraday transactions for each options series, time stamped prices and volumes; and quotes which include 1 min snapshots of best bids and offers (NBBOs) during a trading day for each series. The quotes data also include synchronous NBBOs for the underlying stocks at the time of option quotes. The intra-day daily data cover the period from 2010 to 2018, and, when merged and after imposing filters described below, exceed 100 TB in size.

Trades data are merged with quotes by timestamps to sign the trades using tick rule. If a trade occurs above the bid-ask midpoint it is classified as a buy, and if it is below the bid-ask midpoint, as a sell. If a trade takes place at the midpoint, we look at the previous midpoint or trade whichever comes first as a benchmark to sign the trade. If the previous midpoint is the same, we search for the first different midpoint to sign the trade. The signed buy and sell transactions are used to compute net order imbalances. We use OpionMetrics, CRSP and Compustat data as well. CRSP/Compustat provide identifiers for S&P500 index constituents. We use equity options on S&P500 firms as they are substantially more liquid compared to the rest of CRSP universe. We identify these firms on the daily bases.

From OptionMetrics we first use end-of-day bid-ask quotes. We cross-check 4pm (16:00) closing quotes from CBOE/LiveVol and OptionMetrics to confirm that the data match. We then use OptionMetrics option contracts identifiers (optionid's) and security identifiers (secid's) to merge with CRSP permno's to identify equity options on S&P500 firms in LiveVol data. We merge LiveVol and OptionMetrics data by ticker, cp_flag (Call or Put), time to expiration, strike price and date.

We also use OptionMetrics deltas and vegas which are computed accounting for a possibility of an early exercise. Open interest data are provided by both OptionMetrics and LiveVol and they are identical.

For options contracts we impose the following filters in the end of the day.

Equity option quotes with dollar quoted spreads greater than $3 are deleted. We also delete illiquid options contracts with daily dollar volume weighted effective relative spreads greater than 70%, and options with mid-point quoted prices below 50 cents in the beginning of intervals we measure returns. Finally, we exclude options contracts which violate obvious no-arbitrage bounds based on the end-of-day closing OptionMetrics quotes: for calls, the price must be less than the current stock price, for puts it must be less than the strike. Note that in our empirical analysis these filters are not forward looking as discussed by Duarte et al. (2023). That is every time we analyze the data or portfolio performance on day t, the filters are applied on day t-1, as the information for day t would not be available from real investment perspective.

To control for possible data entry errors in synchronous bid-ask quotes of underlying stocks, stock quotes with quoted bid-ask spreads greater than 99 cents are deleted. To avoid the expiration dates jumps and extreme volatility and being able to compute monthly returns while focusing on the most traded maturities, we only use options with 30 to 180 days left to expiration.

2.2 Variable Construction

Straddle returns are computed for each pair of at-the-money call and put options on the same underlying, with the same strike price and time to expiration. At-the-moneyness is defined as in Bollen and Whaley (2004) for absolute values of deltas between 0.375 and 0.625. We thus only retain at-the-money calls and puts in our analysis and all subsequent statistics are based on this sample selection.[1] Options straddle returns are computed on a contract level first, and they are prevous day price weighted of corresponding calls and puts pairs in the straddle.[2] We then compute weighted average returns on a firm level across contracts, using dollar open interest from the previous day as a weight. Therefore, our final filter is the availability of non-zero open interst outstanding for a pair of calls and puts on a day, $t-1$, before we estimate straddle returns, t.

We also compute options order imbalances as follows:

$$\text{OIM}_{S}=\frac{\sum_{s}\left|\Delta_{s}\right|\left(\text{ BuyVolume }_{s}-\text{ SellVolume }_{s}\right)}{\sum_{s}\left(\text{ BuyVolume }_{S}+\text{ SellVolume }_{s}\right)}$$

where s denotes option series, call or put. Buy and Sell volumes are signed in intra-day trading data using the tick rule, and $|\Delta_s|$ is an absolute value of option delta. We compute net order imbalances across all contracts for a given firm. These order imbalances include both end-users, i.e. option investors, as well as options market makers, OMMs, trades. OMMs are always on the opposite end of imbalances which represent shocks to their inventories.

To compute OMMs inventory levels, we use the data on signed trading volumes for various groups of customers obtained from the Chicago Board Options Exchange (CBOE) and the International Securities Exchange (ISE). Unlike order imbalances, signed trading volumes for a day are available only in the end of the day. Therefore, for OMMs inventories we can only estimate end-of-day positions. We follow Ni et al. (2021) methodology who use similar data to infer OMMs inventory positions. Here we use all options contracts and only exclude contracts with extreme deltas, below 0.2 or above 0.98. CBOE/ISE Open/Close data contain eight categories of volume for each option series at the close of every trade day: open buy, open sell, close buy and close sell by public investors

[1] The main results documented in this paper are not sensitive to the sample selection and are observed across all other options

[2] We obtain similar results using equal-weights. We use price-weighting to avoid the findings being driven by "penny-stock" like option contracts.

classified as customers and firm proprietary traders. For each option series, we cumulate the buy and sell trades of the public customers and firm proprietary traders to estimate the long and short open interests of the two groups of customers, and then estimate the net market maker position as the negative of the sum of the public customer and firm proprietary trader open interests. Thus, for each option series for the period of 2010 to 2018, we estimate buy and sell open interest by cumulating the CBOE and ISE open buy, close sell, open sell and close buy volumes as follows:

$$\text{OpenInterest}\ _{j,t}^{\text{Buy,y}} = \text{OpenInterest}\ _{j,t-1}^{\text{Buy,y}} + \text{Volume}\ _{j,t}^{\text{OpenBuy,y}} - \text{Volume}\ _{j,t}^{\text{CloseSell,y}}\ ,$$
$$\text{OpenInterest}\ _{j,t}^{\text{Sell,y}} = \text{OpenInterest}\ _{j,t-1}^{\text{Sell,y}} + \text{Volume}\ _{j,t}^{\text{OpenSell,y}} - \text{Volume}\ _{j,t}^{\text{CloseBuy,y}}\ ,\boldsymbol{q}$$

where $Volume_{j,t}^{OpenBuy,y}$ and $Volume_{j,t}^{OpenSell,y}$ are volumes from investor class y to establish new purchased and written positions, and $Volume_{j,t}^{CloseBuy,y}$ and $Volume_{j,t}^{CloseSell,y}$ are volumes to close existing written and purchased positions, respectively. The OMMs inventory is estimated as net open interest taken with the opposite sign:

$$\text{NetOpenInterest}\ _{j,t} = -\left[\ \text{OpenInterest}\ t_{j,t}^{\text{Buy,y}} - \text{openInterest}\ _{j,t}^{\text{Sell,}}\ \right]$$

where $NetOpenInterest_{j,t}$ is the net open interest of OMMs in option series j. For each underlying stock on day t, we compute delta and vega scaled OMMs inventories by summing over different option series as:

$$\Delta\ \text{Inventory}\ _t = \sum_{j=1}^{N_t}\ \text{NetOpenInterest}\ _{j,t}\Delta_j$$

and

$$\text{Inventory}\ _t = \sum_{j=1}^{N_t}\ \text{NetOpenInterest}\ _{j,t}\vartheta_j$$

Where N is the number of option series available for trading for the underling stock and day t. We use delta-scaled inventory to have OMMs average inventory positions expressed in the number of underlying stocks, and we use vega scaled inventory to measure volatility exposure of OMMs overnight positions. For equity contracts CBOE and ISE data cover about 66% of overall trading volume in the US.

2.3 Summary Statistics

Table 1 presents summary statistics of straddle returns for each 30 min. interval of the trading day. The first return is computed from 9:35am to 10am, where we skip the first 5 min of the day to avoid the excess volatility at the opening. Consistent with the previous literature, we confirm that options returns are negative on average. Interestingly, they are more negative in the morning and become monotonically less negative through the day towards the closing. For example, the means of the first two morning returns are -0.07% and -0.12%.[3] As the day progresses, these returns are increasing with the closing 30 min return averaging the negative 4 bps. Further, returns in the morning, for the first two periods, are substantially more volatile compared to the rest of the day returns. The monotonic increase in returns throughout the day is not driven by outliers as we observe it across all percentiles, and for the median.

Table 2 presents trades and various liquidity measures summaries for each 30 min interval from 9:30am till 4pm.[4] The liquidity measures we use are relative effective spreads, price improvement, realized spreads and price impact. Effective spreads are estimated as the absolute difference between transacted priced and bid-ask midpoint, scaled by the midpoint. Price improvement is the difference between the trade price and quoted ask price (for buys) or quoted bid price (for sells), scaled by the bid-ask midpoint. Realized spread is the difference between transaction price and the mid-ask midpoint 5 min of the trade, scaled by the bid-ask midpoint price at the moment of trade. The price impact is the difference between the midpoint 5 min after the trade and the midpoint at the moment of trade for buys, or between the midpoint of trade and the midpoint 5 min after the trade for sells, both scaled by the midpoint of trade. Panel A presents results for calls and Panel B for puts. These are calls and puts which we use to compute straddle returns in Table 1.

Signing trades in this table is less accurate using tick rule as we have only 1-min snapshots of quoted bid and ask prices, and we use the latest available 1 min interval preceding the trade to make buy vs sell identifications. In the modern markets 1 min is very long time with hundreds of transactions happening within. The most effected variable is delta-scaled order imbalances. Yet, its statistics confirm the stylized facts reported in the previous literature. For both calls and puts the

[3]If we use the first 5 min of the day to have a complete, 9:30am to 10am returns, we get two first returns of similar magnitudes.

[4]Here we include the first 5 min of trading to account for the opening call transacted volumes

order imbalances are negative as the end-users in equity options are net sellers on average (Garleanu et al., 2008; Christoffersen et al., 2018). The order imbalances on average are similar across 30 min intra-day intervals, with calls imbalances being more negative compared to puts.

Other statistics in Table 2 reflect more distinctive patterns. For example, the number of trades is always higher in the morning, the first 30 min interval. It decreases during the rest of the day and then increases towards the closing interval, representing an asymmetric U-shape, with the lower side of U occurring in the last 30 min of the trading day. Similarly, sum of trade size, or the sum of contracts traded, has a distinctive U-shape with the highest trade size in the morning, then lowering during the day, and finally inching up in the last 30 min of the day. The sum of dollar trading volume has very similar pattern with the highest trading volume in the morning and the second highest volume at the closing interval.

As far as liquidity measures are concerned, consistent with the morning jolt stylized fact, illiquidity is higher in the earlier, morning, intervals of the day, measured by both effective or realized spreads and price impact. Price improvements are also higher in the beginning of trading day.

Overall, it appears, the morning and the closing intervals represent distinctive trading patterns and intensity compared to the rest of the day. We next access whether this distinctive trading patterns also correspond to the intra-day return seasonality.

3 Option Return Intra-day Seasonality

For each day, for each 30 min interval we compute option straddle, delta-neutral, returns. Thus, for each day we have 13 30-min returns. Next, similar to Heston et al. (2010), we run a cross-sectional regression of half-hour stock-option returns on returns lagged by k half-hour periods:

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{it} \tag{1}$$

where $r_{i,t}$ is the option return on stock i in the half-hour interval t. The slope $\gamma_{k,t}$ is the variable of interest and it represents the response of returns at half-hour t to returns over interval lagged by k half-hour. For an easier exposition purposes we fix k=26, which captures 2 consecutive trading days.

Figure 1 presents regression results for coefficients, the upper panel, and their respective t-statistics, the lower panel, for the period 01/01/2010 to 12/30/2018. The intra-day seasonality results in option returns are even more pronounced compared to the stock returns seasonality reported in Heston et al. (2010). First, similar to the stock returns evidence, the adjacent lagged returns are negatively correlated highlighting return reversals from one half-hour interval to another. Second, every 14th lag return has positive $\gamma_{k,t}$ coefficient with remarkably high t-statistics. This coefficient represents positive return auto-correlation between two identical 30-min intervals on days 1 and 2. For example if the opening 30 min return on day 1 is high, it will be high at the opening of the next day, and the reverse is true.[5] Note, because these are delta neutral option straddle returns, the effect of the underlying stocks is fully eliminated. Therefore, this intra-day return seasonality pattern is purely attributed to the options market.

3.1 Morning and Afternoon Momentum

Figure 2, Panel A, further presents similar regression coefficients but controlling for the time of the left-hand-side variable, while Panel B presents corresponding t-statistics. For example, the top left chart presents cross-sectional regression coefficients of regressing 3:30pm to 4pm, named 4pm, option returns on their 26 lags. We observe a strong reversal effect in adjacent returns during the day, similar to Figure 1. We also observe a strong positive coefficient between 4pm return today, and similar 4pm return yesterday, and the 4pm return the day before yesterday, with t-statistics exceeding 10, Panel B top-left chart. These positive 14-lag spikes are not observed for 3:30pm returns (the return from 3pm to 3:30pm interval), or any other 30-min return of the day, except 10am (bottom left) or 10:30am returns. The coefficients and their significant are much higher for 10am returns however. Therefore, unlike the stock market evidence (Heston et al., 2010), the seasonality pattern in Figure 1 is driven by two intervals - the early morning opening and late afternoon closing. Further, 10am and 4pm returns are not significantly correlated. The first lagged coefficient for 10am returns, Figure 2, Panel A bottom left, which corresponds to the first lag of 10am return, and is 4pm return of the previous day, is essentially zero, with the negative and insignificantly different from zero t-statistics. Therefore, these two seasonality which drive the whole intra-day seasonality are distinct, and we refer to them as morning and afternoon momentum, respectively.

[5]We also ran this regression with 65 lags which correspond to one week of trading, and controlling for similar time intervals and return lags of the underlying stocks. The results are not affected by adding extra lags or other control variables

To demonstrate economic significance of these two intra-day momentum patterns, Table 3 presents portfolio sorting results for a momentum strategy: the quintile portfolios are formed on day t 10am returns, Panel A, or 4pm, Panel B, straddle returns and High-minus-Low portfolio strategy payoff is estimated for the corresponding returns the following day t+1. The difference form a conventional momentum strategy is that the holding period for day t+1 is only 25 min. That is the strategy goes long at 9:35am best past return performance stock options, winners, based on 10am returns yesterday, and shorts the losers at 9:35am based on 10am returns yesterday, Panel A first panel. This strategy then unwinds this position at 10am today. On average, in our sample period, the half-hour profits for 10am returns achieve 41 bps per day while trading only in the beginning and end of the first 30 min of the day, with highly significant t-statistics. This 41 bps per day result in stunning 103.3% per year (=41bpsx252daysx100). Moreover, Long position on its own, High portfolio, provides on average 14 bps per day and short position another 26 bps per day, both highly statistically significant.

The morning, 10am returns trading profitability signal only persist conditioning on the morning, 10am returns of the previous day. For example, the second panel of Panel A reports results for trading in the last half-hour, 3:30pm to 4pm, while conditioning long and short positions on 10am returns of the previous day. Economic magnitudes of H-L strategy is insignificant, and we observe a reversal rather than any persistence in returns.

Panel B of Table 3 presents similar strategy results but for conditioning on 4pm, 3:30pm to 4pm, straddle returns. Here, trading in the beginning and the end of the last 30 min of the next day results in High-minus-Low portfolio strategy profits of 8 bps per day. While much smaller than the morning momentum, it is still economically meaningful and results in annualized 20% per year. Importantly, as for the 10am returns, this strategy is profitable only conditioning on the past day 4pm returns. If, instead of trading only the last 30 min of the next day, we trade the first 30 min of the next trading day, we observe overnight reversals. Panel B bottom panel presents results of conditioning on 4pm straddle returns of day t to enter the Long and Short positions in the beginning and then to unwind them in the end of the first 30 min after the opening of day t+1. Here we observe the next day, morning reversal where the high portfolio at the closing results in the most negative returns the next morning. This reversals however are consistent with classical market makers inventory strategies of selling at higher prices towards closing to discourage buying pressure at the end of day t, and then covering overnight short positions at lower prices in the morning of day t+1 (Amihud and Mendelson, 1980; Hendershott and Menkveld, 2014).

To make sure the results are not driven by Earnings announcement seasons, Panels C and D report results for our 10am and 4pm momentum strategies, respectively, when we exclude the 5 day event windows around earnings announcement dates. The results are virtually unchanged when we exclude these events from the sample.

Table 4 provides results for morning and afternoon momentum strategy where the daily H-L portfolio returns are accumulated per month. We estimate these portfolios monthly alphas using Fama and French (2015) five factor and Carhart (1997) momentum, six factor model. To estimate information ratio, we use the alphas from these regressions and their residuals. Sharpe and Information ratios in the table are annualized, while alphas are kept monthly. First, the morning momentum strategy has an impressive Sharpe ratio of 4.64, and almost similar Information Ratio, 4.70. It means that these persistently high abnormal returns accompany with very little idiosyncratic variations. The Sharpe and Information ratios of the afternoon momentum are lower but yet economically large, 3.11 and 2.98 respectively.

The risk adjust return, alpha, of the morning momentum strategy is 9.3% per month, or 111.6% per year. The alphas of the afternoon momentum strategy, while significantly lower, are also economically meaningful, with 1.7% per month or 20.4% per year. Overall, the profitability of these momentum strategies are large enough to survive illiquidity and trading costs concerns. Figure 3 presents cumulative for the whole sample returns of these monthly strategies. The out-performance of the morning momentum is quite substantial. We next turn to understanding the economic forces driving these two intra-day momentum patterns.

3.2 Robustness

In this section we examine whether our results are robust to controlling for the lagged stock returns or using 65 (5-day) 30-min interval lagged window (Heston et al., 2010) in equation 1, or whether high-minus-low portfolio sorting profits are sensitive to the option market activeness which we measure with volume levels.

Figure 4 demonstrates the results similar to Figure 1 but for the 5 day regression window. The first panel reports the regression coefficients, and the bottom panel - their respective t-statistics.

The seasonality we report lasts for at least one week, with the coefficients and their significance falling substantially on the last, fifth day of the week.

Figure 5 reports similar results to Figure 4 but now including the control for lagged stock returns which are time-stamp matched to the respective option straddle returns. The effect of stock returns on future option straddle returns is positive, short-lived and mostly limited to one trading day. The option straddle returns remain highly negatively auto-correlated through out the trading day, and every 14th lag is highly positively correlated as in Figure 4. That is stock price movements cannot explain or change the seasonality in option returns.

Table 5 presents the results of high-minus-low momentum strategies conditioning on options volume, Panel A, or the relative to the underlying stock volume - option to stock volume ratio, Panel B. High and Low volume regimes are determined based on whether on the portfolio formation day the volume is above or below historical average respectively. To be concise, we only report results of high-minus low portfolio strategies. We find that for both 10am and 4pm momentum, the performance of high minus low portfolios is higher when the option market is more active, or trades more. This is consistent across both measures of activeness: option trading volume alone, or option to stock volume ratio. The difference is higher for 4pm momentum, where for high option volume the profitability of H-L strategies almost doubles to 11.2 bps vs 5 bps per day for low volume. For 10am momentum, the profitability of H-L portfolio strategies drops from almost 50 bps per day for high volume days to 33 bps per day for low volume days. Overall, we find that morning and afternoon momentum effects are stronger when option market is more active, on higher trading volume days.

4 A Tale of Two Momentum

Two stylized facts has emerged in our analysis so far about the morning versus the afternoon momentum. First, 4pm returns mean-revert the next morning, within the first 30 min after the opening (see Table 3 Panel B). Second, 10am and 4pm returns on the same day are uncorrelated as the regression coefficient of regressing these returns on each other is almost zero (see Figure 2). Thus, the two intra-day momentum patterns seem distinct from each other. In this section, we examine the economic forces driving these two intra-day momentum.

4.1 Inventory Management and Afternoon Momentum

We first explore OMMs inventory theory hypothesis. According to the findings in the previous literature, equity options price pressures are persistent (Garleanu et al., 2008) and these price pressures via market makers inventory channel have persistent price impacts at least in the stock market (Hendershott and Menkveld, 2014; Hendershott et al., 2020). Persistent net imbalance by end-users Garleanu et al. (2008) can create persistent price pressures at the end of the day, especially when it is more difficult to delta-hedge open options positions as it gets closer to the market close, 4pm.

Using signed CBOE/ISE volume data, we estimate OMMs gamma- and vega- inventory exposure for each day and for each underlying stock, similar to Ni et al. (2021). We then sort all stock-options into inventory quintiles from Low (negative exposure), to High (positive exposure). As OMMs accumulate high positive inventory levels, end-users are actively selling options which creates downward pressure on option prices and returns. Likewise, negative inventory positions, Low, are associated with end-user buying demand and upward pressures on option prices and returns.

Table 6 provides quintile portfolio sort results for 10 am and 4pm returns. First, the quintile portfolios are formed in the end of day t-1 based on the end of day inventories, and then the straddle returns are estimated for 10am and 4pm returns the next day, t. For 4pm, we also report t-1 returns to validate price pressure argument (Hendershott and Menkveld, 2014; Hendershott et al., 2020).

Consider Panel A, gamma-inventory exposure. For the portfolio formation day, t-1, the 4pm return pattern is consistent with the inventory price pressure hypothesis. The High inventory portfolio has the lowest return in the end of day t-1, the 4pm return of -7 bps, which almost seven times in absolute value exceeds the Low inventory 4 pm return of -1 bps. The High minus Low difference of -6 bps is highly statistically significant. This difference persists the next day for 4pm returns, although decreasing in absolute value to 3 bps but remaining highly statistically significant.

The 10am return pattern is completely opposite. While High quintile return remains very similar to the 4pm return on day t-1, -7 bps, the Low quintile return reverses from -1 bps during the last 30 min before closing on day t-1 to -10 bps during the first 30 min after the opening the next day, t. For 10am returns, the High-minus-Low return difference is positive rather than negative as for the 4pm returns on day t. This reversal is consistent with the hypothesis of OMMs covering their short overnight inventory positions at the lower prices during the first 30 min after the market opens.

Very similar results are observed in Panel B where quintile portfolios are formed on the vega-inventory exposure of OMMs. We conclude that the persistent price pressures from options end-users and OMMs inventory management practices can result in persistence in the 4pm returns from one day to the next. The inventory hypothesis is not relevant for the morning momentum though.

We then link the afternoon momentum to the inventory hypothesis by sorting on the afternoon return in table 7 Panel A. Specifically, we form quintile portfolios based on 3:30pm to 4pm returns on day t and tabulate end-of-day OMMs inventory positions on the same day t and the following day, $t+1$. We report two values of OMMs net-inventory exposure: (i) delta-scaled inventory to approximate a stock-equivalent level of exposure, and (ii) vega inventory to evaluate volatility exposure.

Based on the inventory hypothesis, we expect the afternoon momentum, or 4pm high and low returns to be associated with with low and high OMMs inventory levels respectively. Indeed, the results in Panel A support this hypothesis. 4pm winners (losers) on day t have significantly lower (higher) OMMs inventory, consistent with a positive (negative) end-of-day price pressure. Such price pressure persists at the end of next trading day ($t+1$), consistent with the afternoon momentum.

Intuitively, inventory shocks are less likely to result in price pressure in the morning since the inventory can be managed and may partially reversed during the day. As a placebo test, when we form quintile portfolios based on 9:35am to 10am returns on day t in Panel B of in table 7 and examine OMMs inventory levels on days t and $t+1$, we do not find significant consistent associations bewteen the morning return and inventory levels.

4.2 Under-reaction and Morning Momentum

The economic magnitudes and persistence of 10am momentum are much higher than those for 4pm. They are not related to the previous end-of-day inventory exposures. Morning trading allows volatility news from the overnight period to be incorporated into morning straddle returns. Mechanically, morning winners and losers are experiencing positive and negative volatility news, respectively. We confirm this pattern in the last column of Table 8 by examining the percentage change in implied volatility (IV) from 4PM on day $t-1$ to 4PM on day t. Morning winners are associated with an average IV change of 0.4164% while morning losers have an average IV change of -0.421%.

Volatility news can occur around earnings announcements. Yet the results of Table 3 Panel C clearly show that we observe strong morning momentum even after excluding the quarterly earnings reporting windows. Other corporate events can also cause IV to change. We manually check whether extreme 10 am returns coincide with news releases about the underlying stocks. We find the evidence that extreme and persistent 10am returns are indeed accompanied with consecutive from one day to another news releases. For example, we first hand pick the extreme stock straddle returns in Low and High portfolios and then look at the news associated with portfolio formation dates for these stocks. The most extreme example with negative straddle returns is Netflix stock options with portfolio formation on July 16, 2015. On this exact day, CNN Money report came out with the headlines:"Netflix is up over 500% in 5 years". These news had follow up news chain for almost a week drawing attention to Netflix of the whole market with analysts revising their price targets. One of the most extreme examples for persistence of positive returns is Monsanto. The following news release came on Friday, after trading hours, April 6, 2018:"Monsanto Co.'s MON shares increased 1.6% following the company's confirmation that its proposed merger with Bayer AG BAYN will be completed by the end of the second quarter 2018". Monsanto enters our extreme positive portfolio on Tuesday, April 10, 2018, in the morning, with an extreme positive straddle return which persist to the next day. It took markets more than one day, Monday, April 9, 2018, to fully react to the news. Needless to say, these are just fragments of overall news. Our sample is comprised of S&P500 companies which have multiple news headlines per hour of the day. Because such an influx of information during and after trading hours, it makes it harder for market participants to fully react or choose which news to focus on for making an adjustment to investment strategies.

If informed trading mostly occurs in the morning session, right after the market open, and if the straddle price on day t does not fully adjust to incorporate the volatility news on that day, then we would expect to see morning momentum. Table 8 reports summary statistics of trading characteristics for quintile portfolios formed to produce the results in Table 3, for 10am momentum portfolios. These summaries are based on trades of calls and puts which enter the straddle returns computation in Table 3, and are the sums across corresponding 30 min time intervals. The trading characteristics are the percentage of trades for the morning 30 min interval as a fraction of all trades for that day. We present summary of these statistics for the portfolio formation day t, and portfolio performance evaluation day $t+1$. The total number of trades is first computed on a contract level, for calls and puts that enter the straddles separately for each 30 min interval during the day. Then, the price weighted average for these trades is computed on a straddle level, where we use the quoted prices of corresponding call and put options in the end of each 30 min interval as the weights. After that, the sum of trades for each 30 min interval is computed on the firm/the underlying stock level by first averaging straddle trades statistics on the firm level for each 30 min interval and then multiplying the average estimates by number of straddles. We obtain very similar estimates as we simply sum across the straddles on the firm level for each 30 min interval. The former approach however reassures the lower impact of out-layers on the the final estimates. Afterwards, the percent of trades for the first 30 min interval is simply the ratio of number of trades for this interval to the sum of all trades across all 30 min intervals during the trading day.

The first two columns of Table 8 show that for morning winners and losers, proportionally more trading occurs during the first 30 minutes of the trading day on both day t and day $t+1$. This pattern supports our underreaction-based interpretation of the morning momentum. Price discovery occurs in the morning. When informed traders underreact to volatility news on day t, morning returns will continue in day $t+1$ as well.

So far our analyses uncover distinctive economic forces that drive the morning and the afternoon momentum. These economic forces predict different future return patterns. Specifically, if underreaction to volatility news drives the morning momentum, then the return continuation in the morning should not be reverted, since it reflects delayed incorporation of fundamental news. In sharp contrast, if the afternoon momentum reflects persistent price pressure, we should observe subsequent reversal since price pressure is transitory.

In table 9, we test this prediction by again forming quintile portfolios based on the first and last half-hour returns on day t, but examine returns during the period immediately following the first and last half-hour on day $t+1$. For example, in Panel A, we examine the return during the period from 10am to 10:30am on day $t+1$. Here, we do not observe a return reversal. Morning winners from day t earn significantly higher return during the first half-hour on day $t+1$ than morning losers from day t (see Table 3 Panel A). Nevertheless, their returns are not significantly different during the subsequent period (10am to 10:30am on day $t+1$).

We observe a very different pattern in Panel B where we examine the afternoon momentum. From Table 3 Panel B, we know that afternoon winners from day t earn a return during the last half-hour on day $t+1$ that is 8.2 bps higher than afternoon losers from day t. But this out-performance is almost completely reverted immediately after. Specifically, the afternoon winners under-perform the afternoon losers by 6.6 bps during the period from 4pm on day $t+1$ to 9:35am on day $t+2$. The return reversal supports our conjecture that persistent inventory-induced price pressure drives the afternoon momentum.

5 Conclusion

In this paper, we uncover novel seasonal patterns in intraday returns on individual stock option straddles. These returns display the same persistent seasonality pattern as those of their underlying stock, even though straddles are delta-neutral. We find straddle return in a given half-hour interval today to positively predicts the return in the same intraday interval tomorrow, especially at the market open and close. These two momentum patterns are driven by different economic forces. While the morning momentum reflects investors' underreaction to volatility shocks, afternoon momentum is driven by persistent inventory management by option market makers.

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Time	**Mean**	**StdDev**	**Min**	**P1**	**P5**	**P10**	**P25**	**Median**	**P75**	**P90**	**P95**	**P99**	**Max**
10:00:00 AM	-0.070%	1.659%	-27.074%	-4.862%	-2.404%	-1.604%	-0.713%	-0.059%	0.552%	1.442%	2.265%	4.900%	68.288%
10:30:00 AM	-0.126%	1.303%	-40.807%	-3.982%	-1.961%	-1.325%	-0.616%	-0.095%	0.373%	1.054%	1.668%	3.571%	55.720%
11:00:00 AM	-0.107%	0.986%	-34.435%	-2.979%	-1.509%	-1.027%	-0.482%	-0.076%	0.264%	0.794%	1.277%	2.709%	25.206%
11:30:00 AM	-0.092%	0.872%	-28.917%	-2.619%	-1.331%	-0.898%	-0.417%	-0.061%	0.226%	0.694%	1.112%	2.398%	28.135%
12:00:00 PM	-0.075%	0.803%	-27.778%	-2.396%	-1.199%	-0.807%	-0.368%	-0.046%	0.206%	0.640%	1.028%	2.213%	42.614%
12:30:00 PM	-0.066%	0.749%	-23.810%	-2.272%	-1.111%	-0.736%	-0.328%	-0.033%	0.191%	0.597%	0.955%	2.055%	38.369%
1:00:00 PM	-0.055%	0.711%	-24.278%	-2.114%	-1.031%	-0.684%	-0.299%	-0.023%	0.179%	0.560%	0.902%	1.963%	35.124%
1:30:00 PM	-0.047%	0.694%	-27.724%	-2.010%	-0.999%	-0.665%	-0.291%	-0.020%	0.181%	0.558%	0.894%	1.966%	31.592%
2:00:00 PM	-0.037%	0.791%	-23.056%	-2.192%	-1.045%	-0.686%	-0.295%	-0.017%	0.195%	0.598%	0.974%	2.216%	37.885%
2:30:00 PM	-0.054%	0.825%	-32.878%	-2.430%	-1.117%	-0.729%	-0.314%	-0.023%	0.199%	0.616%	1.004%	2.286%	36.405%
3:00:00 PM	-0.048%	0.738%	-22.556%	-2.126%	-1.043%	-0.686%	-0.298%	-0.021%	0.186%	0.575%	0.927%	2.079%	34.066%
3:30:00 PM	-0.041%	0.736%	-25.000%	-2.151%	-1.039%	-0.685%	-0.297%	-0.016%	0.202%	0.602%	0.965%	2.079%	24.888%
4:00:00 PM	-0.040%	0.889%	-29.024%	-2.494%	-1.219%	-0.812%	-0.363%	-0.030%	0.249%	0.728%	1.173%	2.618%	44.997%

Notes: The table presents mean, median and percentile summary statistics for 30 min straddle returns during a trading day from 9:35am to 4pm. The returns are computed using at-the-money call and put options of the firms which are constituents of S&P500 index for the period 01/01/2010 to 30/12/2018.

Table 1: Summary Statistics

Panel A. Call Options								
Time	**# of Trades**	**Delta Order Imbalance**	**Sum of Trade Size**	**Sum of Dollar Volume**	**Effective Spread (%)**	**Price Improvement (%)**	**Realized Spread (%)**	**Price Impact (%)**
10:00:00 AM	5.0186	-0.0139	52.9828	194.3716	0.0453	0.0153	0.0175	0.0274
10:30:00 AM	4.5780	-0.0245	53.2566	181.7603	0.0316	0.0114	0.0132	0.0182
11:00:00 AM	4.1114	-0.0276	49.1688	165.0209	0.0293	0.0107	0.0134	0.0158
11:30:00 AM	3.8452	-0.0278	46.8433	156.7867	0.0284	0.0104	0.0138	0.0146
12:00:00 PM	3.6365	-0.0291	44.2758	149.0206	0.0277	0.0103	0.0138	0.0138
12:30:00 PM	3.4898	-0.0290	42.2197	142.7131	0.0270	0.0102	0.0139	0.0131
1:00:00 PM	3.4170	-0.0267	40.7163	138.2070	0.0265	0.0102	0.0139	0.0126
1:30:00 PM	3.3512	-0.0278	41.5864	136.7765	0.0264	0.0101	0.0139	0.0125
2:00:00 PM	3.3550	-0.0292	40.2976	136.5961	0.0264	0.0100	0.0139	0.0125
2:30:00 PM	3.5041	-0.0278	41.4037	138.7769	0.0272	0.0101	0.0139	0.0133
3:00:00 PM	3.5008	-0.0270	41.7398	140.9706	0.0268	0.0101	0.0142	0.0125
3:30:00 PM	3.6261	-0.0280	42.0043	144.6750	0.0267	0.0102	0.0142	0.0125
4:00:00 PM	4.1273	-0.0241	46.0096	162.3454	0.0276	0.0105	0.0147	0.0129
Panel B. Put Options								
Time	**# of Trades**	**Delta Order Imbalance**	**Sum of Trade Size**	**Sum of Dollar Volume**	**Effective Spread (%)**	**Price Improvement (%)**	**Realized Spread (%)**	**Price Impact (%)**
10:00:00 AM	4.1418	-0.0016	44.0033	142.8233	0.0418	0.0151	0.0150	0.0264
10:30:00 AM	4.0100	-0.0134	47.6819	153.0594	0.0291	0.0107	0.0108	0.0182
11:00:00 AM	3.6760	-0.0156	45.5551	146.4571	0.0266	0.0099	0.0108	0.0157
11:30:00 AM	3.4737	-0.0177	43.9640	141.3645	0.0257	0.0097	0.0110	0.0147
12:00:00 PM	3.3155	-0.0163	42.2681	137.3746	0.0251	0.0097	0.0111	0.0140
12:30:00 PM	3.2107	-0.0175	40.9599	134.0539	0.0246	0.0097	0.0112	0.0134
1:00:00 PM	3.1276	-0.0182	39.8641	130.9135	0.0242	0.0096	0.0114	0.0128
1:30:00 PM	3.0930	-0.0172	43.4233	133.5491	0.0241	0.0096	0.0113	0.0127
2:00:00 PM	3.1108	-0.0159	39.2897	127.9650	0.0241	0.0096	0.0113	0.0128
2:30:00 PM	3.2589	-0.0144	39.6261	129.1050	0.0247	0.0097	0.0110	0.0136
3:00:00 PM	3.2580	-0.0146	40.0398	130.5854	0.0243	0.0096	0.0114	0.0128
3:30:00 PM	3.3409	-0.0128	40.3672	134.2393	0.0244	0.0097	0.0116	0.0127
4:00:00 PM	3.6187	-0.0137	41.9273	137.2485	0.0257	0.0102	0.0126	0.0130

Notes: The table presents intra-day trade summary statistics for each 30 min interval from 9:30am till 4pm. The statistics are number of trades computed as the sum of number of transactions for each 30 min interval, delta scaled order imbalances, sum of all contracts traded (sum of trade size), sum of total dollar volume transacted, and liquidity measures such as effective spread, realized spread, price improvement and price impact averaged across all transactions for each 30 min interval. Panel A presents summary stats for call options which enter the straddle returns computations, and Panle B for put options. The time period is from 01/01/2010 to 12/30/2018.

Table 2: Trades Summary Statistics

Panel A. 10AM Momentum Strategy						
9:35AM to 10AM						
	Low	**2**	**3**	**4**	**High**	**H-L**
Return	-0.2640%	-0.1270%	-0.0820%	-0.0230%	0.1474%	0.4116%
Return t-stat	-23.08	-15.42	-10.2	-2.8	13.2	29.02
3:30PM to 4PM						
Return	-0.0340%	-0.0430%	-0.0390%	-0.0420%	-0.0400%	-0.0060%
Return t-stat	-6.29	-8.7	-7.71	-8.5	-7.2	-1.88
Panel B. 4PM Momentum Strategy						
3:30PM to 4PM						
	Low	**2**	**3**	**4**	**High**	**H-L**
Return	-0.0730%	-0.0580%	-0.0420%	-0.0330%	0.0088%	0.0819%
Return t-stat	-13.96	-11.79	-8.58	-6.72	1.35	15.92
9:35AM to 10AM						
Return	-0.0490%	-0.0750%	-0.0740%	-0.0740%	-0.0740%	-0.0250%
Return t-stat	-5.42	-9	-8.87	-9.06	-7.89	-3.76
Excluding Earning Periods						
Panel C. 10AM Momentum Strategy						
	Low	**2**	**3**	**4**	**High**	**H-L**
Return	-0.2580%	-0.1210%	-0.0770%	-0.0190%	0.1573%	0.4149%
Return t-stat	-22.47	-14.3	-9.47	-2.18	13.6	28.42
Panel D. 4PM Momentum Strategy						
	Low	**2**	**3**	**4**	**High**	**H-L**
Return	-0.0780%	-0.0600%	-0.0470%	-0.0370%	0.0064%	0.0842%
Return t-stat	-15.04	-12	-9.53	-7.37	0.97	15.33

Notes: The table presents the results for short-term momentum strategies by entering Long or Short position in the beginning of half-hour interval and unwinding it in the end of the interval of day t+1. The conditional sorts rely on day t straddles returns for the corresponding half-hour intervals of the day. Panel A presents the results for conditioning on 10am, from 9:35am to 10am, straddle returns of day t, and Panel B for 4pm, from 3:30pm to 4pm, returns. Panels C and D describe similar momentum strategy for the sample which excludes Earnings announcement days and 5 day windows around them. The daily sample spans the period from 01/01/2010 to 12/30/2018.

Table 3: Momentum

	Sharpe Ratio	FF6 Alpha	Alpha t-stat	Information Ratio
9:35AM to 10AM	4.6419	0.0930	7.5278	4.6976
3:30PM to 4PM	3.1180	0.0168	5.1595	2.9785

Notes: The table presents monthly 10am and 4pm performance statistics of momentum portfolios reported in Table 3. Here daily momentum profits are cumulated per month, and then the monthly risk adjusted returns, FF6 Alpha and their t-statistics are estimated using Fama and French (2015) five factors and momentum. Sharpe ratios and Information ratios are annualized. The sample period is from 01/2010 to 12/2018.

Table 4: Monthly Momentum

Panel A. High vs Low Option Volume

10 am Momentum	Low	High	**4PM Momentum**	Low	High
	H-L	**H-L**		**H-L**	**H-L**
Return	0.326%	0.49%	**Return**	0.050%	0.112%
Return t-stat	17.24	25.07	**Return t-stat**	9.84	13.7

Panel B. High vs Low Option to Stock Volume ratio

10 am Momentum	Low	High	**4PM Momentum**	Low	High
	H-L	**H-L**		**H-L**	**H-L**
Return	0.361%	0.46%	**Return**	0.049%	0.114%
Return t-stat	19.19	22.42	**Return t-stat**	8.69	14.52

Notes: The table presents the results for short-term momentum strategies by entering Long or Short position in the beginning of half-hour interval and unwinding it in the end of the interval of day t+1. The conditional sorts rely on day t straddles returns for the corresponding half-hour intervals of the day. The portfolio sorts are similar to those in Table 3 where the sample is split into High vs Low Option trading volume, Panel A, or the ratio of Option to Stock trading volumes, Panel B, based on the volume being above or below historical average on day t. The daily sample spans the period from 01/01/2010 to 12/30/2018.

Table 5: Conditioning on Different Option Market Volume Regimes

Panel A. Portfolios Sorted on OMMs Gamma-inventory at the end of day t-1						
9:35AM to 10AM						
	Low	**2**	**3**	**4**	**High**	**H-L**
Return (t)	-0.1020%	-0.0610%	-0.0500%	-0.0650%	-0.0730%	0.0281%
Return t-stat (t)	-11.73	-6.6	-5.56	-7.39	-8.68	4.37
3:30PM to 4PM						
	Low	**2**	**3**	**4**	**High**	**H-L**
Return (t-1)	-0.0110%	-0.0260%	-0.0410%	-0.0530%	-0.0670%	-0.0560%
Return t-stat (t-1)	-1.99	-5.07	-7.91	-10.34	-12.91	-18.09
Return (t)	-0.0240%	-0.0280%	-0.0390%	-0.0460%	-0.0530%	-0.0290%
Return t-stat (t)	-4.5	-5.58	-7.47	-9.03	-10.17	-9.81
Panel B. Portfolios Sorted on OMMs Vega-inventory at the end of day t-1						
9:35AM to 10AM						
	Low	**2**	**3**	**4**	**High**	**H-L**
Return (t)	-0.1000%	-0.0570%	-0.0420%	-0.0660%	-0.0860%	0.0145%
Return t-stat (t)	-12.28	-6.09	-4.34	-7.89	-9.11	2.27
3:30PM to 4PM						
	Low	**2**	**3**	**4**	**High**	**H-L**
Return (t-1)	-0.0180%	-0.0290%	-0.0470%	-0.0530%	-0.0570%	-0.0390%
Return t-stat (t-1)	-3.32	-5.65	-9.37	-10.57	-10.41	-13.12
Return (t)	-0.0260%	-0.0300%	-0.0420%	-0.0480%	-0.0510%	-0.0250%
Return t-stat (t)	-4.92	-5.75	-8.23	-9.59	-9.47	-8.53

Notes: The table presents portfolio sorting results based on end of day options market makers, OMMs, inventories. OMMs inventories are estimated using CBOE/ISE signed volume data originated by end-users. The inventory quintile portfolios are formed on day t-1, and then option straddle returns are estimated for 4pm returns, 3:30pm to 4pm interval, on both day t-1 and day 1, and for 10am returns, 9:35am to 10am interval, on day t. Panel A uses gamma-scaled inventory levels, while Panel B uses vega-scaled inventory. The sample period is from 01/01/2010 to 30/12/2018.

Table 6: Portfolio Sorts based on Options Market Makers Inventory Exposures

Panel A. Sort on 3:30 to 4PM Return (t)						
Vega Inventory (t)						
	Low	2	3	4	High	H-L
Inventory	33092.71	50318.13	45482.65	43031.41	29244.66	-3848.05
t-stats	40.46	40.32	33.45	37.46	38.15	-4.99
Vega Inventory (t+1)						
	Low	2	3	4	High	H-L
Inventory	33134.44	50224.71	45523.26	43152.16	29255.39	-3879.05
t-stats	40.24	40.33	33.33	37.6	38.24	-5.06
Delta Inventory (t)						
	Low	2	3	4	High	H-L
Inventory	869.5563	1364.44	1254.784	1224.246	772.1379	-97.4184
T-stats	30.82	37.4	34.26	32.85	24.63	-3.39
Delta Inventory (t+1)						
	Low	2	3	4	High	H-L
Inventory	872.7048	1352.41	1253.628	1228.307	779.3632	-93.3416
T-stats	31.06	36.94	33.96	33.1	25.2	-3.26
Panel B. Sort on 9:35 to 10AM Return (t)						
Vega Inventory (t)						
	Low	2	3	4	High	H-L
Inventory	28000.47	48151.07	51860.58	46287.39	28883.44	882.9706
t-stats	38.54	40.11	36.39	38	32.77	1.05
Vega Inventory (t+1)						
	Low	2	3	4	High	H-L
Inventory	27934.07	48167.72	51833.25	46360.08	29013.61	1079.538
t-stats	37.99	40.27	36.54	37.92	32.65	1.27
Delta Inventory (t)						
	Low	2	3	4	High	H-L
Inventory	744.8563	1315.249	1416.484	1246.318	802.3462	57.48997
T-stats	27.4	34.1	34.93	33.81	28.63	2.07
Delta Inventory (t+1)						
	Low	2	3	4	High	H-L
Inventory	753.9752	1311.573	1411.141	1253.422	797.104	43.12889
T-stats	27.56	33.84	34.9	34.17	28.3	1.53

Notes: The table presents end-of-day option market makers, OMMs, inventory measures for quintile portfolios sorted on first, 3:30pm to 4pm, Panel A, and last, 9:35am to 10am, Panel B, half-hour returns for each trading day. OMMs inventories are estimated using CBOE/ISE signed volume data originated by end-users and are scaled by option Delta or Vega of each contract. T-statistics are adjusted for autocorrelation and heteroscedasticity. The daily sample period is from 01/01/2010 to 12/30/2018.

Table 7: Option Market Makers Inventory Exposure by Momentum Portfolios

Sort on 9:35AM to 10AM Returns (t)			
	% of All Trades (t+1)	% of All Trades (t)	IV Change (t)
Low	17.6%	23.3%	-0.4210%
2	14.8%	18.0%	0.0259%
3	14.3%	17.2%	0.1929%
4	14.8%	19.2%	0.3126%
High	17.3%	24.5%	0.4164%

Notes: The table reports summary statistics for 10am momentum portfolios for day t, portfolio formation day based on the ranking of straddle returns, and day t+1, the portfolio performance evaluation day. The summary statistics include the number of trades in the first half hour of the day as a percentage of the total trades during the day, and the percentage change in implied volatility from 4PM on day t-1 to 4PM on day t. Only the contracts which enter the straddle computations and their trades are used to report the summaries. The sample period is from 01/01/2010 to 12/30/2018.

Table 8: Trading Statistics by Morning Momentum Quintile Portfolios

Panel A. Sort on 9:35 to 10AM Return (t)						
Return from 10AM (t+1) to 10:30AM (t+1)						
	Low	2	3	4	High	H-L
Return	-0.00129	-0.00124	-0.00114	-0.00118	-0.00137	-0.00008
t-stats	-15.18	-17	-15.42	-15.69	-16.83	-1.5
Panel B. Sort on 3:30 to 4PM Return (t)						
Return from 4PM (t+1) to 9:35AM (t+2)						
	Low	2	3	4	High	H-L
Return	-0.00767	-0.00763	-0.00789	-0.00779	-0.00834	-0.00066
t-stats	-31.25	-33.83	-33.88	-32.72	-34.92	-5.1

Notes: The table presents the results for the next, t+1, day return reversals based on daily, day t, momentum sorted portfolios. In Panel A, quintile portfolios are formed based on 9:35AM to 10AM returns of day t and returns are estimated for the period from 10AM to 10:30AM of day t+1. In Panel B, quintile portfolios are formed based on 3:30PM to 4PM returns of day t and returns are estimated for the period from 4PM on day t+1 to 9:35AM of day t+2. T-statistics are adjusted for autocorrelation and heteroscedasticity. The daily sample period is from 01/01/2010 to 12/30/2018.

Table 9: Return Reversals by Momentum Portfolios

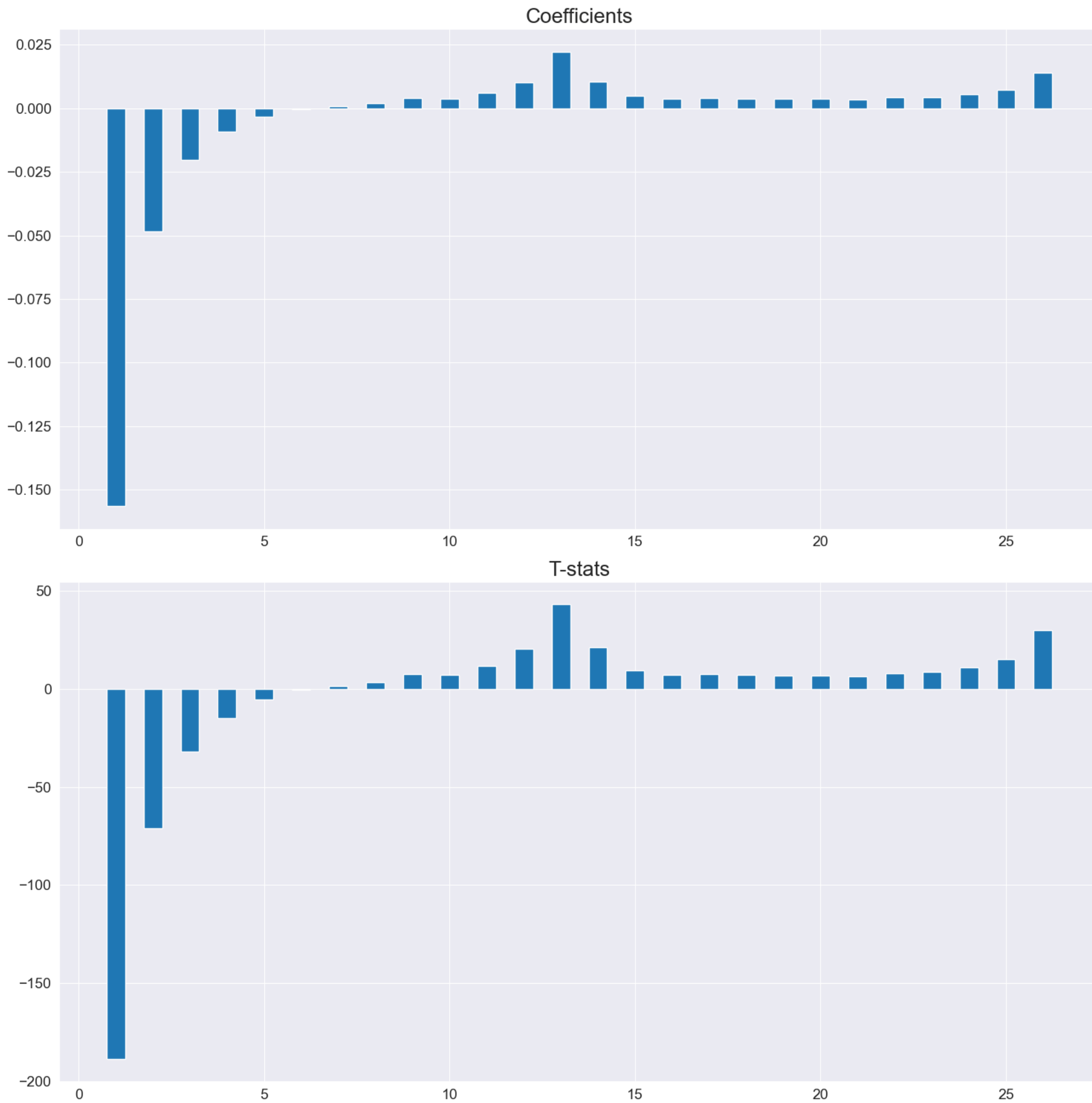
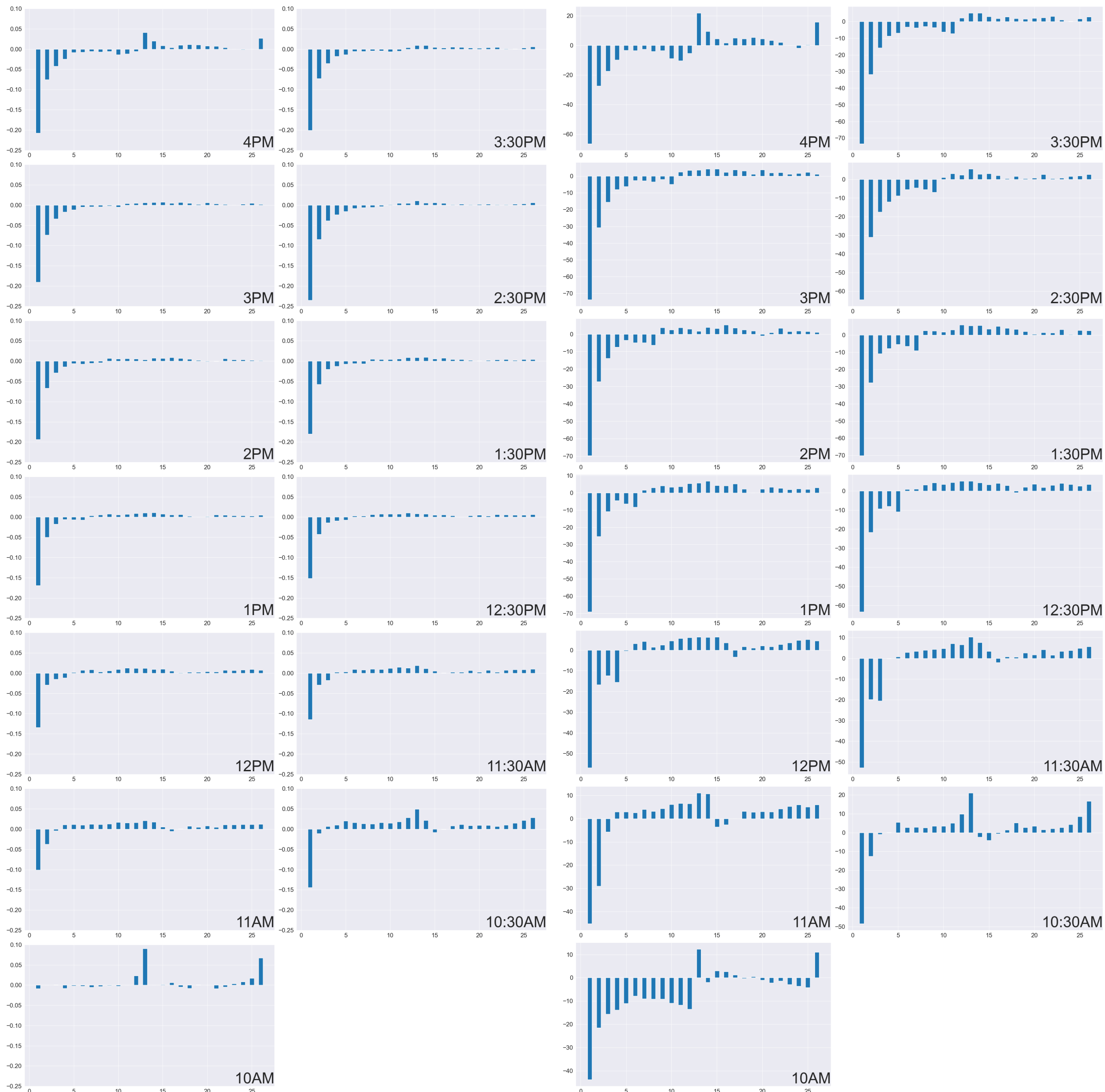


Figure 1: Cross-sectional regressions of half-hour-interval options returns



(a) Coefficients by the half-hour -interval of Left-Hand side variable

(b) T-statistics of the Coefficients by the half-hour -interval

Figure 2: Cross-sectional regressions of half-hour-interval options returns by Time

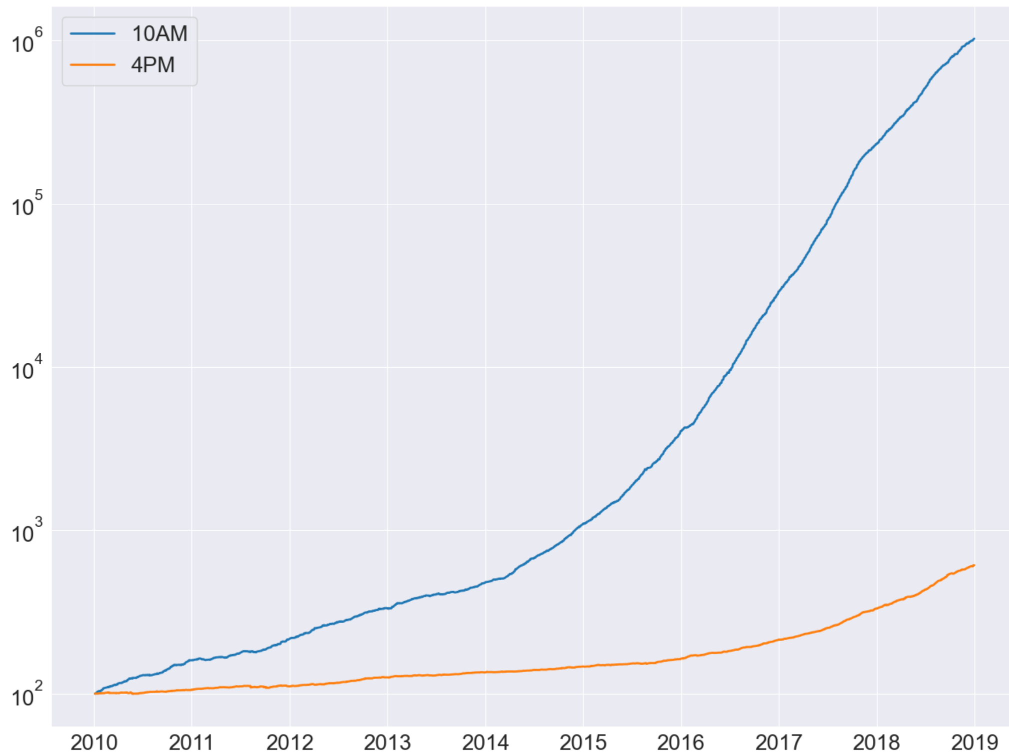


Figure 3: Monthly Momentum Cumulative Return

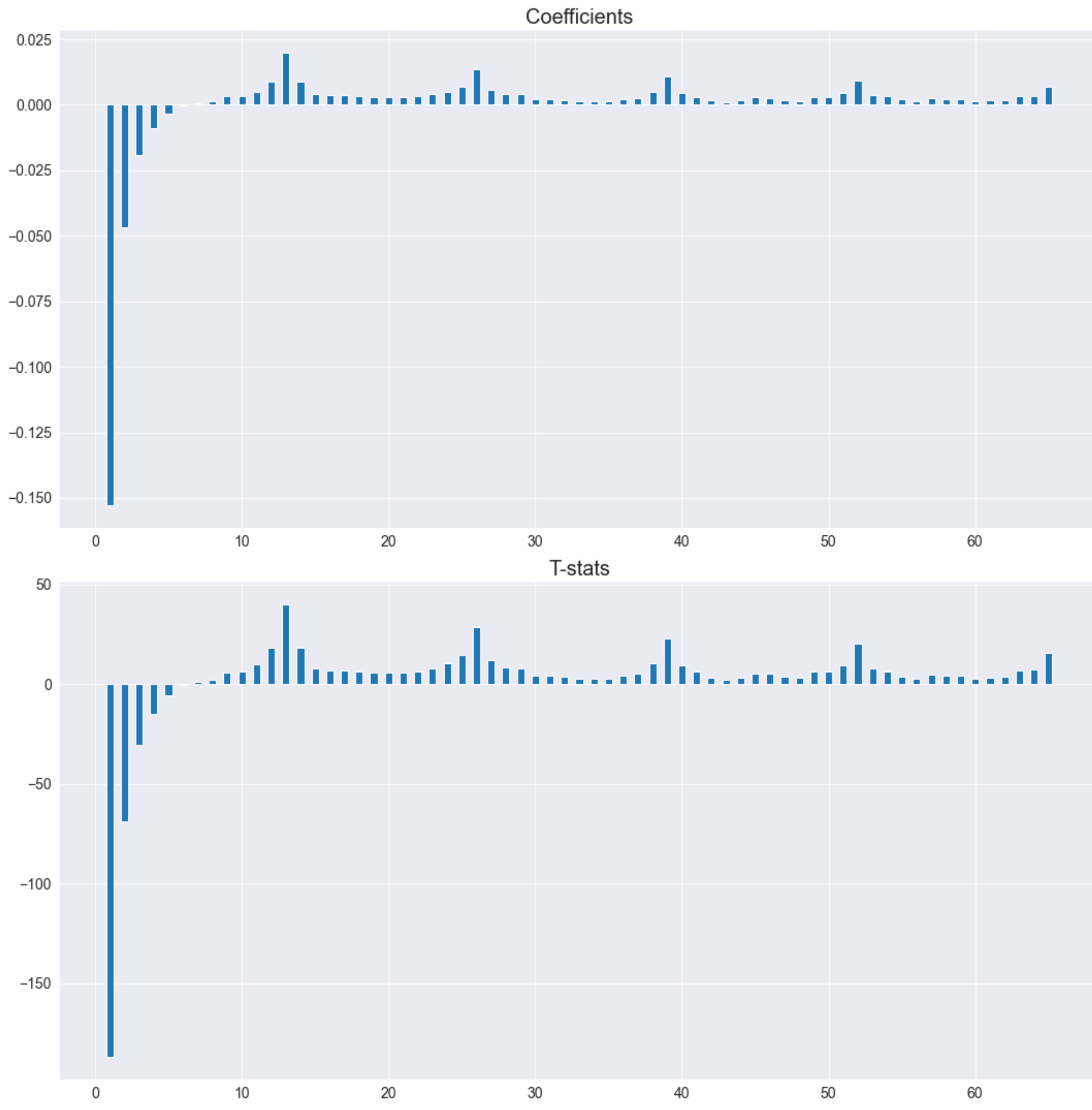


Figure 4: Cross-sectional regressions of half-hour-interval option returns: 5-day window

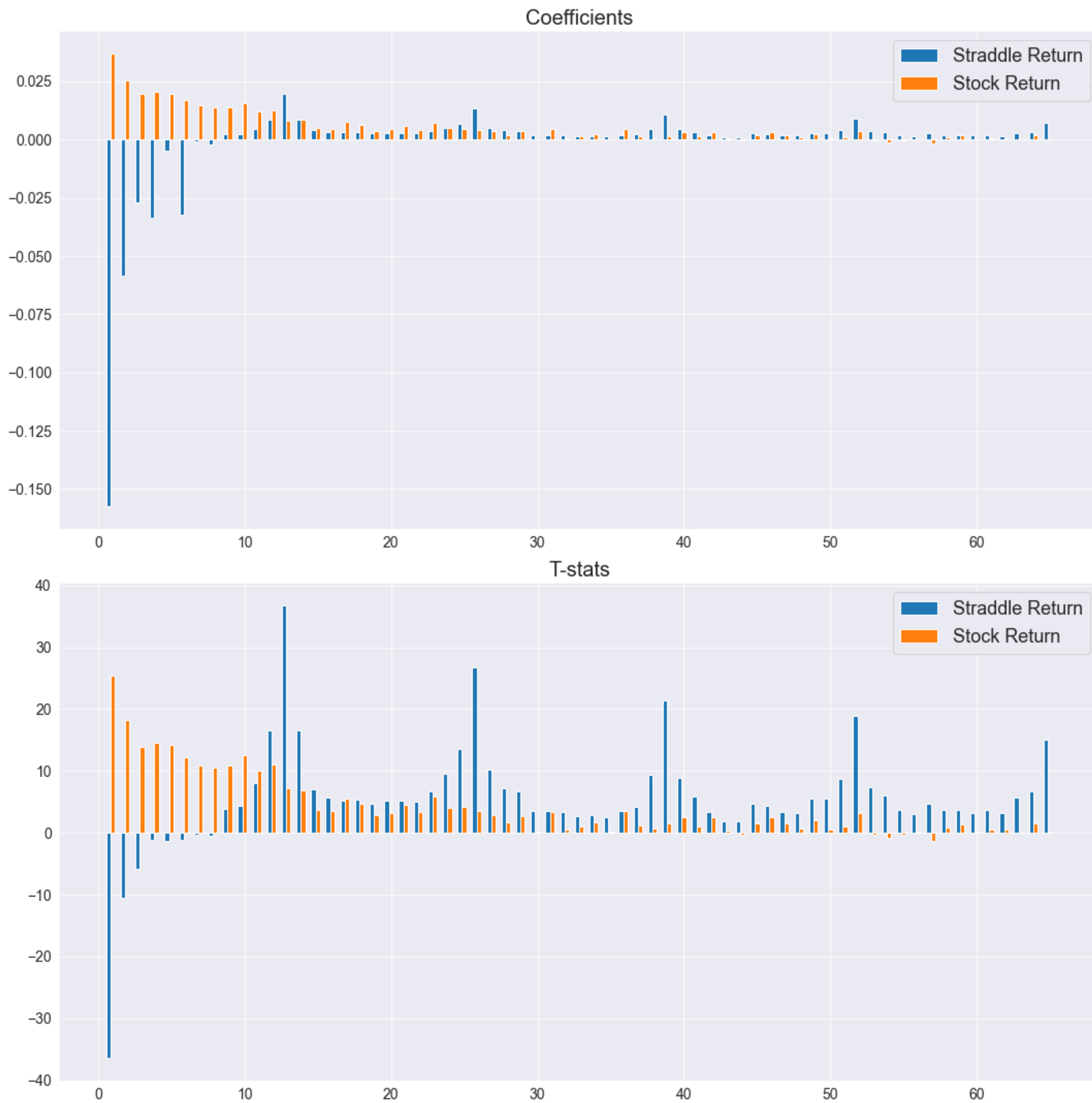


Figure 5: Cross-sectional regressions of half-hour-interval option returns, controlling for stock returns: 5 - day window